

**Examining the adoption, use and diffusion of
tablet devices: A study of small and medium
enterprises in Hungary**

**A Thesis Submitted to the University of Hertfordshire
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Abstract

This thesis addresses why tablet investments in small and medium-sized enterprises (SMEs) may result in routine, low-value use rather than employee-driven innovation. Focusing on Hungarian SMEs, it examines how individual-level factors and organisational support mechanisms shape post-adoption continuance and IT-enabled innovative behaviour with tablet devices.

An explanatory sequential mixed-methods design was employed. In Phase 1 (2014–15), a cross-sectional online survey of 1,040 tablet users in 21 Hungarian SMEs tested an integrated post-adoption model combining Unified Theory of Acceptance and Use of Technology (UTAUT) constructs (performance expectancy, effort expectancy, attitude), personal innovativeness in IT, and organisational support mechanisms (innovation support and involvement facilitation). Partial Least Squares Structural Equation Modelling showed that the model explains substantial variance in continuance intention and IT-enabled innovative behaviour. Organisational mechanisms exerted strong total effects, while personal innovativeness operated as a “double-edged sword”, enabling experimentation where support was present but fuelling frustration where it was absent.

In Phase 2 (2021), semi-structured interviews with 18 employees and managers from nine SMEs (drawn from the original sample) were analysed using the Gioia method. Four aggregate dimensions emerged, emphasising that the alignment between tasks and tablet-supported workflows, the maturation of tablet use over time, and organisational conditions and constraints together shape long-term appropriation.

Integrating both strands, the thesis deepens understanding of employee-driven digital innovation in resource-constrained SMEs, advances post-adoption theory, and offers practical guidance for SME managers and policymakers seeking to close the “second-level” digital divide from access to innovative use.

Keywords: Post-adoption, Innovative Behaviour, Tablets, SMEs, Hungary, Mixed-Methods, UTAUT

Dedication

To my dearest parents, whose love and unwavering support made this accomplishment possible. Thank you.

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1	INTRODUCTION	23
1.1	INTRODUCTION	23
1.2	RESEARCH PROBLEM	23
1.2.1	CONTEXT OF THE STUDY - SMALL AND MEDIUM ENTERPRISES	23
1.2.2	THE HUNGARIAN CONTEXT.....	24
1.2.3	THE CORE PUZZLE: A 'SECOND-LEVEL' DIGITAL DIVIDE.....	24
1.2.4	THE FALTERING BRIDGE: INNOVATIVE BEHAVIOUR AND ICT USE.....	25
1.2.5	THE RESEARCH GAP AND THE METHODOLOGICAL IMPERATIVE	26
1.3	RESEARCH AIM, OBJECTIVES AND RESEARCH QUESTIONS	28
1.3.1	RESEARCH AIM	28
1.3.2	RESEARCH OBJECTIVES.....	30
1.4	RESEARCH SCOPE.....	30
1.4.1	GEOGRAPHICAL AND ORGANISATIONAL SCOPE	31
1.4.2	TECHNOLOGY SCOPE	31
1.4.3	TEMPORAL SCOPE	31
1.4.4	THEORETICAL SCOPE.....	32
1.5	METHODOLOGICAL FRAMEWORK	32
1.5.1	PHILOSOPHICAL FOUNDATION AND RESEARCH DESIGN.....	32
1.5.2	PHASE 1: QUANTITATIVE CROSS-SECTIONAL ANALYSIS (2014-15)	33
1.5.3	PHASE 2: QUALITATIVE RETROSPECTIVE EVALUATION (2021)	33
1.5.4	PHASE 3: INTEGRATION AND META-INFERENCES	34
1.5.5	TEMPORAL GAP DISCUSSION	35
1.6	RESEARCH CONTRIBUTIONS.....	35
1.6.1	ACADEMIA.....	35
1.6.2	INDUSTRY	36
1.6.3	POLICYMAKERS.....	36
1.7	CHAPTER 1 SUMMARY	36
2	LITERATURE REVIEW & CONCEPTUAL THEORETICAL DEVELOPMENT	39
2.1	INTRODUCTION	39
2.2	CONTEXT REVIEW	40
2.3	THEORETICAL BACKGROUND	43
2.3.1	INTRODUCTION.....	43
2.3.2	DIGITAL DIVIDE.....	43
2.3.3	DIFFUSION OF INNOVATIONS	45
2.4	ICT ADOPTION, INNOVATION, AND DIGITAL TRANSFORMATION.....	48
2.4.1	ICT ADOPTION AND THE DASAT FRAMEWORK.....	48
2.4.2	EMPLOYEE-DRIVEN INNOVATION.....	52
2.4.3	POST-ADOPTION ICT USE IN SMES.....	55
2.4.3.1	INTRODUCTION	55
2.4.3.2	KEY THEMES IN POST-ADOPTION SME RESEARCH	56
2.4.3.3	RESEARCH GAPS AND LIMITATIONS.....	58
2.5	THEORETICAL FRAMEWORKS ON TECHNOLOGY ADOPTION.....	59
2.5.1	INTRODUCTION.....	59
2.5.2	THEORETICAL FRAMEWORK: UTAUT	60

2.5.2.1	SELECTING UTAUT	60
2.5.2.2	REVIEWING UTAUT.....	62
2.5.2.3	UTAUT APPLICABILITY TO SMES	67
2.5.3	INNOVATIVENESS, INNOVATIVE BEHAVIOUR AND INNOVATION	68
2.5.4	OVERVIEW.....	70
2.6	THEORETICAL AND CONCEPTUAL FRAMEWORK	70
2.6.1	MODEL DEVELOPMENT.....	70
2.6.2	CONSTRUCT DEFINITIONS.....	73
2.6.3	HYPOTHESES DEVELOPMENT.....	76
2.6.3.1	H1 PERFORMANCE EXPECTANCY → ATTITUDE	76
2.6.3.2	H2 PERFORMANCE EXPECTANCY → CONTINUANCE INTENTION	77
2.6.3.3	H3 EFFORT EXPECTANCY → ATTITUDE	77
2.6.3.4	H4 EFFORT EXPECTANCY → PERFORMANCE EXPECTANCY	78
2.6.3.5	H5 ATTITUDE → CONTINUANCE INTENTION.....	79
2.6.3.6	H6 ATTITUDE → IT-ENABLED INNOVATIVE BEHAVIOUR	79
2.6.3.7	H7 IT-ENABLED INNOVATIVE BEHAVIOUR → CONTINUANCE INTENTION.....	80
2.6.3.8	H8 PERSONAL INNOVATIVENESS IN IT → IT-ENABLED INNOVATIVE BEHAVIOUR.....	81
2.6.3.9	H9 INVOLVEMENT FACILITATION → IT-ENABLED INNOVATIVE BEHAVIOUR.....	81
2.6.3.10	H10 INNOVATION SUPPORT → IT-ENABLED INNOVATIVE BEHAVIOUR.....	82
2.6.3.11	H11 PERSONAL INNOVATIVENESS IN IT → CONTINUANCE INTENTION	83
2.6.3.12	H12 INNOVATION SUPPORT → INVOLVEMENT FACILITATION.....	83
2.6.3.13	H13 INNOVATION SUPPORT → PERFORMANCE EXPECTANCY.....	84
2.6.3.14	MEDIATION HYPOTHESES.....	85
2.6.4	MAPPING THE CONCEPTUAL MODEL TO THE DASAT CYCLE.....	87
2.7	CHAPTER SUMMARY AND CONCLUSION	90
3	RESEARCH METHODOLOGY	92
3.1	INTRODUCTION	92
3.2	RESEARCH METHODOLOGY FRAMEWORK	92
3.2.1	INTRODUCTION.....	92
3.2.2	PHILOSOPHIES	94
3.2.2.1	INTRODUCTION	94
3.2.2.2	POSITIVISM.....	95
3.2.2.3	INTERPRETIVISM	96
3.2.2.4	REALISM	96
3.2.2.5	PRAGMATISM	97
3.2.2.6	CONCLUSION	98
3.2.3	DEDUCTION	100
3.2.4	INDUCTION	100
3.2.5	ABDUCTION	100
3.2.6	OVERVIEW.....	101
3.3	METHODICAL CHOICES.....	102
3.3.1	QUANTITATIVE METHODS	102
3.3.2	QUALITATIVE METHODS.....	103
3.3.3	MIXED METHODS	104
3.3.3.1	MIXED METHODS: PARADIGMATIC STANCE	105
3.3.3.2	MIXED METHODS: TRIANGULATION	105

3.3.4	CAUSALITY AND INFERENCE	106
3.3.5	OVERVIEW.....	107
3.4	RESEARCH STRATEGIES.....	109
3.4.1	EXPERIMENT	109
3.4.2	SURVEY RESEARCH	109
3.4.3	CASE STUDY	111
3.4.4	ACTION RESEARCH	111
3.4.5	GROUNDING THEORY.....	112
3.4.6	ETHNOGRAPHY	113
3.4.7	ARCHIVAL RESEARCH	113
3.4.8	NARRATIVE INQUIRY	113
3.5	TIME HORIZONS	113
3.5.1	CROSS-SECTIONAL.....	113
3.5.2	LONGITUDINAL	114
3.6	SELECTED RESEARCH METHODOLOGY	114
3.6.1	PHILOSOPHY & METHODOLOGICAL CHOICE.....	114
3.6.2	APPROACH TO REASONING	115
3.6.3	STRATEGIES.....	115
3.6.4	TIME HORIZON	115
3.6.5	PRIMARY AND SECONDARY DATA SOURCES	115
3.7	QUANTITATIVE DATA COLLECTION AND DATA ANALYSIS TOOLS	116
3.7.1	INTRODUCTION.....	116
3.7.2	SELECTION OF QUANTITATIVE DATA ANALYSIS METHOD.....	116
3.7.3	QUANTITATIVE DATA COLLECTION PROCESS	119
3.7.4	SAMPLING	120
3.7.4.1	INTRODUCTION	120
3.7.4.2	PILOT STUDY SAMPLE SELECTION	120
3.7.4.3	MAIN STUDY SAMPLE SELECTION	121
3.7.5	CLUSTERING AND ROBUSTNESS	122
3.7.6	COMMON METHOD VARIANCE	123
3.7.7	DATA SCREENING.....	125
3.7.8	NONRESPONSE BIAS	126
3.7.9	SCALE DISCUSSION	127
3.7.10	MEASUREMENT AND STRUCTURAL MODEL EVALUATION PROTOCOL	128
3.8	QUALITATIVE DATA COLLECTION AND DATA ANALYSIS TOOLS	130
3.8.1	INTRODUCTION.....	130
3.8.2	SELECTION OF QUALITATIVE DATA ANALYSIS METHOD.....	130
3.8.2.1	INTRODUCTION	130
3.8.2.2	CONTENT ANALYSIS.....	131
3.8.2.3	THEMATIC ANALYSIS	131
3.8.3	THEMATIC ANALYSIS METHODS.....	132
3.8.3.1	REFLEXIVE THEMATIC ANALYSIS	132
3.8.3.2	CODEBOOK/TEMPLATE THEMATIC ANALYSIS	132
3.8.4	GIOIA METHODOLOGY: IMPLEMENTATION	133
3.8.5	INTERVIEW PROTOCOL AND SAMPLING	135
3.8.5.1	OVERVIEW.....	135
3.8.5.2	RECRUITMENT STRATEGY: GATEKEEPER-MEDIATED ACCESS.....	135
3.8.5.3	SELECTION CRITERIA FRAMEWORK.....	137

3.8.5.4	INTERVIEW PROTOCOL DESIGN	138
3.9	RESEARCH PLAN	139
3.9.1	DESIGN AND PURPOSE	139
3.9.2	PHASE 1 – QUANTITATIVE SURVEY (PRIMARY STRAND)	140
3.9.3	INTEGRATION POINT A – CONNECTING TO PHASE 2	141
3.9.4	PHASE 2 – QUALITATIVE INTERVIEWS (FOLLOW-UP STRAND)	142
3.9.5	INTEGRATION POINT B – INTERPRETATION & META-INFERENCES	142
3.9.6	INFERENCE QUALITY AND RIGOR	143
3.9.7	ETHICS AND GOVERNANCE	143
3.9.8	LIMITATIONS AND CONTINGENCIES	143
4	PILOT TEST AND FINAL SURVEY DEVELOPMENT	145
4.1	INTRODUCTION	145
4.2	PILOT SURVEY QUESTIONNAIRE DEVELOPMENT	145
4.3	DEVELOPMENT OF QUESTIONNAIRE	147
4.3.1	INTRODUCTION	147
4.3.2	CORE UTAUT CONSTRUCTS	149
4.3.3	INNOVATIVE BEHAVIOUR-RELATED CONSTRUCTS	150
4.3.4	SCALE DISCUSSION	152
4.4	CONTENT VALIDATION	152
4.5	PILOT TEST: ANALYSIS AND FINDINGS	154
4.5.1	SAMPLING AND SAMPLE SIZE	154
4.5.2	DEMOGRAPHICS AND DESCRIPTIVE STATISTICS	155
4.5.3	COMMON METHOD VARIANCE	157
4.5.4	LATENT FACTOR ANALYSIS	157
4.5.4.1	MULTICOLLINEARITY	157
4.5.4.2	FACTORABILITY	158
4.5.4.3	EXPLORATORY FACTOR ANALYSIS VS PRINCIPAL COMPONENT ANALYSIS	158
4.5.4.4	REFLECTIVE CONSTRUCTS AND EFA	159
4.5.4.5	FORMATIVE CONSTRUCTS AND PCA	160
4.5.5	MEASUREMENT MODEL RESULTS	161
4.5.5.1	ANALYSIS OF THE MEASUREMENT MODEL	161
4.6	PILOT CONCLUSIONS	163
4.7	CHAPTER SUMMARY	164
5	QUANTITATIVE ANALYSIS AND FINDINGS	166
5.1	INTRODUCTION	166
5.2	DATA COLLECTION AND DEMOGRAPHICS	168
5.2.1	SAMPLING	168
5.2.2	DATA SCREENING AND EXCLUSIONS	170
5.2.3	DATA NORMALITY	171
5.2.4	PARTICIPANTS AND SAMPLING FRAME	171
5.2.5	COMMON METHOD VARIANCE	175
5.2.6	NONRESPONSE BIAS	175
5.3	CORE ARCHITECTURE	176
5.3.1	INTRODUCTION	176
5.3.2	REFLECTIVE CONSTRUCT EVALUATION	177

5.3.2.1	FACTORABILITY	177
5.3.2.2	CONVERGENT VALIDITY AND RELIABILITY	177
5.3.2.3	DISCRIMINANT VALIDITY	178
5.3.3	FORMATIVE CONSTRUCT EVALUATION.....	179
5.3.3.1	ASSESS FOR COLINEARITY	179
5.3.3.2	EVALUATE OUTER WEIGHTS	179
5.3.3.3	CONTENT VALIDITY	180
5.3.4	STRUCTURAL MODEL ANALYSIS	181
5.3.4.1	INTRODUCTION	181
5.3.4.2	BASELINE MODEL ANALYSIS	181
5.4	UNDER THE HOOD ANALYSIS	185
5.4.1	MEDIATION OVERVIEW.....	185
5.4.2	MEDIATION TYPOLOGY AND SERIAL MEDIATION	186
5.4.3	MEDIATION ANALYSIS.....	187
5.4.4	FINAL MODEL.....	192
5.4.5	LEAVE-ONE-FIRM-OUT SENSITIVITY	197
5.5	BOUNDARY ANALYSIS	198
5.5.1	INTRODUCTION.....	198
5.5.2	MANAGEMENT LEVEL	200
5.5.3	GENDER	201
5.5.4	AGE.....	201
5.5.5	LOCATION.....	201
5.5.6	SECTOR	202
5.5.7	SAMPLE CONCENTRATION	202
5.5.8	OUTLIER ANALYSIS	203
5.5.9	NONRESPONSE BIAS ANALYSIS	204
5.5.10	MULTIGROUP ANALYSIS SUMMARY	204
5.6	TRANSLATING THEORY INTO ACTION	204
5.6.1	IPMA: CONTINUANCE INTENTION TARGET	205
5.6.2	IPMA: IT-ENABLED INNOVATIVE BEHAVIOUR TARGET	206
5.7	CHAPTER SUMMARY	207
5.7.1	OVERVIEW.....	207
5.7.2	KEY STATISTICAL RESULTS.....	209
6	QUALITATIVE ANALYSIS AND FINDINGS	213
6.1	INTRODUCTION	213
6.2	QUALITATIVE METHOD DATA COLLECTION.....	213
6.2.1	RESEARCH QUESTION FOR THE QUALITATIVE PHASE	213
6.2.2	FROM 21 CANDIDATE FIRMS TO 9 INTERVIEW SITES	215
6.2.3	RECRUITMENT	216
6.2.4	TEMPORAL CONTEXT AND RECRUITMENT LIMITATIONS	218
6.2.5	INTERVIEW PROTOCOL.....	219
6.2.6	INTERVIEW ADMINISTRATION.....	220
6.2.7	SATURATION ASSESSMENT: DATA AND THEORETICAL SATURATION	221
6.2.7.1	OVERVIEW.....	221
6.2.7.2	DATA AND THEORETICAL SATURATION	222
6.2.7.3	IMPLICATIONS FOR SAMPLE SIZE.....	223

6.2.8	ETHICAL AND GOVERNANCE PROCEDURES.....	224
6.3	DATA ANALYSIS PROCESS: APPLYING THE GIOIA METHODOLOGY	225
6.3.1	STAGE 1: OPEN CODING AND FIRST-ORDER CONCEPTS	225
6.3.2	STAGE 2: AXIAL CODING AND SECOND-ORDER THEMES	225
6.3.3	STAGE 3: SELECTIVE CODING AND AGGREGATE DIMENSIONS	225
6.3.4	WORKED EXAMPLE OF GIOIA CODING	226
6.3.5	GIOIA AGGREGATE DIMENSIONS AND THEMES	227
6.4	AGGREGATE DIMENSION 1: TASK-TECHNOLOGY FIT AND USE CONTEXTS	228
6.4.1	INTRODUCTION.....	228
6.4.2	THEME 1.1 READING & LIGHT DOCUMENTATION.....	229
6.4.3	THEME 1.2 MEETINGS & COLLABORATIVE WORK	230
6.4.4	THEME 1.3 ROLE-SPECIFIC WORKFLOWS	231
6.4.5	THEME 1.4: BOUNDARIES FOR COMPLEX WORK	232
6.4.6	AGGREGATE DIMENSION 1 SYNTHESIS.....	233
6.5	AGGREGATE DIMENSION 2: TECHNOLOGY MATURATION AND ADOPTION TRAJECTORIES	234
6.5.1	INTRODUCTION.....	234
6.5.2	THEME 2.1: ECOSYSTEM AND PLATFORM MATURATION	235
6.5.3	THEME 2.2: COVID-ACCELERATED CLOUD TRANSFORMATION	236
6.5.4	THEME 2.3: DISCONTINUOUS USAGE PATTERNS	237
6.5.4.1	THEME INTRODUCTION.....	237
6.5.4.2	MECHANISMS DRIVING DISCONTINUOUS USE.....	238
6.5.4.3	DISCONTINUITY AS RATIONAL ADAPTATION	239
6.5.5	AGGREGATE DIMENSION 2 SYNTHESIS.....	239
6.6	AGGREGATE DIMENSION 3: ORGANISATIONAL CONTEXT AND SUPPORT.....	241
6.6.1	INTRODUCTION.....	241
6.6.2	THEME 3.1: ORGANISATIONAL SUPPORT MECHANISMS	241
6.6.2.1	TRAINING AND PEER LEARNING	241
6.6.2.2	MANAGEMENT SUPPORT	242
6.6.3	THEME 3.2: INFRASTRUCTURE CONSTRAINTS	242
6.6.3.1	TECHNICAL INFRASTRUCTURE: CONNECTIVITY.....	242
6.6.3.2	DEVICE LIFECYCLE MANAGEMENT	243
6.6.4	THEME 3.3: FAILED ORGANISATIONAL ROLLOUTS	243
6.6.5	THEME 3.4: SUCCESSFUL ORGANISATIONAL ROLLOUTS.....	244
6.6.6	AGGREGATE DIMENSION 3 SYNTHESIS.....	245
6.7	AGGREGATE DIMENSION 4: INNOVATION-ORIENTED BEHAVIOURS AND EMERGENT USE.....	246
6.7.1	INTRODUCTION.....	246
6.7.2	THEME 4.1: PEER-DRIVEN INNOVATION DIFFUSION	246
6.7.3	THEME 4.2: EMERGENT INNOVATION PROCESSES	247
6.7.3.1	THEME INTRODUCTION.....	247
6.7.3.2	PRAGMATIC PATHWAY: OPPORTUNISTIC PROBLEM-SOLVING.....	247
6.7.3.3	LUDIC PATHWAY: PERIPHERAL EXPLORATION AND PLAYFUL DISCOVERY	248
6.7.3.4	OVERVIEW OF EMERGENT INNOVATION PROCESSES	248
6.7.4	THEME 4.3: CONSTRAINTS ON INNOVATION.....	249
6.7.4.1	THEME INTRODUCTION.....	249
6.7.4.2	TEMPORAL CONSTRAINTS.....	249
6.7.4.3	STRUCTURAL CONSTRAINTS	249
6.7.4.4	OVERVIEW OF CONSTRAINTS ON INNOVATION.....	250
6.7.5	AGGREGATE DIMENSION 4 SYNTHESIS.....	250

6.8	CHAPTER SUMMARY	251
7	DISCUSSION	253
7.1	INTRODUCTION	253
7.2	JOINT DISPLAY 1: PERFORMANCE EXPECTANCY	257
7.2.1	INTRODUCTION.....	257
7.2.2	THE PE MEASUREMENT	258
7.2.3	THE PE MEASUREMENT EVIDENCE FROM DATA.....	259
7.2.4	THE CI MEASUREMENT.....	261
7.2.5	DISCONTINUOUS USAGE DYNAMICS.....	262
7.2.6	DEVICE AND ECOSYSTEM MATURITY	264
7.2.7	SYNTHESIS – PE.....	264
7.3	JOINT DISPLAY 2: PERSONAL INNOVATIVENESS IN IT	267
7.3.1	INTRODUCTION.....	267
7.3.2	MECHANISM 1: POSITIVE INDIRECT PATH	269
7.3.3	MECHANISM 2: NEGATIVE DIRECT PATH	269
7.3.4	SYNTHESIS – PIIT.....	270
7.4	JOINT DISPLAY 3: IT-ENABLED INNOVATIVE BEHAVIOUR	274
7.4.1	INTRODUCTION.....	274
7.4.2	MECHANISM 1: OPERATIONAL TRANSLATION	274
7.4.3	MECHANISM 2: MOTIVATIONAL AMPLIFICATION	275
7.4.4	SYNTHESIS – ITIB.....	276
7.5	ATTITUDE AS THE AFFECTIVE BRIDGE	279
7.6	EFFORT EXPECTANCY: THE FORGOTTEN ENABLER	281
7.7	BETWEEN-METHOD TRIANGULATION: CONVERGENCE AND DIVERGENCE.....	283
7.7.1	INTRODUCTION.....	283
7.7.2	AREAS OF CONVERGENCE	283
7.7.3	PRODUCTIVE DIVERGENCES	283
7.7.4	INTEGRATION IMPLICATIONS.....	284
7.8	FRAMING THROUGH THE SECOND-LEVEL DIGITAL DIVIDE	286
7.8.1	INTRODUCTION.....	286
7.8.2	MOTIVATIONAL ACCESS MECHANISMS	287
7.8.3	SKILLS ACCESS MECHANISMS	287
7.8.4	USAGE ACCESS MECHANISMS	288
7.8.5	SYNTHESIS: CLOSING THE SECOND-LEVEL DIGITAL DIVIDE	290
7.9	CONTRIBUTIONS.....	292
7.9.1	ACADEMIA.....	292
7.9.2	INDUSTRY	292
7.9.3	POLICYMAKERS.....	293
7.10	IMPLICATIONS.....	293
7.10.1	ACADEMIA.....	293
7.10.2	INDUSTRY	293
7.10.3	POLICYMAKERS.....	294
7.11	SUMMARY	294
8	CONCLUSION.....	295
8.1.1	OVERVIEW OF THE STUDY.....	295

8.1.2	REFLECTING ON THE RESEARCH QUESTIONS.....	295
8.1.3	KEY INTEGRATED CONCLUSIONS	297
8.1.3.1	CONCLUSION 1.....	297
8.1.3.2	CONCLUSION 2.....	297
8.1.3.3	CONCLUSION 3.....	298
8.1.3.4	CONCLUSION 4.....	298
8.1.3.5	CONCLUSION 5.....	298
8.2	LIMITATIONS	299
8.2.1	TEMPORAL GAP AND ECOSYSTEM CHANGES (2014-15 vs. 2021).....	299
8.2.2	SME CONTEXT SPECIFICITY.....	299
8.2.3	TECHNOLOGY-SPECIFIC DYNAMICS.....	299
8.2.4	SELF-SELECTION IN QUALITATIVE SAMPLE	300
8.2.5	RETROSPECTIVE MEASUREMENT IN QUALITATIVE PHASE	300
8.2.6	SELF-REPORT AND SINGLE-INFORMANT DATA	300
8.2.7	POSITIVELY PHRASED ITEMS ACROSS THE INSTRUMENT	300
8.2.8	MODEL SPECIFICATION	301
8.3	RECOMMENDATIONS FOR FUTURE RESEARCH	302
8.3.1	INTRODUCTION.....	302
8.3.2	REPLICATING AND EXTENDING THE MODEL IN OTHER CONTEXTS	302
8.3.3	LONGITUDINAL DESIGNS AND USAGE TRAJECTORIES	302
8.3.4	REFINING MEASURES OF TASK-SPECIFIC PERFORMANCE AND CONTINUANCE	302
8.3.5	MULTILEVEL PERSPECTIVES AND ORGANISATIONAL BOUNDARY CONDITIONS	303
8.3.6	SECOND-LEVEL DIGITAL DIVIDE, POLICY AND INTERVENTION STUDIES.....	303
8.3.7	OVERVIEW.....	304
8.4	PERSONAL REFLECTIONS.....	304
	BIBLIOGRAPHY	306
Appendix A	Definitions and Acronyms	336
Appendix B	Context Overview	341
Appendix B1.	SME Definition.....	341
Appendix B2.	Hungarian SMEs Overview	341
Appendix B3.	Tablet Devices Overview	346
Appendix C	Innovativeness and Related Streams	350
Appendix D	Framework Model Comparison	356
Appendix E	Ethics Process and Clearance	363
Appendix F	Philosophies and Paradigm Reviews	365
Appendix F1.	Methodology Development Options.....	365
Appendix F2.	Philosophies and Paradigms.....	367
Appendix F3.	Mixed Methods Paradigmatic Stances	372
Appendix G	Pilot Data.....	374
Appendix G1.	Lawshe Content Validation Table	374

Appendix G2.	Pilot Statistical Data	375
Appendix H	Pilot and Final Survey.....	379
Appendix H1.	Pilot Survey	379
Appendix H2.	Final Survey	381
Appendix H3.	Survey Invitation Letter	383
Appendix H4.	Sample Data Protection Letter	385
Appendix H5.	Sample Acceptance Letter	386
Appendix I	Final Survey Statistics	387
Appendix I1.	Multicollinearity Statistics	387
Appendix I2.	Final Survey Descriptive Statistics	388
Appendix I3.	SME Descriptive Data	389
Appendix I4.	Factor Analysis Tests	389
Appendix I5.	Baseline Model Data	391
Appendix I6.	Fully Augmented Model Data.....	393
Appendix I7.	Final Model Data	395
Appendix I8.	Final Model Mediation Data.....	399
Appendix J	Final Survey Multigroup Analysis Data.....	401
Appendix J1.	MGA Model Data	401
Appendix J2.	MGA Management Level	401
Appendix J3.	MGA Gender	406
Appendix J4.	MGA Age	409
Appendix J5.	MGA Location.....	416
Appendix J6.	MGA Sector	423
Appendix J7.	MGA Size	431
Appendix J8.	MGA Outlier	439
Appendix J9.	MGA Wave Analysis for Nonresponse Bias.....	439
Appendix K	Interview Documentation	440
Appendix K1.	Interview Firm Selection Criteria.....	440
Appendix K2.	Interview Protocol.....	441
Appendix K3.	Gatekeeper Email for Qualitative Follow-up.....	444
Appendix L	Gioia Analysis Further Details	446
Appendix L1.	Stage 1: Open Coding and First-Order Concepts.....	446

Appendix L2.	Stage 2: Axial Coding and Second-Order Themes	447
Appendix L3.	Stage 3: Selective Coding and Aggregate Dimensions.....	447
Appendix M	Gioia Coding Examples	449
Appendix N	Extended Contributions	458
Appendix N1.	Academia	458
Appendix N2.	Industry	459
Appendix N3.	Policymakers	460
Appendix O	Extended Implications	462
Appendix O1.	Academia	462
Appendix O2.	Industry.....	464
Appendix O3.	Policymakers	466

List of Tables

Table 1.1 Detailed research questions showing explanatory sequential design	29
Table 1.2 Thesis structure overview	37
Table 2.1 Classification of EDI processes	54
Table 2.2 Summary of ICT Adoption Frameworks	61
Table 2.3 Constructs for conceptual model	73
Table 2.4. Conceptual model to DASAT Mapping	89
Table 3.1 Philosophy Overview	94
Table 3.2 Rationale for PLS-SEM	118
Table 3.3 Procedural remedies for Common Method Bias	123
Table 3.4 PLS-SEM standards summary table.....	129
Table 4.1 Constructs for the conceptual model	147
Table 4.2. Expert Panel.....	153
Table 4.3 Pilot demographics data	156
Table 4.4 Pilot descriptive statistics.....	156
Table 4.5 PLS-SEM standards summary table.....	161
Table 4.6 Pilot validity and reliability.....	162
Table 4.7 Pilot discriminant validity	162
Table 4.8 Pilot HTMT analysis	163
Table 5.1 Construct names and abbreviations	166
Table 5.2 Summary of initial H1-H13 hypotheses.....	167
Table 5.3 Location and sector	172
Table 5.4 Organisational role by sector (n, column % within sector).....	173
Table 5.5 Age × gender distribution (n, % of total).....	173
Table 5.6 Nonresponse bias statistics	176
Table 5.7 PLS-SEM standards summary table.....	177
Table 5.8 Latent variables final data analysis.....	177
Table 5.9 Discriminant validity final data analysis.....	178
Table 5.10 HTMT final data analysis	179
Table 5.11 Outer weights initial run	179
Table 5.12 Critical IS-IF items	180
Table 5.13 Hypothesis summary baseline model	182
Table 5.14 R ² of latent variables baseline model.....	183
Table 5.15 Effect size (f ²) baseline model	184

Table 5.16 Construct cross-validated redundancy (Q^2 predict) baseline model	185
Table 5.17 M1 mediation analysis	187
Table 5.18 M2 mediation analysis	187
Table 5.19 M3 mediation analysis	188
Table 5.20 M4 mediation analysis	188
Table 5.21 M5 mediation analysis	189
Table 5.22 M6 mediation analysis	189
Table 5.23 M7 mediation analysis	190
Table 5.24 M8 mediation analysis	190
Table 5.25 M9 mediation analysis	191
Table 5.26 M10 mediation analysis	191
Table 5.27 M11 mediation analysis	191
Table 5.28 M12 mediation analysis	192
Table 5.29 Baseline and final model comparison	194
Table 5.30 Hypothesis summary	195
Table 5.31 Mediator chains final model	196
Table 5.32 MICOM steps with description	198
Table 5.33 Importance–Performance Map for Continuance Intention (CI)	205
Table 5.34 Importance–Performance Map for IT-enabled Innovative Behaviour (ITIB)	207
Table 5.35 Hypothesis summary (final model)	209
Table 5.36 Significant indirect effects on CI (final model)	211
Table 5.37 Significant indirect effects on ITIB (final model)	211
Table 5.38 Total effects (final model)	212
Table 6.1 Construct names and abbreviations	214
Table 6.2 SME interviewee list	217
Table 6.3 Gioia ladder worked example	227
Table 6.4 Gioia data structure from first-order concepts to aggregate dimensions	228
Table 7.1 Joint display overview	253
Table 7.2 Gioia data structure from first-order concepts to aggregate dimensions	255
Table 7.3 Construct names and abbreviations	255
Table 7.4 Joint display 1: PE	266
Table 7.5 Joint display 2: PIIT	272
Table 7.6 Joint display 3: ITIB	277

List of Appendix Tables

Table 9.1 Definitions / Acronyms.....	336
Table 9.2 SME Definition European Commission (European Commission, 2005)	341
Table 9.3 Enterprises in the EU-28 in 2013 (Muller et al., 2014)	341
Table 9.4 Enterprises in Hungary in 2013 (European Commission, 2014).....	342
Table 9.5 Enterprise typology in Hungary (adapted from Vecsenyi 1999 p 49).....	343
Table 9.6 Overview of Innovation and Innovativeness.....	350
Table 9.7 ITIB Streams	351
Table 9.8 Overview of Use Innovativeness Streams of Research	353
Table 9.9 Use Innovativeness Constructs and Items.....	354
Table 9.10 Six-Stage IT Implementation Model (Cooper & Zmud, 1990 p 124-125).....	362
Table 9.11 Ethics Summary	363
Table 9.12 Research Methodology Frameworks (adapted from Crotty, 1998).....	366
Table 9.13 Paradigms at a Glance	370
Table 9.14 CVR calculation.....	374
Table 9.15 Pilot full descriptive statistics	375
Table 9.16 Pilot Kaiser-Meyer-Olkin measure	376
Table 9.17 Pilot Bartlett's sphericity test.....	376
Table 9.18 Pilot VIF	377
Table 9.19 Pilot factor analysis results	377
Table 9.20 Pilot PCA results	378
Table 9.21 Multicollinearity statistics	387
Table 9.22 Final survey descriptive statistics	388
Table 9.23 SME Response Data.....	389
Table 9.24 KMO final model.....	389
Table 9.25 Bartlett's test final model.....	390
Table 9.26 PCA final model.....	390
Table 9.27 Baseline model data.....	391
Table 9.28 Baseline model outer loadings.....	392
Table 9.29 Baseline model outer weights.....	393
Table 9.30 Augmented model data	393
Table 9.31 R ² of Latent Variables Final Model	395
Table 9.32 f ² Final Model	395

Table 9.33 Construct Cross Validated Redundancy (Q^2 predict) Final Model	397
Table 9.34 Final model data	397
Table 9.35 Significant indirect effects (final model, bootstrapped, two-tailed)	399
Table 9.36 MGA model path coefficients	401
Table 9.37 MGA model R^2	401
Table 9.38 Management levels for group analysis	402
Table 9.39 Compositional invariance (Employee vs Manager) initial results	402
Table 9.40 Compositional invariance (Employee vs Manager) updated results	403
Table 9.41 Equality of means (Employee vs Manager)	403
Table 9.42 Equality of variances (Employee vs Manager)	404
Table 9.43 Path coefficients (Employee vs Manager)	404
Table 9.44 R^2 differences (Employee vs Manager)	405
Table 9.45 f^2 differences (Employee vs Manager)	405
Table 9.46 Gender records for MGA	406
Table 9.47 Compositional invariance, means and variances (Male vs Female)	406
Table 9.48 Path coefficients (Male vs Female)	407
Table 9.49 R^2 differences (Male vs Female)	408
Table 9.50 f^2 differences (Male vs Female)	408
Table 9.51 Age records for MGA	410
Table 9.52 Compositional invariance, means and variances (18-30 vs 31-40)	410
Table 9.53 Path coefficients (18-30 vs 31-40)	410
Table 9.54 R^2 differences (18-30 vs 31-40)	411
Table 9.55 f^2 differences (18-30 vs 31-40)	411
Table 9.56 Compositional invariance, means and variances (18-30 vs 41-80)	412
Table 9.57 Path coefficients (18-30 vs 41-80)	412
Table 9.58 R^2 differences (18-30 vs 41-80)	413
Table 9.59 f^2 differences (18-30 vs 41-80)	413
Table 9.60 Compositional invariance, means and variances (31-40 vs 41-80)	414
Table 9.61 Path coefficients (31-40 vs 41-80)	415
Table 9.62 R^2 differences (31-40 vs 41-80)	415
Table 9.63 f^2 differences (31-40 vs 41-80)	416
Table 9.64 Compositional invariance, means and variances (Capital vs City)	417
Table 9.65 Path coefficients (Capital vs City)	418
Table 9.66 R^2 differences (Capital vs City)	418

Table 9.67 f^2 differences (Capital vs City)	419
Table 9.68 Compositional invariance, means and variances (Capital vs Rural).....	419
Table 9.69 Path coefficients (Capital vs Rural).....	420
Table 9.70 R^2 differences (Capital vs Rural).....	420
Table 9.71 f^2 differences (Capital vs Rural)	421
Table 9.72 Compositional invariance, means and variances (City vs Rural).....	421
Table 9.73 Path coefficients (City vs Rural).....	422
Table 9.74 R^2 differences (City vs Rural)	422
Table 9.75 f^2 differences (City vs Rural).....	423
Table 9.76 Sector data for MGA.....	425
Table 9.77 Compositional invariance, means and variances (ICT vs Manufacturing)	425
Table 9.78 Path coefficients (ICT vs Manufacturing)	425
Table 9.79 R^2 differences (ICT vs Manufacturing)	426
Table 9.80 f^2 differences (ICT vs Manufacturing).....	426
Table 9.81 Compositional invariance, means and variances (ICT vs Services).....	427
Table 9.82 Path coefficients (ICT vs Services).....	427
Table 9.83 R^2 differences (ICT vs Services).....	428
Table 9.84 f^2 differences (ICT vs Services)	428
Table 9.85 Compositional invariance, means and variances (Manufacturing vs Services)	429
Table 9.86 Path coefficients (Manufacturing vs Services)	430
Table 9.87 R^2 differences (Manufacturing vs Services)	430
Table 9.88 f^2 differences (Manufacturing vs Services).....	431
Table 9.89 SME size data for MGA.....	432
Table 9.90 Compositional invariance, means and variances (SME16 vs SME19).....	432
Table 9.91 Path coefficients (SME16 vs SME19).....	433
Table 9.92 R^2 differences (SME16 vs SME19).....	433
Table 9.93 f^2 differences (SME16 vs SME19)	434
Table 9.94 Compositional invariance, means and variances (SME16 vs SMEREST)	434
Table 9.95 Path coefficients (SME16 vs SMEREST)	435
Table 9.96 R^2 differences (SME16 vs SMEREST)	436
Table 9.97 f^2 differences (SME16 vs SMEREST).....	436
Table 9.98 Compositional invariance, means and variances (SME19 vs SMEREST)	437
Table 9.99 Path coefficients (SME19 vs SMEREST)	437
Table 9.100 R^2 differences (SME19 vs SMEREST)	438

Table 9.101 f^2 differences (SME19 vs SMEREST)	438
Table 9.102 Compositional invariance, means and variances (FULL vs OUTLIER)	439
Table 9.103 Compositional invariance, means and variances (Early vs Late)	439
Table 9.104 SME shortlist for interviews	440
Table 9.105 SME z-scores for shortlist.....	441
Table 9.106 Interview protocol	441
Table 9.107 Gioia coding examples (first-level).....	455

List of Figures

Figure 1.1 Three-phase explanatory sequential mixed-methods design	33
Figure 2.1 Reader's roadmap	39
Figure 2.2 Digital Transformation Framework (DASAT) (Kahveci, 2025).....	51
Figure 2.3 UTAUT Model	64
Figure 2.4 Expectation Confirmation Model (Bhattacharjee, 2001).....	65
Figure 2.5 Conceptual model for continuance and IT-enabled innovative behaviour in SMEs ...	73
Figure 2.6 Dual-track mapping: DASAT and UTAUT	88
Figure 3.1. Research Methodology Onion (adapted from Saunders et al., 2019)	93
Figure 3.2 Research plan	140
Figure 5.1 Conceptual model for continuance and IT-enabled innovative behaviour in SMEs .	168
Figure 5.2 Gantt chart with survey waves in SMEs	169
Figure 5.3 Sector composition by location	172
Figure 5.4 Baseline structural model (theory-constrained)	182
Figure 5.5 Mediation outcomes (adapted from Zhao et al. 2010)	186
Figure 5.6 Final structural model	195
Figure 5.7 IPMA Continuance Intention.....	205
Figure 5.8 IPMA IT-enabled Innovative Behaviour	206
Figure 6.1 Conceptual model for continuance and IT-enabled innovative behaviour in SMEs .	215
Figure 6.2 Gioia information saturation curve	223
Figure 7.1. Digital Transformation Framework (DASAT) (Kahveci, 2025).....	256
Figure 7.2 Dual-track mapping: DASAT and UTAUT	257

List of Appendix Figures

Figure 9.1 Innovative Activities EU-27 vs Hungary 2010 (European Commission, 2014)	345
Figure 9.2 Worldwide Tablet Shipments 2010-2024 (million units) (IDC, 2025b)	347
Figure 9.3 Task Technology Fit Model (Goodhue & Thompson, 1995)	357
Figure 9.4 TAM and TTF Combined Model (Dishaw & Strong, 1999)	357
Figure 9.5 Reasoned-Action Approach	358
Figure 9.6 Technology Acceptance Model (Davis, 1989)	359
Figure 9.7 TAM-based Models (Venkatesh & Bala, 2008)	360
Figure 9.8 Integrated TAM-User Satisfaction Model	361
Figure 9.9 Methods Map (adapted from O’Gorman & MacIntosh, 2015)	366
Figure 9.10 Gioia example	457

1 INTRODUCTION

1.1 Introduction

This chapter presents the research problem of this research study by commencing with an introduction to the SME context and the specific characteristics of Hungarian SMEs, then articulates the core research puzzle around the second-level digital divide and innovative use of ICT. The chapter proceeds to set out the research aim, objectives, and questions, followed by a statement of the study's scope and boundaries. A brief overview of the mixed-methods methodological framework is then provided, along with a summary of the anticipated contributions to academic theory, management practice, and public policy. The chapter concludes with an outline of the structure of the thesis.

1.2 Research Problem

1.2.1 Context of the Study - Small and Medium Enterprises

Small and Medium Enterprises (SMEs) are widely recognised as the backbone of economic development, both globally and within the European Union (EU) (Ayyagari et al., 2007; Bella et al., 2024). The definition of Small and Medium Enterprises varies greatly across relevant organisations and countries (Ayyagari et al., 2007; Nandan, 2009). This study follows the EU statistical convention of defining SMEs as enterprises with fewer than 250 employees, and these firms represent 99.8% of all enterprises in the EU-27, employing 65.2% of the workforce and generating 53.1% of the total gross value added (GVA) as of 2023 (Bella et al., 2024).

However, this economic backbone is fragile (Eggers, 2020). SMEs face distinctive challenges that differentiate them from larger enterprises, most notably resource constraints and limited access to financing (Miklian & Hoelscher, 2021). These constraints become especially pronounced during economic downturns, as evidenced by the prolonged recovery period following the 2007-2009 financial crisis or the COVID-19 pandemic (Eggers, 2020; Miklian & Hoelscher, 2021).

To provide a historical example, the 2007-2009 financial crisis severely impacted SMEs across the EU (Muller et al., 2014). During the initial crisis period (2008-2011), SMEs showed resilience in some areas compared to large enterprises. However, by 2012 they were trailing large enterprises both in terms of employment and value added (Muller et al., 2014). It was only by 2017 that the EU-27 overall reported a full recovery and considerable growth in the SME sector (average 3.5% per year) (Muller et al., 2017). This recovery backdrop formed the context for SMEs participating in the questionnaire wave of this study (2014-2015).

1.2.2 The Hungarian Context

This fragility is especially pronounced in the post-transition economies of Central and Eastern Europe. Even in 2017, Hungarian SMEs were still lagging behind their EU counterparts in terms of the number of enterprises, employment, and GVA growth (Muller et al., 2017).

One potential pathway for improvement focuses on Information and Communication Technologies¹ (ICT) usage in SMEs (Nandan, 2009; Passerini et al., 2012; Passerini et al., 2007). In terms of connectivity and broadband infrastructure, Hungary seems to be doing well: Very High-Capacity Network (VHCN) coverage is above the EU average (84.1% vs 78.8%), and Fibre to the Premises (FTTP) coverage is standing at 76.2% against an EU average of 64% (European Commission, 2025).

However, Hungarian firms face deep structural challenges rooted in post-socialist transition dynamics and persistent digitalisation gaps (Endrődi-Kovács & Stukovszky, 2022; European Commission, 2025; Papanek, 2010). Hungary consistently ranks below the EU average on digital economy indicators, placing 21st out of 28 EU members in the Digital Economy and Society Index (DESI) as of 2020 (European Commission, 2025). Even worse, only 10-20% of Hungarian SMEs are considered digitalised, positioning the country 26th out of 28 in business digitalisation and e-commerce metrics (Endrődi-Kovács & Stukovszky, 2022).

Recent improvements show promise (e.g. cloud adoption 37% versus EU average 39%) (Mihályi & Molnár, 2025; Smartcommerce Consulting, 2024). However, representative data from 600 Hungarian SMEs (February 2024) reveals a complex digitalisation landscape characterised by "islands of maturity" alongside structural weaknesses. While digital finance capabilities have improved (65% adoption rate driven by online banking and e-invoicing), critical areas such as AI adoption (3.7% vs. EU 8%) and online sales capability (70% conducting no online sales) remain underdeveloped (Smartcommerce Consulting, 2024).

1.2.3 The Core Puzzle: A 'Second-Level' Digital Divide

This digitalisation usage gap reveals a critical research blind spot. Some Hungarian SMEs do not suffer from a traditional 'first-level' digital divide (van Dijk, 2012): they have devices and connectivity (Endrődi-Kovács & Stukovszky, 2022; Marciniak et al., 2021). The problem is a

¹ In its most generic form, Information Communication Technology – ICT – represents technologies that support data and information processing, storage and analysis, as well as data and information transmission and communication, via the Internet and other means, see Weber, D. M., & Kauffman, R. J. (2011). What drives global ICT adoption? Analysis and research directions. *Electronic Commerce Research and Applications*, 10(6), 683-701. <https://doi.org/10.1016/j.elerap.2011.01.001>

'second-level' digital divide: a gap in skills access and usage access (Hargittai, 2002; Van Dijk, 2019).

Various programs supported Hungarian SMEs in access to ICT (e.g., Sándor Demján Programme) (European Commission, 2025; Marciniak et al., 2021; Szigethy-Ambrus, 2025). However, the premise of this study is that even those firms that have solved the access problem and employees have been provisioned with devices may face challenges.

These firms face a 'second-level' digital divide: gaps in skills and usage capabilities that prevent employees from appropriating technology for meaningful, productive, and innovative work (Endrődi-Kovács & Stukovszky, 2022). This is the critical juncture where technology deployment fails to become value creation. The mere presence of a device does not guarantee its effective use (Jasperson et al., 2005; Sabeh et al., 2021). This multi-dimensional divide creates an imperative to move beyond firm-level adoption metrics and examine the employee-level beliefs, attitudes, and behaviours that directly drive technology value creation. The central puzzle of this research is to understand why this paradox exists.

1.2.4 The Faltering Bridge: Innovative Behaviour and ICT Use

Understanding this paradox requires recognising that the bridge between technology adoption and value creation often falters because organisations focus on continuance rather than innovation. These are two fundamentally different post-adoption outcomes: merely continuing to use technology versus innovatively appropriating it to create value:

- Continuanace Intention (CI): The intention to simply continue using the technology for its prescribed functions (Nabavi et al., 2016). This represents a baseline level of acceptance but may not, in itself, generate new value.
- IT-enabled Innovative Behaviour (ITIB): The intention and enacted behaviours through which employees generate ideas, champion them, and translate them into practice (Hoyrup et al., 2012; Torkzadeh et al., 2005). This is the mechanism of Employee-Driven Innovation (EDI) and represents the true return on investment, where employees actively repurpose the general-purpose tool to solve new problems, optimise workflows, and create novel value (Hoyrup et al., 2012).

ICT adoption and use, particularly mobile information technologies, are presented as a solution to SME constraints, offering competitive advantages through streamlined internal processes, cost reductions, and enhanced innovation capacity (Dibrell et al., 2008; Hervé et al., 2020; Passerini

et al., 2012; Tarutė & Gatautis, 2014). The tablet² device is an ideal focal technology for studying this phenomenon. Its general-purpose nature, mobility, and touch interface create 'affordances'—opportunities for action—that support both routine work and emergent, innovative applications (Magsamen-Conrad et al., 2015; Quade & Leimstoll, 2017).

1.2.5 The Research Gap and the Methodological Imperative

Most mobile ICT-related studies in organisations are consumer-focused (e.g. Chong et al., 2012; Venkatesh et al., 2012) or executed in an educational or academic environment (e.g. Alvarez et al., 2011; Courtois et al., 2014; Çuhadar, 2014). Even in organisational studies, the user-centric approach to mobile commerce is mostly discussed, including the evaluation of efficiency and effectiveness in specific use cases (e.g. Gebauer & Ginsburg, 2009; Gebauer & Shaw, 2004). More technical papers focus on specific functionalities, such as cloud computing (Gupta et al., 2013) or security concerns (Mark & Karen, 2014).

Innovation studies in SMEs typically apply organisational lenses (e.g. Gumusluoğlu & Ilsev, 2009; Scozzi et al., 2005; Taródy, 2012), but there is limited empirical research that examines how a specific technology prompts innovative behaviour at the individual and socio-technical levels (Xerri & Brunetto, 2011).

While recent work has begun examining the overall value of smartphones and tablets in SMEs (Quade & Leimstoll, 2017), the mechanisms linking tablet capabilities to employee-driven innovation remain underexplored.

Beyond mobile ICT and tablet-specific work, a substantial body of information systems research has examined the adoption and continuous use of organisational technologies more generally. Continuance models such as the expectation-confirmation model and the technology continuance model show that post-adoption behaviour is shaped by users' evolving evaluations of usefulness, ease of use, satisfaction and habit rather than by initial adoption drivers alone (Bhattacharjee & Lin, 2015; Limayem et al., 2007). However, these models primarily focus on continuance intention and satisfaction; they do not explicitly discuss employee-driven innovation as a post-adoption outcome.

² Tablet device is defined as a mobile computer that is easy to carry due to its slate-shape, has a minimum 7 inch color display and supports direct input via a touchscreen or pen-enabled interface, see Alvarez, C., Brown, C., & Nussbaum, M. (2011). Comparative study of netbooks and tablet PCs for fostering face-to-face collaborative learning. *Computers in Human Behavior*, 27(2), 834-844. <https://doi.org/10.1016/j.chb.2010.11.008>

A limited number of studies emphasise that employees repeatedly decide which features to appropriate, extend or abandon, producing extended, integrated or emergent usage patterns over time (Al-Natour & Benbasat, 2009; Jasperson et al., 2005). While these studies clarify generic mechanisms of technology continuance, they are typically conducted in larger organisations, focus on specific enterprise systems (e.g. ERP, web services) and rarely address resource-constrained SMEs or general-purpose mobile devices used across diverse work tasks.

In SME contexts, empirical work on post-adoption and continuance has tended to concentrate on particular application domains. For example, Al-Hattami et al. (2023) find that perceived relative advantage shapes both attitude and satisfaction, which in turn drive continued use of digital accounting solutions. Sectoral and country studies using firm-level indicators likewise show that post-adoption benefits depend on aligning ICT with existing processes and capabilities (Giotopoulos et al., 2017). However, as the systematic review in Chapter 2 demonstrates, such studies are fragmented across sectors and technologies and only partially clarify how individual employees in SMEs creatively extend ICT in their daily work.

Taken together, this literature exhibits important limitations that define the research gap for the present study. Most SME studies adopt firm-level perspectives (e.g., owner-manager attitudes, aggregate ICT indices) or focus on narrow systems such as accounting, e-commerce or ERP. They are predominantly cross-sectional, capturing only a single snapshot of use, and typically operationalise post-adoption success as continuance intention rather than innovative appropriation or creative use of technology. Chapter 2 highlights additional gaps: limited longitudinal evidence on how SME ICT use evolves over time, theoretical fragmentation across adoption and continuance frameworks, measurement challenges in capturing innovative work behaviour, and very little tablet-specific post-adoption research in Central and Eastern European SMEs.

Studies employing technology acceptance models such as the Unified Theory of Acceptance and Use of Technology (UTAUT) can predict which factors correlate with use. For example, a quantitative model might show that managerial support predicts innovative IT use. However, such models are largely silent on the 'how' and 'why': they cannot explain the lived mechanisms through which these relationships unfold in specific contexts. Qualitative explanation is therefore required to complement and deepen the insights derived from such models.

These limitations create a three-fold research gap: (1) a contextual gap concerning post-adoption use in SME organisational settings rather than consumer or educational contexts; (2) a theoretical gap regarding innovative behaviour at the individual socio-technical level rather than solely

through organisational lenses; and (3) a methodological gap, where mixed-methods designs are needed to connect the ‘what’ with the ‘how’ and ‘why’ of post-adoption outcomes. This dissertation responds to this methodological imperative by employing an explanatory sequential mixed-methods design. A large-scale quantitative survey is first used to model the relationships between individual factors, organisational support and innovative behaviour (the ‘what’). Guided by these results, an in-depth qualitative interview study then explores the socio-technical mechanisms that drive these relationships in practice (the ‘how’ and ‘why’), with the integrated interpretation presented in Chapter 7.

1.3 Research Aim, Objectives and Research Questions

1.3.1 Research Aim

Motivated by the identified gaps on post-adoption ICT use in SMEs, the limited focus on employee-driven innovation at the individual level, and the scarcity of studies involving tablet usage in under-digitalised EU regions, this research seeks a deeper insight into these areas, geographically concentrating on Hungary as a context where these gaps can be meaningfully explored, the following aim is formed:

To examine and understand how individual-level factors and organisational support mechanisms shape the post-adoption use and innovative appropriation of tablet devices by employees in Hungarian SMEs.

A core methodological limitation in existing research on technology adoption and post-adoption use—particularly in SMEs—is that research questions are typically aligned with a single-method design. Quantitative studies tend to pose confirmatory, deductive questions (e.g. “How does X influence Y?” or “Does the model fit the data?”), which are well-suited to testing structural relationships but do not discover underlying mechanisms. Conversely, qualitative studies often formulate open, process-oriented questions (e.g. “How do practices emerge or develop over time?”) without being explicitly linked to prior quantitative findings. As mixed-methods scholars note, this separation weakens inference quality because it prevents systematic integration of predictive and explanatory insights (Merchant et al., 2021; Tashakkori & Creswell, 2007). This thesis directly addresses that methodological limitation by explicitly structuring its research questions across quantitative, qualitative and integrative strands within a single explanatory sequential design.

For this study, a principal research question was developed first. Then, according to the guidelines of mixed-methods research, sub-questions were developed with a quantitative, qualitative, and

synthesis focus to target the mixed-methods strands appropriately (Table 1.1) (Merchant et al., 2021).

Principal Research Question (PRQ): How do individual-level factors (cognitive, affective, and trait-based) and organisational-level support mechanisms interact to shape the post-adoption continuance and IT-enabled innovative behaviour of employees using tablet devices within the socio-technical context of Hungarian SMEs?

The PRQ is operationalised through three sub-research questions (SRQ1–SRQ3). Together, they align with the quantitative, qualitative and integrative strands of the explanatory sequential mixed-methods design, thereby addressing the methodological limitations identified above (Table 1.1).

Table 1.1 Detailed research questions showing explanatory sequential design

Sub-questions (SRQs)	Research paradigm & Methodology	Primary Chapter
SRQ1. What are the structural relationships between individual perceptions, personal traits, organisational support, innovative use and post-adoption behaviours among tablet device users in Hungarian SMEs?	Positivist, quantitative (PLS-SEM), deductive. Predict: What factors predict post-adoption behaviours?	Ch 4, Ch 5
SRQ2: What organisational, contextual, and task-related mechanisms shaped post-adoption outcomes (continuance, discontinuance, innovative use) over time, and how do these mechanisms relate to the structural relationships identified in the quantitative phase?	Interpretivist, qualitative, inductive. Explain & contextualise: How and why do structural relationships evolve? What mechanisms shaped outcomes retrospectively? What are the lived mechanisms?	Ch 6
SRQ3: How do the qualitative findings (mechanisms, processes) explain, expand, and contextualise the quantitative results (predictive paths) to produce an integrated, actionable framework for fostering	Both quantitative and qualitative results – synthesis, abduction. Integrate: How do results synthesise to create a	Ch 5, Ch 6, Ch 7

Sub-questions (SRQs)	Research paradigm & Methodology	Primary Chapter
employee-driven digital innovation in resource-constrained environments?	new, deeper understanding?	

1.3.2 Research Objectives

To answer the research aims, the following objectives are formulated:

1. Theoretical Framework Development: Based on a systematic literature review, develop a comprehensive theoretical and conceptual framework that integrates post-adoption technology acceptance (UTAUT with attitude reinstated) with IT-enabled innovative behaviour (ITIB) and organisational support mechanisms. The model will specify structural relationships and hypothesised paths enabling empirical testing of how tablet adoption and innovative use emerge in SME contexts.
2. Quantitative Analysis – SRQ1: Quantitatively test and validate the theoretical model using quantitative data collection and analysis, including Structural Equation Modelling (SEM). This objective includes a pilot test and a large-scale survey with statistical analysis.
3. Qualitative Analysis – SRQ2: Conduct semi-structured interviews with employees and managers from participating SMEs to validate, clarify, and expand upon quantitative findings. This qualitative phase will provide contextual understanding of the mechanisms underlying statistical relationships.
4. Integration and Implications – SRQ3: Systematically integrate the quantitative predictions and qualitative explanations using joint-display analysis to generate a set of robust, mixed-methods meta-inferences that solve the dissertation's core research puzzle. Synthesise quantitative and qualitative findings to establish contributions to academic knowledge, policy development, and SME practice. Develop actionable recommendations to support employee-driven innovation through effective organisational support and technology appropriation strategies.

1.4 Research Scope

This study focuses on post-adoption use of tablets (e.g., iPads, Android, and Surface tablets) in contexts where employees have moved beyond initial trial periods into sustained use. The research scope includes several important boundaries, addressed in this section.

1.4.1 Geographical and Organisational Scope

The research is situated within Hungary, providing insights into technology use patterns in a post-transition economy with specific digital development challenges. While this geographical focus limits immediate generalisability, it offers valuable insights for similar Central and Eastern European contexts. The research targets SMEs (fewer than 250 employees) across various sectors, acknowledging that these organisations face distinctive resource constraints and structural characteristics that differentiate them from large enterprises or micro-enterprises. Within the EU classification (European Commission, 2005; Appendix B1), this encompasses medium-sized (50–249 employees), small (10–49), and micro (<10) firms.

1.4.2 Technology Scope

Tablets were chosen as the focal technology for this study because they represent general-purpose mobile ICT. Tablets have the potential to support both routine (continuance) and novel (innovative) work practices. This focus enables examination of sustained use patterns and innovative appropriation behaviours rather than only initial adoption decisions.

1.4.3 Temporal Scope

This study encompasses two distinct temporal phases, enabling examination of post-adoption outcomes over time.

- A. Quantitative Phase (2014-15). Cross-sectional survey data collection included pilot testing (2014) followed by the main data collection wave (September 2014 – February 2015). This period captured tablet adoption dynamics during the early adoption era in Hungarian SMEs, characterised by post-financial crisis recovery, nascent tablet technologies, and emerging enterprise mobility practices.
- B. Qualitative Phase (2021). Follow-up semi-structured interviews (June – October 2021) were conducted with members of the original 2014-15 survey cohort. The 6-7-year interval between phases enables retrospective evaluation of post-adoption trajectories—sustained use, discontinuance, routinization, and innovative appropriation—providing rare empirical access to long-term outcomes of technology appropriation.

The methodological implications and integration approach are detailed in Section 1.5 (Methodological Framework).

1.4.4 Theoretical Scope

The study primarily adopts an individual-level lens while acknowledging organisational and technological influences. The theoretical framework emphasises how employees' thoughts (cognitions), feelings (affect), and actions (behaviours) interact when using technology, rather than focusing purely on technological features or economic cost-benefit calculations. This individual-level focus reflects the premise that technology value emerges from employee appropriation practices, not technology characteristics alone.

1.5 Methodological Framework

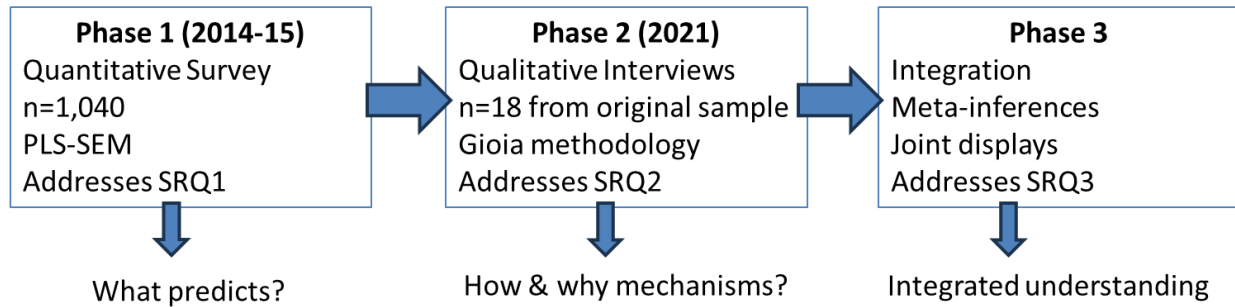
1.5.1 Philosophical Foundation and Research Design

This study adopts an explanatory sequential mixed-methods design with a dual-paradigm approach. This philosophical position recognises that complex research questions—such as understanding both what factors predict continuance (quantitative) and how organisational mechanisms enable innovation (qualitative)—require methodological pluralism (Johnson, 2017).

The research unfolds in three connected phases (Figure 1.1): first, a quantitative survey (2014-15) identifies statistical relationships between individual factors, organisational support, and post-adoption behaviours (addressing SRQ1); second, qualitative interviews (2021) explain the mechanisms underlying these relationships through retrospective evaluation (addressing SRQ2); third, systematic integration generates meta-inferences that synthesise insights across both phases (addressing SRQ3).

This design deliberately incorporates a temporal dimension. The quantitative phase captured early tablet adoption patterns during a period of resource constraints and technological immaturity in Hungarian SMEs. The qualitative phase, conducted six to seven years later, enabled participants to reflect on their entire adoption journey—revealing long-term outcomes such as sustained use, discontinuance, routinization, or innovative appropriation that are invisible in immediate post-adoption studies.

Figure 1.1 Three-phase explanatory sequential mixed-methods design



1.5.2 Phase 1: Quantitative Cross-Sectional Analysis (2014-15)

The first phase employed cross-sectional online surveys to test structural relationships between key constructs. The questions were formed using the detailed literature review that was the secondary data of this study. Following pilot testing in 2014 (n=148), the main data collection occurred between September 2014 and February 2015, yielding 1,040 valid responses from tablet users across 21 Hungarian SMEs. This sample provides adequate statistical power for Partial Least Squares Structural Equation Modelling (PLS-SEM), the primary analytical technique used to evaluate the theoretical model (Hair et al., 2022).

The survey measured individual-level constructs (Personal Innovativeness in IT, Performance Expectancy, Effort Expectancy, Attitude), organisational support mechanisms (Innovation Support, Involvement Facilitation), and post-adoption outcomes (IT-enabled Innovative Behaviour, Continuance Intention).

PLS-SEM analysis identified which factors significantly predict post-adoption behaviours and quantified the strength of these relationships, directly addressing SRQ1: What are the structural relationships between individual perceptions, personal traits, organisational support, and post-adoption behaviours? This led to the primary data of this study.

1.5.3 Phase 2: Qualitative Retrospective Evaluation (2021)

To triangulate, essentially verify and validate the earlier quantitative data, a qualitative approach was pursued for the second phase. This phase employed semi-structured interviews conducted between June and October 2021 with 18 participants (employees and managers) from 9 SMEs included in the original quantitative sample. The second phase employed semi-structured interviews conducted between June and October 2021 with 18 participants (employees and managers) from 9 SMEs included in the original quantitative sample. Participants were selected

from individuals who completed the 2014-15 survey and remained with their organisations, providing continuity for retrospective reflection.

The six to seven-year interval between phases positions this qualitative work as a summative evaluation. Rather than capturing immediate post-adoption reactions, participants reflected on their entire tablet adoption trajectory—from initial 2014-15 implementation through subsequent evolution. Interview questions explored what organisational practices supported or hindered innovative use, how technology appropriation evolved over time, why some employees sustained innovative behaviours while others reverted to routine use, and what critical junctures shaped adoption outcomes.

This retrospective approach enabled retrospective process tracing—a methodology where participants identify causal mechanisms, critical events, and temporal sequences that shaped outcomes over time (Langley et al., 2013). While retrospective accounts involve recall considerations and potential hindsight bias (Pentland, 1999), they provide unique access to patterns and mechanisms that emerge only with temporal distance. The triangulation took place with the understanding of these temporal limits – the temporal gap is discussed further in section 1.5.5 and in Chapter 3.

Interview data were analysed using the Gioia methodology (Magnani & Gioia, 2023), a rigorous inductive approach that systematically moves from participant language (first-order concepts) through researcher interpretation (second-order themes) to aggregate theoretical dimensions. This analysis directly addresses SRQ2: What organisational, contextual, and task-related mechanisms shaped post-adoption outcomes, and how do these mechanisms relate to the structural relationships identified in the quantitative phase?

1.5.4 Phase 3: Integration and Meta-Inferences

The third phase systematically integrates quantitative predictions and qualitative explanations to generate meta-inferences—integrated insights that emerge from combining both methodological strands. Integration employs joint-display analysis (presented in Chapter 7), which visually connects quantitative findings (structural path coefficients, hypothesis results) with qualitative findings (Gioia themes describing mechanisms and processes).

Given the temporal distance between phases, integration focuses on theoretical mechanisms that remain conceptually stable across contexts rather than claiming direct causal linkages between 2014 survey data and 2021 interview responses. For example, rather than claiming "2021 interviews explain why IS→ITIB had $\beta=0.33$ in 2014," integration examines how organisational

support mechanisms enable employee-driven innovation—a theoretical dynamic likely operating in both early-adoption (2014-15) and mature-adoption (2021) contexts, though operationalised differently given technological and organisational evolution.

Integration explicitly addresses both continuity (theoretical mechanisms that remained stable over time) and evolution (how mechanisms adapted as technology matured and organisations developed digital capabilities). This approach addresses SRQ3: How do qualitative findings explain, expand, and contextualize quantitative results to produce an integrated, actionable framework?

The study adopts Venkatesh et al.'s (2013) criteria for mixed-methods quality: design quality (rigour in instrument development), interpretive rigour (credibility, transferability), and integration quality (coherence of meta-inferences). By explicitly framing temporal considerations and focusing integration on conceptually stable mechanisms, the study maintains inference quality while acknowledging the complexity inherent in the research design.

1.5.5 Temporal Gap Discussion

The six to seven-year interval between quantitative and qualitative phases enables retrospective evaluation of long-term post-adoption outcomes—sustained use, discontinuance, routinization, and innovative appropriation—which are rarely accessible in cross-sectional studies. While this temporal distance introduces considerations regarding technological evolution and retrospective sense-making, it also provides unique empirical access to adoption trajectories and mechanisms that emerge only over time. These methodological issues are further detailed in Chapter 3 (Research Methodology).

1.6 Research Contributions

1.6.1 Academia

The study develops and validates a new, integrated model of post-adoption innovative behaviour, extending UTAUT by empirically demonstrating the distinct roles of Continuance Intention and IT-enabled Innovative Behaviour. It reveals the complex, "double-edged sword" nature of personal innovativeness in mandated contexts (where high innovativeness can drive both value-creating experimentation and disruptive workarounds). The study also provides a rare, mechanism-based explanation of how organisational support constructs (IS and IF) function in practice.

1.6.2 Industry

The findings provide an actionable framework for SME managers. It moves beyond "buy more tech" to identify specific, high-leverage levers for fostering innovation, such as distinguishing between "use" and "innovation" and prioritising Involvement Facilitation and Innovation Support. It provides practical evidence of why technology rollouts fail and how to design for success.

1.6.3 Policymakers

For policymakers in Hungary and other post-transition economies, the study highlights that closing the "first-level" digital divide (access) is insufficient. Policy interventions must now focus on closing the "second-level" divide by funding programs that build employee skills, peer-support networks, and managerial capability for supporting digital innovation.

These theoretical, practical, and policy contributions are developed systematically throughout the subsequent chapters, as outlined below.

1.7 Chapter 1 Summary

This chapter has introduced a critical puzzle in contemporary digital transformation: why do some organisations successfully leverage technology investments to drive innovation while others see their technology investments languish in routine, low-value use? The research focuses specifically on Hungarian small and medium-sized enterprises, where this gap between technology access and innovative use represents both a significant competitive disadvantage and a broader manifestation of the 'second-level digital divide'—where disparities shift from infrastructure access to capability utilisation.

The central research question asks: What factors predict and explain how individuals use technology innovatively after adoption, and what organisational support mechanisms enable this transformation? Addressing this question requires understanding both the statistical relationships between individual characteristics, organisational support, and post-adoption behaviours (the 'what' question) and the underlying mechanisms through which organisational practices enable or constrain innovative appropriation over time (the 'how' and 'why' questions).

To answer this multifaceted question, the study employs an explanatory sequential mixed-methods design spanning two temporal phases. Quantitative surveys conducted in 2014-15 identified which factors predict innovative technology use among 1,040 tablet users across Hungarian SMEs, establishing structural relationships between personal traits, organisational support mechanisms, and innovation outcomes. Qualitative interviews conducted in 2021 with

participants from the original sample explored how these relationships manifested in practice, revealing the organisational conditions, critical junctures, and evolutionary processes that shaped long-term adoption trajectories. The integration of these two phases generates meta-inferences that offer both predictive precision and explanatory depth—providing actionable insights for managers, policymakers, and scholars.

The study makes four primary contributions. Theoretically, it advances post-adoption research by integrating individual-level, organisational-level, and temporal perspectives that are typically examined in isolation. Methodologically, it demonstrates how mixed-methods designs with temporal distance can capture adoption dynamics invisible in cross-sectional studies. Practically, it provides evidence-based guidance for SME managers designing organisational support systems that enable employee-driven innovation. Additionally, for policymakers, it offers policy implications for addressing digital capability gaps in resource-constrained contexts beyond simple infrastructure investment.

Table 1.2 provides a roadmap of the dissertation structure, showing how each chapter builds toward answering the central research question and delivering the contributions outlined above.

Table 1.2 Thesis structure overview

CHAPTER	CONTENTS
Chapter 1 Introduction	The first chapter summarises key elements for the reader and introduces the topic. The research problem is discussed and identified. Research gap is noted, with a definition of research aims, objectives and research questions. The study is positioned within broader debates about technology adoption, innovation, and SME development.
Chapter 2 Literature Review & Conceptual Theoretical Development	This chapter provides a comprehensive review of relevant literature streams, including SME contexts, tablet technologies, digital divide concepts, ICT adoption theories, and innovation frameworks. The chapter develops the theoretical model integrating UTAUT, ITIB, and organisational support constructs.
Chapter 3 Research Methodology	This chapter details the philosophical stance, methodological choices, data collection procedures, and analytical approaches. It justifies the mixed-methods design and explains integration procedures for combining quantitative and qualitative insights.
Chapter 4 Pilot Analysis & Findings	This chapter presents results from the pilot study,

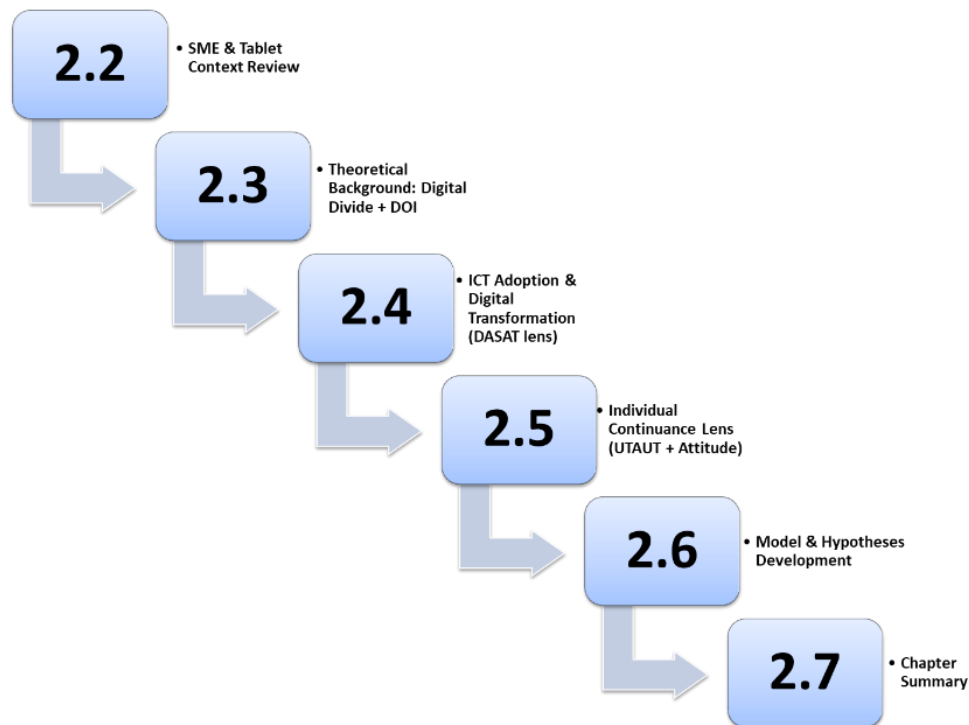
CHAPTER	CONTENTS
	including instrument refinement and initial construct validation.
Chapter 5 Quantitative Analysis and Findings	The fifth chapter reports comprehensive results from the main survey, including descriptive statistics, measurement model validation, structural model testing, and hypothesis evaluation using PLS-SEM.
Chapter 6 Qualitative Analysis and Findings	The sixth chapter presents the interview phase with the qualitative thematic analysis. Results of the quantitative and qualitative phases are connected shortly as a preparation for the final chapter.
Chapter 7 Discussion	This chapter integrates the quantitative and qualitative findings through joint displays and develops meta-inferences that synthesise insights across methodological strands. It focuses on explaining how structural relationships are enacted through socio-technical mechanisms in Hungarian SMEs, thereby addressing the integrative sub-question (SRQ3). It then outlines the contributions and implications.
Chapter 8 Conclusion	Finally, the eighth chapter restates the research questions and presents the key integrated conclusions of the study. The chapter acknowledges the study's limitations, proposes directions for future research, and closes with personal reflections on the doctoral journey.

2 LITERATURE REVIEW & CONCEPTUAL THEORETICAL DEVELOPMENT

2.1 Introduction

Chapter 1 framed the core puzzle of this thesis as a second-level digital divide in Hungarian SMEs: many firms have technology and connectivity, yet employees often fail to appropriate these tools for meaningful, innovative work. The principal research question asks how individual-level factors (cognitive, affective and trait-based) and organisational support mechanisms together shape post-adoption continuance and IT-enabled innovative behaviour with tablets in this context. Figure 2.1 provides a roadmap of the chapter.

Figure 2.1 Reader's roadmap



This chapter develops the theoretical foundations needed to address that question. It first revisits the SME and tablet context and the notion of digital inequality, focusing on skills and usage gaps rather than access alone. It then introduces Diffusion of Innovations (DOI) as a temporal lens on how technologies move from introduction to routinisation in organisations. Building on this, the chapter reviews ICT adoption, innovation and digital transformation in SMEs, including the DASAT framework. The chapter examines employee-driven innovation and related concepts such as personal innovativeness and IT-enabled innovative behaviour. UTAUT (with Attitude reinstated) is positioned as the core individual-level backbone, complemented by innovativeness

and organisational support constructs that are particularly relevant in mandated-use SME settings.

The central premise is that employees who use tablets to generate novel, work-relevant ideas are more likely to continue using them, and that this behavioural pathway is shaped by both beliefs about usefulness and ease of use and by the organisational conditions that support experimentation and involvement. On this basis, Section 2.6 develops the theoretical and conceptual model, defines the study's constructs and hypotheses, and maps them onto the DASAT cycle.

2.2 Context Review

As outlined in Chapter 1 (Section 1.2), small and medium-sized enterprises (SMEs) constitute the dominant form of business organisation in the European Union and in Hungary, accounting for the majority of enterprises and a substantial share of employment and value added, with more detailed statistics provided in the Appendix B (Bella et al., 2023, 2024). At the same time, Hungarian SMEs continue to face structural challenges, such as limited access to financing, uneven managerial competencies and relatively slow adoption of innovative practices, which may inhibit rapid economic recovery and growth (Endrődi-Kovács & Stukovszky, 2022; Keszey & Zsukk, 2017; Kovács & Nemeslaki, 2024; Papanek, 2010; Rahman et al., 2017). These factors combine to make SMEs both central to economic performance and acutely vulnerable to external shocks.

In the Hungarian context, digital infrastructure indicators (such as broadband coverage and availability of very-high-capacity networks) compare favourably with many EU peers, yet firm-level digitalisation remains patchy (European Commission, 2025). As discussed in Chapter 1, survey and policy reports point to an uneven picture in which “pockets” of advanced digital practice coexist alongside many SMEs that rely on basic office tools and legacy systems (Smartcommerce Consulting, 2024). Hardware such as desktop computers, laptops, smartphones and tablets may be present, but the extent to which these tools are integrated into everyday workflows, decision-making and innovation activities varies widely between firms (Endrődi-Kovács & Stukovszky, 2022; Marciniak et al., 2021). This suggests that, for many SMEs, the primary bottlenecks lie not in the physical availability of devices but in how they are appropriated, supported and embedded in work practices.

Within this environment, tablet devices form the focal artefact for the present study. Mobile information technology has historically encompassed smartphones, PDAs and pen-enabled

tablets, emphasising portability (Sharples & Beale, 2003). With the launch of the iPad in 2010, tablets emerged as a distinct slate-form factor: colour touch displays, instant-on operation and wireless connectivity (Wi-Fi/cellular), operated primarily by direct touch or pen input (Alvarez et al., 2011). To avoid ambiguity with large-screen phones, this study adopts a 7-inch lower screen-size bound for tablets (Hur et al., 2014; Lee et al., 2017). At the time of the 2014-2015 SME survey, detachable 2-in-1s were not yet widespread. Therefore this study treats tablets as a coherent artefact category for analysis despite the emergence of such hybrids in premium segments.

Tablets are suitable for a broad range of business tasks: reading and annotating documents, accessing cloud-based systems, capturing photos and video, supporting presentations, or interacting with specialised applications in sales, logistics and fieldwork (Quade & Leimstoll, 2017). However, this flexibility is both an advantage and a disadvantage in the SME context. Because the "correct" way to use a tablet is not inscribed in the hardware, the burden of discovering value shifts to the user. In a large enterprise, an IT department might provision tablets with a custom suite of apps and a mandatory training program. In an SME, employees may be handed a device and told to "figure it out." This reliance on the individual employee's initiative makes the post-adoption phase critical. In practice, the value of the tablet depends on how individual employees perceive their usefulness and ease of use, and how well the devices fit the tasks and systems that structure their work (Quade & Leimstoll, 2017).

Tablets also sit at the intersection of personal and organisational technology: many employees are familiar with similar devices in their private lives, yet workplace use is shaped by organisational policies, infrastructure and expectations. This interplay of individual, technological and organisational factors is central to the research model developed in this thesis.

At the time of the 2014-2015 survey, literature explicitly connecting mobile/digital tools to employee innovative behaviour in SMEs remained comparatively sparse (with Quade & Leimstoll, 2017 a key outlier), creating a clear empirical gap. In those years, however, tablet sales were at their best (Appendix B). A total of 230 million units were shipped in 2014: these numbers decreased and plateaued in the following years. While these are overall numbers, the plateau in tablet shipments does not signal exhaustion of value; rather, it reflects a shift from novelty purchases to context-dependent, task-specific acquisition. This makes tablets an ideal candidate to study how employee perceptions and organisational support transform a broadly provisioned device into either dormant hardware or a catalyst for IT-enabled innovation. Any discussion of tablet adoption in SMEs must recognise that the tablet is not a stable artefact but part of a rapidly

evolving mobile ecosystem. During the data collection period of this study (2014–2021), tablets shifted from relatively self-contained “thick clients”, running stand-alone applications and storing data locally, towards “thin client” interfaces to cloud-based services and shared repositories. This trajectory matters because a given tablet performance expectancy score (e.g. “3 out of 5”) has a different meaning at different points on this evolution. Consequently, this study provides an opportunity to examine how changing ecosystems shape the perceived and realised value of tablets.

Throughout this thesis, a critical distinction shapes the analysis: adoption refers to the organisational decision to acquire and deploy a technology, while appropriation refers to how employees internalise, adapt, and repurpose that technology in practice (Boudreau & Robey, 2005). This distinction is especially important for general-purpose devices like tablets. Organisations can make adoption decisions centrally (purchase tablets, provision them to employees, deploy infrastructure). Appropriation, however, remains fundamentally distributed—each employee, each role, each task context generates unique appropriation pathways.

While SMEs are frequently portrayed through a “deficit” lens of resource poverty, this view risks underestimating their adaptive capacity. Rather than simply lacking financial, human and technological resources, many SMEs engage in forms of organisational bricolage, that is, “making do” by recombining available resources in novel ways to address local problems and opportunities (Senyard et al., 2014). In such environments, formal strategic investment in digital innovation is often limited, but employees improvise with whatever devices, applications and data they can access.

The central puzzle of this research is why organisational adoption of tablets often stalls at routine use (reading email, light note-taking) rather than progressing toward meaningful innovation. The answer lies not in adoption mechanics but in appropriation dynamics—the micro-level mechanisms through which individual beliefs, organisational supports, and task contexts interact to shape what employees do with the tablets. They may appropriate tablets for transformative work or default to familiar alternatives. Or they may use them temporarily and ignore them before another use cycle (Attig & Franke, 2020; Dhir et al., 2024). These are all viable outcomes in ICT context. This chapter develops the theoretical lenses needed to investigate these appropriation mechanisms.

Therefore, the study of tablet adoption in SMEs is not merely a study of hardware penetration; it is a study of appropriation. It requires an analytical framework that can distinguish between “routine use” (using the device as a substitute for paper) and “innovative use” (using the device

to transform a business process). This distinction is central to the research model developed later in this chapter.

2.3 Theoretical Background

2.3.1 Introduction

Before turning to specific technology acceptance and continuance models, it is necessary to clarify two foundational issues.

First, Chapter 1 framed the core puzzle of this thesis as a second-level digital divide (Van Dijk, 2019) in Hungarian SMEs: many firms have solved the basic access problem, yet employees still struggle to appropriate digital tools—such as tablets—for meaningful, innovative work. This section therefore revisits the digital divide literature.

Second, the study requires a temporal lens on how innovations spread and stabilise in organisational settings. Diffusion of Innovations (DOI) theory (Rogers, 2003) offers a classic account of how new technologies move from awareness to routinisation at population level.

2.3.2 Digital Divide

The term digital divide originally defined broad inequalities in access to information and communication technologies (ICTs) across and within societies (Van Dijk, 2019). Early work emphasised infrastructure and connectivity gaps, often framed as a new axis of global inequality: “...today’s world is divided not by ideology but by technology...” (Sachs, 2000).

However, the closing of the physical access gap (internet access) did not result in the disappearance of information inequality. On the contrary, research began to observe that disparities in the benefits derived from the internet were persisting, and in many cases, widening, even among populations with equal access to technology (Hargittai, 2002, 2003). First conceptualised by Eszter Hargittai (2002), the second-level digital divide refers to the inequalities in digital skills, autonomy, and usage patterns that result in differential outcomes for users who are already connected.

van Dijk’s (2019) causal model provides a more fine-grained conceptualisation. He distinguishes four successive forms of access:

- A. Material access – physical possession of devices and connectivity.
- B. Mental or motivational access – basic interest in, and willingness to engage with, digital technologies.

- C. Skills access – operational, formal and strategic competences required to use ICT effectively.
- D. Usage access – opportunities to apply ICT in meaningful tasks and settings.

The concept of the second-level digital divide is typically deployed to describe societal inequalities in skills and usage. In an organisational setting, however, the same logic can be captured more precisely through the notion of an assimilation gap: the lag between acquiring a technology and integrating it into everyday work practices in a way that transforms performance (Fichman & Kemerer, 2002; Jasperson et al., 2005). The historical policy focus in Europe has largely targeted material access; however, evidence shows that as physical connectivity improves, inequalities increasingly shift to skills and usage (van Dijk, 2008). A large share of European and Hungarian SMEs now have basic connectivity and devices (Endrődi-Kovács & Stukovszky, 2022; European Commission, 2025; Kurakova et al., 2021). EU-based studies show that for SMEs it is not primarily the lack of devices that constrains ICT and e-business uptake, but deficits in motivational and skills access (Arendt, 2008). The relevant question is not whether firms have technology, but whether employees possess the skills, motivation and opportunities to transform that technology into productive, innovative use—precisely the problem that second-level digital divide focuses on. Within the EU, policy has accordingly shifted from subsidising infrastructure towards fostering digital skills and meaningful usage (van Dijk, 2008).

Against this backdrop, the Hungarian case can be read as a micro-level representation of second-level divides. As Chapter 1 documented, national indicators reveal “islands of maturity” alongside broad pockets of under-utilisation: many SMEs have broadband and devices, yet struggle with underdeveloped digital capabilities, managerial support and experimentation cultures (Endrődi-Kovács & Stukovszky, 2022; Kadarova et al., 2023; Mezei et al., 2016; Smartcommerce Consulting, 2024). This suggests that the binding constraints lie in skills access (employee competences, confidence, attitudes) and usage access (opportunities, time, organisational permission) rather than material access.

Existing studies, however, typically measure the skills gap with quantitative assessments (e.g., self-reported digital competencies), or qualitatively describe support deficits (e.g., lack of training, inadequate managerial encouragement) (Acilar et al., 2021; Raihan et al., 2024). These studies do not, however, model or test organisational or individual mechanisms—such as motivational, psychological, or workflow-specific pathways—by which skill gaps directly influence post-adoption behaviour (Aissaoui, 2021). Reviews highlight the need for future research to probe these mechanisms, especially as the field has matured beyond access issues and is increasingly

concerned with digital skills and outcomes (Vassilakopoulou & Hustad, 2021). Researchers recommend taking into account multiple aspects, forming comprehensive models and establishing a better understanding of the complex phenomenon of digital divide (Choudrie et al., 2020).

This thesis, therefore, uses the digital divide concept in a deliberately micro-level sense. First, it treats Hungarian SMEs as operating beyond the first-level divide: tablets and connectivity are available to employees (SMEs provide them). Second, it interprets the second-level divide as a joint deficit in skills and usage access that prevents employees from moving from basic use to usage that transforms work practices (Brynjolfsson & McAfee, 2014; Jaspersen et al., 2005). Third, it operationalises these divides through individual beliefs (performance and effort expectancies, attitudes), trait-level dispositions (personal innovativeness in IT) and organisational enablers (innovation support, involvement facilitation), which together shape continuance intention and IT-enabled innovative behaviour (Sections 2.6-2.7).

In short, the digital divide is not treated here as a purely infrastructural or national-level phenomenon, but as a set of micro-mechanisms through which skills and usage opportunities become unequally distributed within “digitally equipped” SMEs—a framing that will be revisited in the discussion of second-level divides in Chapter 7.

2.3.3 Diffusion of Innovations

Diffusion of Innovations (DOI) (Rogers, 2003) theory provides the classic framework for understanding how new ideas, practices or technologies spread over time. An innovation is defined as any idea or object perceived as new by an individual; diffusion describes how that innovation is communicated through channels over time among members of a social system. Adoption at the population level is thus conceived as the aggregate outcome of many individual adoption decisions.

Rogers (2003) conceptualises individual adoption as a five-stage decision process:

1. Knowledge (also called Awareness) represents an individual’s exposure to an innovation.
2. Persuasion, an individual actively seeks related information or receives information about the salient characteristics of the innovation.
3. Decision represents the adoption decision.
4. Implementation, an individual acts based on the Decision stage.
5. Confirmation, an individual reflects and re-evaluates whether to continue or discontinue with the adoption.

This standard five-stage decision sequence can imply that the “innovation” is a relatively fixed artefact. For the purposes of this thesis, the most critical phase is neither initial adoption nor routinisation, but what organisational scholars have called mutual adaptation: the period in which technologies and organisational routines are mutually adjusted (Leonard-Barton, 1988). In the tablet context, this involved migrating files to cloud services, redesigning meeting protocols, reconfiguring data entry practices and renegotiating the division of labour between devices. The present study, therefore, treats the innovation not as “a tablet” but as a moving configuration of hardware, software and work practices.

For the present study, DOI plays a background rather than a central role. Its main contribution is to supply a time axis for thinking about tablet use in SMEs: from awareness, through trial, to routinisation and potential infusion.

Rogers’ organisational innovation-decision process reframes diffusion as a sequence of collective choices and adaptations inside the organisation rather than as isolated individual decisions (Rogers, 2003). It begins with Agenda-Setting, where managers and key stakeholders recognise a performance gap or strategic problem that may require change and start scanning for possible solutions. In Matching, a specific innovation is identified and judged to be an appropriate response to that problem. If the decision is positive, the process moves into Redefining/Restructuring, in which both the innovation and existing structures are modified: workflows, roles, and routines are adjusted, and if necessary, the innovation itself is customised. The final stages stabilise and normalise the change. During Clarifying, the innovation becomes more widely used, its purpose and benefits are communicated, and its meaning is negotiated across different groups. In Routinising, the innovation is fully integrated into everyday operations: it is embedded in standard operating procedures, and no longer seen as a special project or experiment. Taken together, these five stages emphasise that successful diffusion is as much about organisational learning and restructuring as it is about the initial adoption decision; the innovation becomes “real” only when it has been clarified and routinised in the fabric of organisational life.

However, several limitations make DOI insufficient as the primary explanatory lens here.

First, classic DOI assumes a relatively voluntary adoption context. In the Hungarian SMEs studied, tablet provision is often mandated, which compresses the early stages of the adoption process. Management makes the primary decision to purchase (the “Decision” stage), and employees are then mandated to execute the “Implementation” stage. Consequently, the variance in outcomes shifts: the relevant research question becomes not “will they adopt?” but “how will they appropriate the mandated tool?”. The key variation arises after initial adoption—in the extent

to which employees continue to use tablets and appropriate them in innovative ways. Routinisation is a question, not a given outcome.

Second, DOI implicitly assumes that adoption is the rational, correct outcome and rejection represents a failure or lag. In the context of general-purpose tablets in SMEs, this assumption may be problematic: rejection may be the rational response by an employee who discovers that the tablet actually hinders their specific workflow.

Third, DOI largely operates at the level of populations and organisations; it does not specify detailed post-adoption mechanisms linking individual beliefs, organisational supports and innovative behaviour.

Although the UTAUT-based post-adoption framework is developed later in Section 2.5.2, it is necessary at this point to establish how DOI's diffusion-level assumptions are reconciled with the individual-level post-adoption perspective adopted in this thesis. The foregoing discussion shows that DOI and post-adoption continuance models make different assumptions about user agency and organisational context.

Regarding user agency, DOI distinguishes two decision processes. In its classic individual innovation-decision formulation, adoption is voluntary: individuals decide whether and when to adopt based on their perception of an innovation's attributes (relative advantage, compatibility, complexity, trialability, and observability) (Rogers, 2003). In its organisational formulation, adoption is a collective or authority decision, made on behalf of the organisation's members (Rogers, 2003). It is this second process that characterises the context of the present study: tablets were provisioned by management and employees were expected to use them. The relevant question was therefore not "will they adopt?" but "how, and how innovatively, will they appropriate what has been mandated?". Individual agency does not disappear in this setting, but its expression shifts. Rather than being exercised primarily at the initial adoption decision, agency is exercised continuously through appropriation - selecting which tasks to use the tablet for, which features to explore, and whether to experiment with novel applications (Boudreau & Robey, 2005; Jaspersen et al., 2005). UTAUT conceptualises this constrained form of agency at the individual level. It does not assume that organisational users are completely free to adopt or reject a technology; rather, it explains how users form beliefs about performance and effort, how these beliefs shape attitude and intention, and how these relationships are conditioned by experience, facilitating conditions, social influence and voluntariness (Venkatesh et al., 2003). In the adapted post-adoption framework used in this thesis, Attitude is reinstated to capture users' experience-based evaluation of the technology within this constrained setting. In the mandated SME context

of this study, the organisational adoption decision is therefore treated as given, while individual agency is located in post-adoption evaluation, continuance, routine use and innovative appropriation. Consequently, UTAUT-based and related post-adoption models can be adapted to examine contexts where individual voluntariness is reduced or absent (Brown et al., 2002; Venkatesh et al., 2003).

Regarding organisational context, DOI treats the organisation as the social system through which diffusion channels operate and in which adoption, implementation and routinisation unfold (Rogers, 2003). This provides a useful temporal and contextual backdrop, but it operates at a higher level of abstraction than the behavioural mechanisms examined in this thesis. Post-adoption models, and particularly the extensions of UTAUT employed here, foreground organisational context as a more immediate predictor of individual behaviour. Innovation Support and Involvement Facilitation are therefore not treated merely as background conditions, but as structural enablers or constraints that shape post-adoption outcomes directly (see Section 2.6).

This study resolves the tension through an explicit division of labour between the two traditions. At the population level, DOI provides the temporal backdrop. The rapid growth of global tablet shipments leading up to the 2014–15 data collection period (Appendix B3) provides a broader technology-life-cycle backdrop, indicating that tablets were still moving from novelty towards wider assimilation on the diffusion curve. DOI also supplies the reinvention, routinisation, and mutual adaptation concepts that help interpret long-term appropriation trajectories (Leonard-Barton, 1988; Rogers, 2003). At the organisational level, the DOI organisational innovation-decision process explains how tablets entered these firms through authority decisions. UTAUT-based post-adoption theory then takes over as the primary explanatory lens, providing the individual-level belief–intention–behaviour mechanisms, together with organisational predictors, needed to explain why some employees progress from basic use to innovative appropriation within that mandated provisioning context. The two frameworks are therefore used at different analytical levels rather than treated as competing explanations: DOI explains the macro-trajectory and organisational entry of the technology through authority decisions, while post-adoption theory explains the micro-mechanisms of individual appropriation within that trajectory.

2.4 ICT Adoption, Innovation, and Digital Transformation

2.4.1 ICT Adoption and the DASAT Framework

ICT can help SMEs to formalise processes, integrate information flows and reconfigure customer/supplier touchpoints, although such outcomes are far from automatic. In this thesis,

tablets are a pragmatic entry point: they put workflow, data capture and collaboration tools directly in employees' hands, making post-adoption behaviour the real performance lever.

The use of ICT in enterprises has grown considerably: in many enterprises, both intra- and interorganisational work systems rely on ICT-enabled functionalities and processes (Jasperson et al., 2005). Literature emphasises the transformative role ICT can play in supporting SMEs, enabling improved decision-making, productivity, customer engagement, and overall business agility (Dibrell et al., 2008; Passerini et al., 2012). As enterprise work has become tightly coupled to digital systems, value creation increasingly depends on how users appropriate tools after rollout—feature uptake, workflow fit, and emergent use—rather than on “go-live” alone (Gupta et al., 2013; Spithoven et al., 2013). This dependence has intensified over time as capabilities expanded (e.g., analytics/AI), making process improvement and information systems design mutually constraining choices (Brynjolfsson & McAfee, 2014; Lee & Kim, 1996; Newman & Zhao, 2008; Yusuf et al., 2024).

In light of these changes, a macro-level framework should be selected for the organisational perspective. Several established models were evaluated to contextualise the organisational environment of tablet adoption.

The Technology-Organisation-Environment (TOE) framework (Tornatzky & Fleischer, 1990) was considered for its robust identification of contextual drivers. However, TOE is fundamentally a determinant framework rather than a process model; while it excels at predicting whether a firm adopts based on static factors (e.g., firm size, competitive pressure), it offers limited granularity regarding the temporal evolution of digitalisation capabilities (Zhu et al., 2006).

While Rogers' (2003) organisational innovation process (Agenda-Setting to Clarifying / Routinising) provides a temporal sequence, it often assumes a linear progression that does not adequately capture the recursive, capability-building nature of digital transformation in resource-constrained SMEs. The traditional Six-Stage IT Implementation Model (SiSIT) model proceeds similarly from Initiation to Infusion in organisations (Cooper & Zmud, 1990) (see Appendix D).

However, the adoption of tablets in organisations is not just a linear process: it follows a more complex route (Quade & Leimstoll, 2017). Recent work reframes adoption as a capability-building cycle rather than a one-off decision. In general, the Digital Transformation (DT) concept accepts this cycle and is defined as “a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies” (Vial, 2019).

Specifically, the DASAT framework positions SME digitalisation as four interlinked phases—Digital Awareness (DA) → Digital Strategy & Roadmap (DSR) → Digital Adoption & Implementation (DAI) → Digital Transformation–Continuous Improvement (DTCI) —with each phase feeding the next (and back again) through learning loops (Kahveci, 2025).

The decision to adopt the DASAT framework was driven by its specific alignment with the SME context and the "second-level" digital divide focus of this study. Unlike stage models (e.g., SiSIT) which are often rigid, DASAT is more flexible and establishes a cycle with four major elements:

- **Digital Awareness (DA)** refers to the organisation's ability to sense and understand digital trends, technologies, and risks. It encompasses digital literacy, scanning the environment for opportunities and threats, and recognising where existing business models could be enhanced through digital solutions.
- **Digital Strategy and Roadmap (DSR)** translates this awareness into a coherent strategic direction. It involves defining clear digital priorities aligned with the overall business strategy, selecting target areas and technologies, and developing a sequenced roadmap that allocates resources, responsibilities, and timelines for transformation initiatives.
- **Digital Adoption and Implementation (DAI)** is the execution phase, where planned initiatives are piloted, rolled out, and embedded in day-to-day work. This includes technology deployment, process redesign, training and change management, and resolving integration issues.
- **Digital Transformation Continuous Improvement (DTCI)** focuses on monitoring outcomes, learning from implementation, and iteratively refining both technologies and organisational practices. It embeds feedback loops, performance metrics, and experimentation so that insights from use feed back into renewed awareness and strategy, making digital transformation an ongoing capability rather than a one-off project.

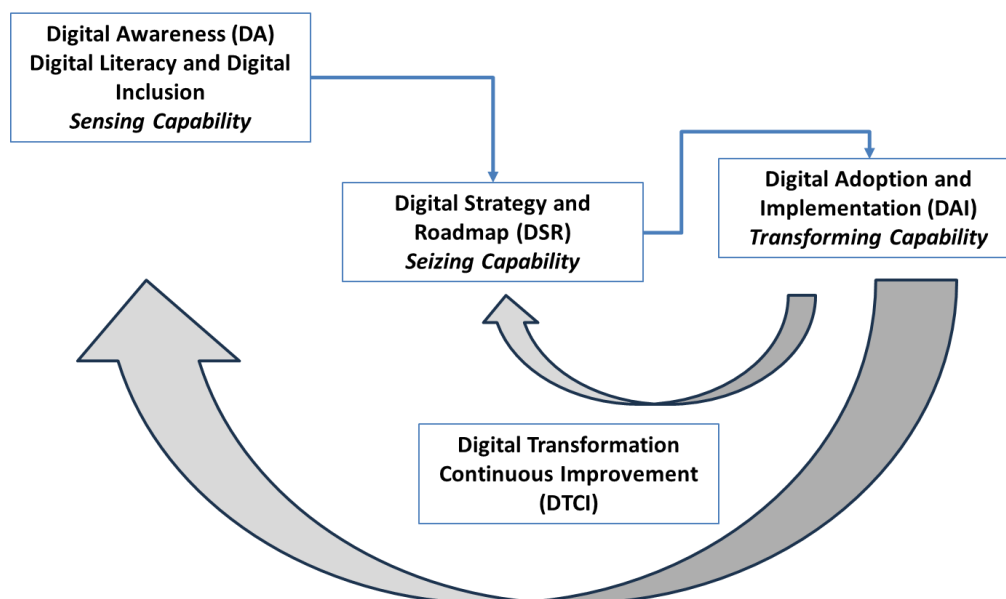
These stages help to better understand the Hungarian context, where the barrier is often not infrastructural availability but managerial "mental access" and strategic recognition of value (Endrődi-Kovács & Stukovszky, 2022). Furthermore, DASAT distinguishes between the technical act of DAI and the ongoing process of DTCI. This distinction provides the necessary theoretical scaffold to situate this study's core argument: that purchasing tablets (DAI) is merely a precursor to the employee-driven innovation (DTCI) required for value creation.

This structure aligns with the dynamic capabilities view (sensing–seizing–transforming), clarifying why adoption matters: it develops the firm's ability to continually sense technologies, seize opportunities via strategy, and transform operations through iterative improvement (Figure 2.2):

- DA → DSR: awareness/literacy enables realistic, targeted digital strategy.
- DSR → DAI: strategy prioritises and resources adoption/implementation.
- DAI → DSR: implementation feedback refines and re-prioritises strategy.
- DAI → DTCl: doing creates organisational learning for continuous improvement.
- DTCl → DA: improvement processes lift future awareness/literacy for the next cycle.

In SMEs, this cyclical perspective helps reconcile short-term operational pressures with longer-term transformation: adoption decisions both depend on and reshape strategy, while continuous improvement raises the organisation's digital awareness/literacy, priming the next round of investments (Kahveci, 2025). For tablets, the cycle operates where it matters most—at the employee level—so integration quality and learning loops (not device counts) drive realised value.

Figure 2.2 Digital Transformation Framework (DASAT) (Kahveci, 2025)



Consequently, DASAT serves as the organisational container for the individual-level analysis. It allows the research to map static variables (like innovation support) to dynamic organisational phases. By framing the study within DASAT, the investigation moves beyond a binary view of adoption (adopted/not adopted) to a maturity-based view, where "post-adoption" is understood not as a static end-state, but as the active "Digital Transformation" phase where IT-enabled innovative behaviours are either cultivated or constrained by the firm's strategic maturity.

And this leads to the core distinction between Routine Use and Innovative Use.

- Routine Use: Using the technology in a standardised way for prescribed tasks (e.g., answering email).

- **Innovative Use:** Using the technology in novel ways to support task performance, often experimenting with features not originally intended for that task.

While adoption studies frequently count the presence of technology as a proxy for performance, empirical evidence suggests that the mere "standardised" or "routine" use of a system often fails to generate significant value or competitive advantage (Li et al., 2013b; Popovič et al., 2018). Jaspersen et al. (2005) argue that "post-adoptive" behaviours—specifically exploring and extending features—are the true drivers of IT value, yet these behaviours remain largely unmeasured in traditional SME adoption surveys. This thesis argues that Innovative Use is the critical missing link in understanding the successful use of mobile technology. Consequently, the next step is to consider innovative behaviours.

2.4.2 Employee-Driven Innovation

The focus on innovative behaviours connects this study to the broader literature on innovation management, specifically Employee-Driven Innovation (EDI) (Hoyrup, 2012). In resource-constrained SMEs with limited formal R&D, Employee Driven Innovation (EDI) is the primary pathway through which ICT investments translate into innovation.

A literature review revealed that employees' innovation is often studied under different labels, such as individual innovation (Bunce & West, 1995), innovative behaviour (Janssen et al., 2004; Kleysen & Street, 2001), ideation (Ford, 1996) and the more recent Employee-Driven Innovation (Hoyrup et al., 2012).

Before turning to Employee-Driven Innovation, it is necessary to clarify what this study means by an innovative work practice, and how it relates to the concepts of innovativeness, innovative behaviour, and innovation. These terms are often used interchangeably in the literature, yet they represent analytically distinct phenomena (Crossan & Apaydin, 2010; de Jong & den Hartog, 2010).

Innovation refers here to realised novelty at the organisational level: new or significantly improved products, services, processes, or administrative methods, typically assessed through performance outputs or counts (Crossan & Apaydin, 2010). Innovativeness, by contrast, is a relatively stable individual propensity: a tendency to seek out and try novel ideas or technologies (Goldsmith & Flynn, 1995). In the IT domain, this is operationalised as Personal Innovativeness in IT (PIIT), a domain-specific trait capturing readiness to experiment under uncertainty (Agarwal & Prasad, 1998). Innovative behaviour occupies the space between propensity and outcome: it refers to the work-related actions through which employees generate ideas, champion them, and

translate them into practice (de Jong & den Hartog, 2010; Kleysen & Street, 2001). These constructs are conceptually distinct and can be understood as temporally related: innovativeness predisposes, behaviour enacts, and innovation may materialise as the accumulated, selected product of many enacted behaviours (see Appendix C for a full overview).

In this study, an innovative work practice refers to an employee-level, technology-enabled way of performing work in which the tablet is perceived as helping the employee identify, develop, try out, or adapt novel or improved ways of performing work tasks. It does not require that the practice has already resulted in a formally recognised organisational innovation. Rather, it captures the ideation and exploratory-use stage of innovation, where employees use the tablet to support new ways of solving problems, organising work, accessing information, collaborating, or improving task performance. For the purposes of this study, the concept is delimited in three ways:

- *It is measured at the individual and subjective level:* it is assessed through employees' self-reported perceptions of the tablet's contribution to idea generation and task improvement.
- *It is technology-mediated:* the practice is captured through the employee's perceived experience of repurposing or extending a digital artefact (here, a tablet), reflecting the cognitive and motivational orientations associated with the innovative use of technology.
- *It is contextually situated:* whether the tablet is perceived as enabling innovative ideation depends on how well it fits the employee's task context, the employee's propensity to experiment, and the organisational conditions that support or constrain exploration.

Crucially, innovative work practice in this sense is distinguished from routine use, where employees rely on prescribed tablet functions without attempting to alter or improve existing work practices. Using a tablet to read emails represents routine use; using it to develop or trial a shared collaborative workflow that replaces an existing paper-based sign-off process represents an innovative work practice in this sense. It is also distinct from innovation outcomes, which capture realised novelty at the organisational level (Crossan & Apaydin, 2010). Accordingly, the scale used in this study captures employees' self-reported perception that tablet use supports the ideation stage of innovative work practice, rather than objectively verified innovation outcomes (Torkzadeh et al., 2005).

In summary, innovative work practice in this thesis refers to the employee-level, tablet-enabled ideation and exploratory use that situates individual innovativeness (PIIT) and innovative behaviour (ITIB) within the pathway toward potential organisational innovation outcomes. This conceptualisation is appropriate for the present study for three reasons. First, in SMEs with limited

formal R&D, innovative work practices at the individual level can constitute the primary pathway through which ICT investments translate into organisational value (Hoyrup, 2012). Second, tablets - as general-purpose devices deployed across diverse task contexts - create the affordance conditions under which such practices can emerge: their mobility, touch interaction, and rich ecosystems support both routine and emergent use (Magsamen-Conrad et al., 2015; Quade & Leimstoll, 2017). Third, measuring innovative work practices at the employee level rather than the firm level avoids the aggregation bias that characterises most SME adoption research, where owner-manager reports proxy for the entire workforce (Lee et al., 2023; Parker & Castleman, 2009). Section 2.5.3 returns to these distinctions when positioning PIIT and ITIB within the conceptual model. With this conceptual grounding established, the section now turns to Employee-Driven Innovation in more detail.

Employee-driven Innovation (EDI) is defined as: “Employee-driven innovation refers to the generation and implementation of new ideas, products and processes – including the everyday remaking of jobs and organisational practices – originating from interaction of employees, who are not assigned to this task. The processes are unfolded in an organisation and may be integrated in cooperative and managerial efforts of the organisation. Employees are active and may initiate, support or even drive/lead the processes.” (Hoyrup, 2012 p 24). In this study, innovative work practices constitute one mechanism through which such “everyday remaking of jobs and organisational practices” can occur in tablet-mediated work.

One way to further specify EDI is to classify practices according to how innovative ideas spread in the organisation, distinguishing more local, informal adaptations from more formalised, system-level innovations (first-to-third order EDI, see Table 2.1) (Hoyrup, 2012; Price et al., 2012). For the purposes of this study, first- and second-order EDI are most relevant, as SMEs typically rely on informal employee adaptation, problem-solving and manager-supported idea development rather than the fully formalised, top-down innovation systems associated with third-order EDI.

Table 2.1 Classification of EDI processes

Type	Definition
First-order EDI	Bottom-up approach, dependent on how employees relate to their job. The immediate, short-term goal of an individual is not necessarily innovation, but rather adaptation or reconstruction of work practices. However, it does lead to innovation as a central outcome from the organisational point of view.

Type	Definition
Second-order EDI	It is a mixture of bottom-up and top-down approaches. Managers may seek or support employees' innovative ideas, but the entire process is not systematised and is driven as much by the employee as the management.
Third-order EDI	Top-down approach: formal processes are in place to seek or invite ideas from employees. Employees are also involved in developmental projects, participate in brainstorming or other similar meetings aimed at innovation in the organisation.

Objective measures such as patent counts or specific numbers of technical innovations are typically available only for specific occupations or assignments (e.g. engineers, scientists, R&D departments). Creativity scholars have called for more research where innovation and everyday work performance are not synonymous (Crossan & Apaydin, 2010; de Jong & den Hartog, 2010; Mumford, 2003). This research responds to this call by evaluating innovativeness and innovative behaviour at the employee level in SMEs.

2.4.3 Post-Adoption ICT use in SMEs

2.4.3.1 Introduction

To ground this focus on employee-level innovativeness in actual ICT-use patterns, a targeted literature review of post-adoption ICT use in SMEs was conducted using a structured approach across multiple academic databases (EBSCO, Scopus, Web of Science, Google Scholar) covering the period 2011-2025. Core early papers were included through citation checks. The search strategy employed the following key terms: "SME post-adoption ICT," "small business technology continuance," "SME post-implementation," "technology appropriation SMEs," "ICT continuance intention," and "SME digital technology behaviour". Initial searches yielded 680 articles, which were refined through inclusion criteria. The main target was to select empirical studies examining post-adoption behaviours and sustained ICT use in small and medium enterprises. After removing duplicates and applying quality criteria, 45 studies were selected for detailed analysis and synthesis – key papers and research gaps are summarised below.

Three distinct waves can be recognised across this timeframe:

- The Mobile Revolution (2011–2015): The integration of smartphones and tablets into workflow management, moving beyond communication to core business processing (Quade & Leimstoll, 2017)

- The Cloud Era (2015–2020): The shift from on-premise servers to SaaS (Software as a Service) models, lowering cost barriers but raising issues of trust and security (Lutfi, 2022).
- The Pandemic and Post-Pandemic Acceleration (2020–2025): A period of "forced" digitalisation where survival depended on remote capabilities, leading to a focus on agility, resilience, and the rapid assimilation of e-commerce and digital collaboration tools (Ardiansah et al., 2024; Kumar & Ayedee, 2021)

The next section provides an overview of some of the key themes.

2.4.3.2 Key Themes in Post-Adoption SME Research

Continuance and Sustained Use

In the early 2010s, research was predominantly concerned with the barriers to entry: cost, infrastructure, and lack of awareness. As the timeline progresses toward 2025, the literature pivots to the quality of use. The distinction between "symbolic adoption"—where a system is purchased but barely used—and "extended use"—where features are exploited to their full potential—has become a focal point of inquiry (Wang & Hsieh, 2006).

Research on SME post-adoption behaviour reveals that initial adoption does not guarantee sustained use or successful integration. Al-Hattami et al. (2023) demonstrated that factors determining continuance intention for digital accounting systems among SMEs differ significantly from initial adoption drivers. Their study of 146 SMEs found that relative advantage emerged as the strongest predictor of both attitude and satisfaction, which subsequently influenced continuance intention. The Expectation-Confirmation Model (ECM) (Bhattacharjee, 2001) has proven particularly relevant in SME contexts – a similarly accounting information system-focused study revealed the importance of managerial support (Lutfi, 2022). Recent research documents "IS use resumption" as a distinct phase where users re-engage after periods of dormancy (Platzer et al., 2025).

Innovation and Creative Appropriation

Post-adoption ICT use in SMEs frequently involves creative appropriation and innovative applications beyond the original intended purposes. Jasperson et al. (2005) identified that SMEs demonstrate significant post-adoptive behaviours, including "extended use" (using more system features) and "emergent use" (novel applications of the technology). These behaviours are particularly pronounced in SMEs due to their organisational flexibility and proximity to operational processes.

Parthasarathy and Bhattacharjee (1998) distinguished between replacement discontinuance (switching to superior alternatives) and disenchantment discontinuance (ceasing use due to dissatisfaction) in their seminal study of post-adoption behaviour in the context of online services. Their findings revealed that SMEs showing higher service utilisation and stronger network externalities during initial adoption were more likely to continue usage, while later adopters were more susceptible to disenchantment and discontinuance.

Across the SME literature, ICT-enabled digitalisation is consistently linked to stronger innovation outcomes: it equips employees with collaboration and mobility tools that heighten engagement and creativity (Chung et al., 2015), improves the firm's capacity to sense and seize opportunities and orchestrate resources for growth (Kallmuenzer et al., 2024), and yields measurable gains in product, service, organisational, and process innovation when effectively implemented (Escoz Barragan et al., 2025; Quade & Leimstoll, 2017).

Organisational Factors Enabling Post-Adoption Value

SME post-adoption success is heavily influenced by organisational readiness and management support. Giotopoulos et al. (2017) analysed 2,582 Greek SMEs and found that post-adoption ICT benefits were maximised when organisations aligned technology investments with internal capabilities and existing business processes. This alignment was particularly critical for smaller firms with limited resources to absorb implementation mistakes.

The role of employee ICT competency in post-adoption phases differs from that in the adoption phases. While technical skills are crucial for initial implementation, post-adoption value creation depends more on business process understanding and creative problem-solving capabilities. Zamani et al. (2022) found that SMEs with higher organisational innovativeness demonstrated superior post-adoption performance, suggesting that technical factors may be secondary in sustained ICT use. In effect, dispersed employee initiatives scale into organisation-level innovation performance when complemented by innovation-oriented HR practices and foundational digital skills (Escoz Barragan et al., 2025).

Sibassaha et al. (2025) demonstrate that digital transformation's link to employee innovation is channelled not by transformational leadership alone, but by organisational appraisal practices and innovation culture. These findings suggest that innovation support (cultural messaging, management endorsement) must be operationalised through concrete practices to matter in practice. This underscores the study's focus on employee beliefs and organisational support and facilitation as mechanisms connecting ICT/DT to innovation.

Contextual Factors and Environmental Influences

Post-adoption ICT behaviour in SMEs is significantly influenced by external environmental factors. The COVID-19 pandemic provided a natural experiment demonstrating how environmental pressures can accelerate post-adoption innovation. Kumar and Ayedee (2021) documented how SMEs that had already adopted basic ICT suddenly expanded their usage to include e-commerce, social media marketing, and digital customer engagement during lockdowns.

Industry context also shapes post-adoption patterns. Taruté and Gatautis (2014) identified that service sector SMEs showed different post-adoption trajectories compared to manufacturing SMEs, with service firms more likely to expand ICT use into customer-facing applications while manufacturing firms focused on internal process optimisation.

Recent work also shows that intermediaries (clusters, associations, consultancies) often catalyse adoption trajectory for SMEs by spotting opportunities, co-creating business models with SME stakeholders, and "revamping" local ecosystems to sustain and scale DT beyond one-off pilots (Hafeez et al., 2025).

2.4.3.3 Research Gaps and Limitations

Based on the literature review, the following gaps were identified:

- **The Technological Artefact Gap: Deconstructing the "Mobile".** A significant limitation in current literature is the lack of technological specificity. Studies frequently aggregate diverse devices—smartphones, tablets, and wearables—under the umbrella of "mobile technologies" or m-solutions (Quade & Leimstoll, 2017). This study specifies tablets and differentiates them from other m-solutions.
- **The Methodological Gap: Cross-Sectional Snapshots.** The field is saturated with cross-sectional studies employing variance theories (e.g., TOE, TAM, UTAUT) and a singular viewpoint that captures adoption at a single point in time (Lutfi, 2022). This approach fails to capture the temporal dynamics of post-adoption infusion. There is a critical need for research to explain the mechanisms of how usage behaviours mature and why discontinuance occurs over time (Al-Hattami & Almaqtari, 2023). This study follows a cross-sectional survey (2014-15) with an interview phase (2021) to evaluate temporal dynamics.
- **The Level of Analysis Gap: Firm-Level Bias vs. Employee.** SME research shows a pervasive firm-level bias, often relying on owner-managers as the sole informants to proxy for the entire organisation (Lutfi, 2022). Recent studies highlight that digital transformation

outcomes depend heavily on individual appraisal (challenge vs. threat) and bottom-up innovative behaviour, yet these factors remain under-researched in the specific context of SME tablet usage (Pahos et al., 2025; Sibassaha et al., 2025). This study completes both the survey and the follow-up interviews at the employee level.

- **The Outcome Gap: Continuance vs. Innovative Behaviour.** Standard post-adoption models (like the Expectation-Confirmation Model) typically treat the routine continued use of a system as the ultimate dependent variable (Al-Hattami & Almaqtari, 2023). However, for SMEs to bridge the "second-level digital divide", routine use is insufficient. There is a gap in research modelling IT-enabled Innovative Behaviour (ITIB) as a distinct outcome separate from, and subsequent to, continuance. Current literature often fails to distinguish between employees who merely "use" the device and those who "innovate" with it to alter workflows and create value (Sibassaha et al., 2025). This study specifically models ITIB as a separate outcome.

This study addresses these gaps via an individual-level continuance lens and by foregrounding IT-enabled innovative behaviour (ITIB) as the pathway from traits and context to sustained use. The focal device is a tablet, and a mixed-methods approach is used. The next chapter formalises the individual post-adoption pathway—UTAUT with Attitude reinstated—to explain how beliefs translate into sustained tablet use and innovative behaviour in Hungarian SMEs.

2.5 Theoretical Frameworks on Technology Adoption

2.5.1 Introduction

This section narrows the literature review from broad adoption/diffusion perspectives to the specific individual-level mechanisms that explain continued use of tablets in Hungarian SMEs. Building on the prior discussion of uneven digital uptake and SME adoption realities, the goal here is to select and justify an individual framework that can account for post-adoption beliefs and behaviours in a mandated setting. The research adopts the Unified Theory of Acceptance and Use of Technology (UTAUT) as the core lens because its belief–intention logic is well established in organisational contexts and readily adapted to continuance. In a post-adoption environment, Attitude is reinstated as a proximal, experience-based appraisal that shapes both innovative use and continuance intention.

Where helpful conceptually—but without adding unmeasured constructs—continuance insights from ECM/TCM are referenced: day-to-day experience naturally invites an informal comparison between expectations and reality ("confirmation"), which influences users' overall evaluative

stance (“attitude/satisfaction-like”). In this study’s cross-sectional design, those processes are treated as background mechanisms through which experience updates Performance Expectancy and Attitude, which then drive IT-enabled innovative behaviour and Continuance Intention. Section 2.5 details UTAUT and its adaptation to this post-adoption, mandated SME context; Section 2.6 then progresses to the theoretical and conceptual model development.

2.5.2 Theoretical Framework: UTAUT

2.5.2.1 Selecting UTAUT

Various theoretical frameworks have been formulated to focus on ICT adoptions in organisations: the Technology, Organisation and Environment (TOE) approach (Tornatzky & Fleischer, 1990), the Institutional Theory (InT) (Oliveira & Martins, 2011), or the Small Business User IT Satisfaction (SBUSIT) approach (Palvia, 1996). In addition, individual-level frameworks were formulated from the user point of view, such as the Task Technology Fit (TTF) (Goodhue & Thompson, 1995), the Reasoned-Action Approach (RAA) (Fishbein & Ajzen, 2010), or the Technology Acceptance Model (TAM) and its subsequent variants (Davis, 1989; Venkatesh et al., 2003). See Appendix D for a compact overview. An individual unified model - Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) integrates many of the above models and is used extensively.

Authors naturally recommended the combination of various models, dealing with both individual and organisational levels. As an example, a combination of TOE, TAM and DOI resulted in a complex model to explain e-commerce adoption in SMEs (Awa et al., 2015). While useful, multi-level combinations require data across organisational, environmental and individual levels that were not feasible in the Hungarian SME context.

Most frameworks emphasise initial adoption; the focus in this study is post-adoption at the individual level in mandated (provisioned) SME settings. UTAUT is therefore the most applicable backbone, with TOE/InT mainly firm-level (Oliveira & Martins, 2011) and SBUSIT is better suited to bespoke applications than to general-purpose devices like tablets. UTAUT has also been applied in SMEs and in tablet contexts. A short comparative summary of these models is provided in Table 2.2.

Table 2.2 Summary of ICT Adoption Frameworks

Theoretical Framework	Organisational or Individual level	Individual Adoption or Post-adoption Phase	Comments
TOE	Organisational	Adoption	Primarily organisational model, individual extension is limited.
InT	Organisational	Adoption	Primarily organisational model, individual extension is limited.
SBUSIT	Individual	Adoption	Individual, relies on but relies on firm-level approaches and indicators, thus has a different focus and requires a more focused application. Better for tailored apps than devices.
TTF	Individual	Adoption	Needs a specific task to achieve the best results: different tasks will be assigned to different SMEs for tablet usage, and comparison would be difficult. Emergent use is not measured in this model.
RAA	Individual	Both	Generic model, components are subsumed in UTAUT.
TAM	Individual	Both	A widely used model in ICT research, constructs are refined within UTAUT.
UTAUT	Individual	Both	Extensive, well-formulated model, applicable at various points during the adoption process. Adaptable. Tested in SME environments.

While each framework offers insights, UTAUT is selected for this study for four reasons. First, UTAUT is explicitly designed for organisational adoption contexts, integrating multiple predecessors (e.g., TAM, Theory of Planned Behaviour, DOI) and thus consolidating fragmented individual-level theory (Venkatesh et al., 2003). Second, unlike TOE and InT (primarily firm-level), UTAUT operates at the employee level, making it suitable for understanding individual beliefs, attitudes, and behaviours. Third, unlike TTF (task-specific) or SBUSIT (application-specific), UTAUT is generalisable across devices and tasks, allowing comparison across diverse tablet use cases in SMEs. Finally, unlike earlier TAM variants, UTAUT has been validated in post-adoption contexts (through studies of continuance intention and long-term usage), not solely initial adoption (Venkatesh et al., 2003).

The addition of Attitude (ATT)—reinstated in this study after UTAUT's original omission in the 2003 model—reflects post-adoption emphasis on affective bonds and emotional attachment to

technology rather than initial utilitarian drivers alone. This reintroduction of Attitude follows recent calls to reconsider affect in technology acceptance (Brown et al., 2025; Rouibah et al., 2016).

2.5.2.2 Reviewing UTAUT

The Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) unifies elements from: Theory of Reasoned Action (TRA) (Davis et al., 1989), Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000), Motivation Model (MM) (Bagozzi et al., 1992), Theory of Planned Behaviour (TPB) and a combination of TAM and TPB (Taylor & Todd, 1995), Model of PC Utilisation (Thompson & Higgins, 1991), Innovation Diffusion Theory (Moore & Benbasat, 1991; Rogers, 2003), and Social Cognitive Theory (Compeau et al., 1999).

The UTAUT model (see Figure 2.3) includes Performance Expectancy (PE), defined as “the degree to which the individual believes that using the system will help him or her to attain gains in job performance” (Venkatesh et al., 2003). PE is typically the strongest predictor of intention in both voluntary and mandatory settings (Agarwal & Prasad, 1998; Davis, 1993; Venkatesh & Davis, 2000; Venkatesh et al., 2003). Related measures vary, but capture a common usefulness/performance perception (Davis, 1989, 1993; Moore & Benbasat, 1991; Thompson & Higgins, 1991; Venkatesh et al., 2003). However, in the case of general-purpose devices such as tablets, PE is unlikely to be a monolithic, “global” assessment. Rather, employees appraise utility in relation to one or more dominant tasks—for instance, supporting client meetings, accessing documentation on the move or capturing field data (Oliveira et al., 2014).

Effort Expectancy (EE) is defined as “the degree of ease associated with the use of the system” (Venkatesh et al., 2003). While Performance Expectancy captures outcome beliefs, Effort Expectancy represents the access pathway—the cognitive ease required to reach those outcomes. EE operates as an enabler: when interfaces demand excessive mental effort, users exhaust cognitive resources on navigation rather than task performance or feature exploration (Sweller et al., 1998). High EE (low perceived effort) frees capacity for recognising performance value and experimenting with novel uses. This aligns with van Dijk's (2019) “skills access” dimension—employees require not only devices but also manageable interfaces that translate capabilities into accessible workflows. EE also enables task-technology fit realisation: a tablet may objectively suit a task, but if the interface is cumbersome, users abandon it before discovering value. Ease of use thus acts as a prerequisite for PE formation in post-adoption contexts (Goodhue & Thompson, 1995).

Social Influence (SI) is defined as “the degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003).

Finally, Behavioural Intention (BI) represents the individual’s intention to use the system, which is a predictor of actual Use Behaviour, subject to Facilitating Conditions (FC). FC is defined as “the degree to which an individual believes that an organisational and technical infrastructure exists to support the system” (Venkatesh et al., 2003).

The UTAUT model expanded on TAM in a variety of ways and integrated other concepts into the model (Venkatesh et al., 2003). In addition, the names of the core items became more descriptive (Effort Expectancy, Performance Expectancy). UTAUT also specified four moderators as follows:

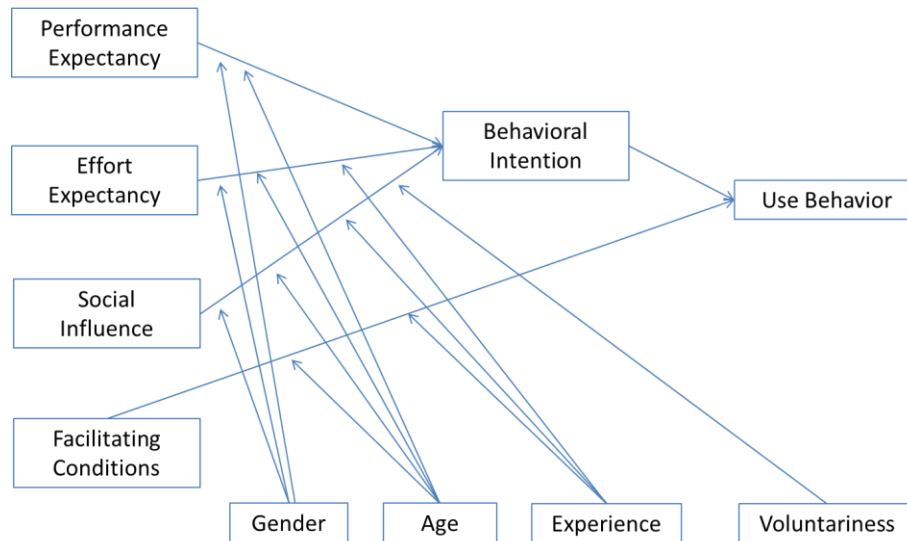
Gender: Proposed to moderate the effects of performance expectancy, effort expectancy, and social influence on behavioural intention. For example, performance expectancy is suggested to be more salient for men, while effort expectancy may be more salient for women, particularly older women.

Age: Hypothesised to moderate the impact of all four core constructs. For instance, younger workers might place more emphasis on performance expectancy, while older workers might be more influenced by effort expectancy and social influence. Age also moderates the effect of facilitating conditions on usage.

Experience: Prior experience with similar systems or the specific technology is expected to moderate the effects of effort expectancy, social influence on behavioural intention, and facilitating conditions on usage behaviour. As experience increases, the impact of effort expectancy on intention tends to diminish.

Voluntariness of Use: This refers to whether the use of the technology is perceived as voluntary or mandatory. Voluntariness is posited to moderate the relationship between social influence and behavioural intention, with social influence being more significant in mandatory settings.

Figure 2.3 UTAUT Model



The original study demonstrated UTAUT's superior explanatory power (~69–70% of BI, ~50% of Use Behaviour), outperforming the eight individual models, establishing UTAUT as a leading model.

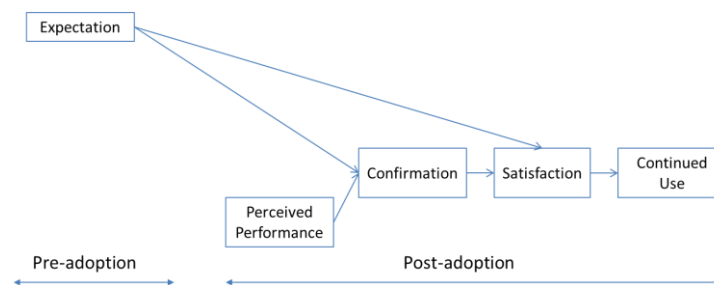
Extensions include UTAUT2, a consumer-focused variation adding hedonic motivation (the fun or pleasure derived from using a technology), price value (cognitive trade-off between perceived benefits and monetary cost), and habit (the extent to which individuals tend to perform behaviours automatically due to learning) to the model, which are less relevant to the SME settings in this study (Morosan & DeFranco, 2016; Venkatesh et al., 2012). Another well-known variation is the Two-stage Continuance Model (TCM), which distinguishes between pre-usage beliefs and post-usage beliefs (Venkatesh et al., 2011). A meta-analysis recommends reintroducing Attitude in many contexts (Dwivedi et al., 2019; Dwivedi et al., 2020). This study accordingly reinstates Attitude as a proximal, experience-based appraisal in post-adoption.

The UTAUT model, upon its introduction, offered significant advancements through integration and higher explanatory power. However, UTAUT is not without its limitations. Parsimony is affected by moderators, and early validations were in large organisations with mandatory use—raising contextual questions for SMEs with distinct resources and routines. Nonetheless, UTAUT has been employed in SME settings (e.g., WLAN planning) and performs adequately with contextual adaptation (Anderson & Schwager, 2004; Mursalin, 2012). In line with the post-adoption focus, Section 2.6 reinstates Attitude and incorporates IT-enabled Innovative Behaviour (ITIB) as a behavioural conduit to continuance.

There are a large number of studies referring to UTAUT, but a detailed meta-analysis in 2011 found that out of 450 citations, only 43 studies actually used UTAUT constructs (Dwivedi et al., 2011). Four meta-analyses (Dwivedi et al., 2011; Hwang & Lee, 2018; Khechine et al., 2016; Taiwo & Downe, 2013b) confirm robustness; most researchers observe weaker effects and frequently ignore moderators. Performance Expectancy is typically the strongest predictor of Behavioural Intention (Dwivedi et al., 2011; Khechine et al., 2016). In continuance extensions, hedonic/enjoyment and Attitude often show notable effects; security tends to be small (Hwang & Lee, 2018). Relevant to this study, the model has been validated in a multi-generational tablet usage scenario, although the moderators (e.g., gender) did not show effects (Magsamen-Conrad et al., 2015).

Cross-sectional studies increasingly clarify whether they target pre-, adoption, or post-adoption stages (Nabavi et al., 2016). This study explicitly targets post-adoption continuance in mandated SME use. In continuance studies, the focus shifts to antecedents of repeat behaviour (Bhattacharjee, 2001), addressed either longitudinally or via cross-sectional post-adoption designs (as here). Early longitudinal work (Davis et al., 1989) removed Attitude for parsimony, but continuance contexts often reintroduce an evaluative affect (Attitude/Satisfaction). Expectation Confirmation Model (ECM) and Two-stage Continuance Model (TCM) are referenced conceptually (confirmation → satisfaction → continuance), but this research does not add unmeasured constructs; PE is treated as experience-updated usefulness and Attitude as the affective channel in this cross-sectional model (Bhattacharjee, 2001; Bhattacharjee & Premkumar, 2004; Venkatesh et al., 2011).

Figure 2.4 Expectation Confirmation Model (Bhattacharjee, 2001)



ECM is shown on Figure 2.4 with the Confirmation construct. TCM similarly introduces post-usage confirmation — the degree to which actual experiences either meet or fail to meet users' initial expectations (Venkatesh et al., 2011). By emphasising pre-usage expectations and post-usage experience (including disconfirmation and, in some settings, trust), these models explain how continuance intentions form. This approach requires pre- and post-adoption measurement to

model how confirmation shapes satisfaction and updates beliefs/attitudes (Venkatesh et al., 2011). ECM/TCM posits that confirmation and satisfaction drive continuance; TCM separates pre- vs post-usage beliefs. Within DASAT, “confirmation-like” learning is operationalised by DAI metrics and DTCL reviews comparing expected vs realised benefits, which loop back to DSR (refining the roadmap) and DA (diffusing literacy). This strengthens the rationale for modelling continuance in an SME setting where organisational feedback cycles directly condition individual beliefs. However, synchronising tablet adoption timing across multiple Hungarian SMEs was infeasible. Consequently, the model estimates UTAUT beliefs with Attitude reinstated (PE, EE, ATT → ITIB/CI). This research, therefore, acknowledges ECM/TCM mechanisms: employees informally compare expectations with experience (“confirmation”) and form an overall affective evaluation (“satisfaction”). In this cross-sectional design, these constructs are not modelled; rather, they are treated as background processes through which day-to-day use updates PE and Attitude, thereby influencing ITIB and continuance intention (Bhattacharjee, 2001; Bhattacharjee et al., 2008; Bhattacharjee & Premkumar, 2004; Limayem et al., 2007; Venkatesh et al., 2011). ECM/TCM concepts inform the theoretical narrative, but Satisfaction and Habit are not measured; instead, Attitude is used as a parsimonious post-adoption proxy consistent with mandated use contexts.

Comparisons show that parsimonious models (e.g., TAM) sometimes rival richer continuance models cross-sectionally (Hong et al., 2006), but this does not preclude using UTAUT with Attitude for post-adoption in organisations (Liao et al., 2009). Longitudinal evidence further suggests that Attitude becomes more stable and influential with experience (Liao et al., 2009). Other acceptance models have continuance variants (e.g., TPB in mobile data; (Boakye, 2015)), but this study retains UTAUT: UTAUT (with minor modifications) has been used in post-adoption SME studies (Nabavi et al., 2016); effects can differ by stage (e.g., PE/SI stronger pre-adoption (Šumak & Šorgo, 2016)).

It should be noted that while the original UTAUT (2003) excluded Attitude at initial adoption for parsimony and collinearity reasons, continuance contexts differ. With accrued experience, users form comparatively stable evaluative affect toward the artefact, and continuance models (e.g., UTAUT extension or ECM derivatives) commonly re-introduce Attitude (or Satisfaction). In mandated or quasi-mandated contexts such as many SMEs—where management acquires tablets and expects employees to use them—Intention to Use risks collapsing into an indicator of compliance rather than genuine acceptance. Under these conditions, Attitude captures something qualitatively different: the individual’s internal evaluation of the technology (“Do I enjoy using it?”),

“Do I see it as valuable for my work?”) rather than their willingness to conform. ATT therefore marks the boundary between ritualistic use, where employees comply with minimum expectations, and infused use, where they explore and appropriate the technology in richer ways. Within DASAT, implementation learning (DAI) and improvement routines (DTCI) provide the experience that updates PE and Attitude (Bhattacharjee, 2001; Limayem et al., 2007). Consistent with this, the study reinstates Attitude and introduces ITIB as the behavioural conduit to CI.

A systematic literature review highlighted that the most commonly used models in continuance situations are ECM, TAM, TPB and UTAUT (Nabavi et al., 2016). However, only a small share focus on organisational users, so applying UTAUT in SME post-adoption should add useful evidence (Nabavi et al., 2016).

2.5.2.3 UTAUT Applicability to SMEs

UTAUT is widely used in organisations, but SME-specific applications remain comparatively fewer. One of the more complex papers applies UTAUT in SMEs to examine digitalisation adoption in two European nations (Kwarteng et al., 2024).

The focus is digitalisation intentions and adoption decisions of owner-managers — a wider scope than device-level tablet use. The data compares national characteristics between the Czech Republik and Slovakia. In addition to the usual UTAUT items (PE, EE, FC; SI dropped), the study adds Competitive Pressure (CP) and includes country as a moderator. Globally, the model explained $R^2 \sim 45.8\%$ for intention to digitalize. PE, FC and CP significantly affect owner-managers intentions, while EE is not significant; FC is the key predictor in both countries, and EE is the weakest—possibly because owner-managers are already familiar with digital technologies (Kwarteng et al., 2024).

Another study—from rural SMEs in South Africa—combines UTAUT elements with TOE to discuss the usage of information technology for growth (Dandadzi & Seeletse, 2025). Without statistical testing, the authors qualitatively underline PE and note that limited know-how can impede value realisation.

A literature review synthesising Indonesian SME studies concludes—again qualitatively—that PE, EE, and SI shape intention and use of e-accounting (Sembiring et al., 2024).

Another systematic review of UTAUT/UTAUT2 for MSMEs in non-OECD countries (manager-owner perspective) reviews 48 studies; UTAUT constructs are examined more often than UTAUT2. Over half of the studies target value-chain applications; 16 are organisation-wide. The review finds PE and FC strong, EE generally weaker (Lee et al., 2023).

UTAUT's constructs are adapted and extended to fit SME contexts—including digitalisation and sector-specific applications—demonstrating flexibility (Kwarteng et al., 2022; Kwarteng et al., 2024). Studies have incorporated moderators such as organisational size, culture, personal initiatives, trust and competitive pressure to enhance contextual relevance (Kwarteng et al., 2024; Wismantoro & Susilowati, 2021). However, SMEs' unique characteristics—resource constraints, informal structures, idiosyncratic decision-making—are often inadequately captured by UTAUT's generic constructs (Idris et al., 2017; Parker & Castleman, 2009). The model may overlook environmental, personal and organisational factors critical in SME post-adoption phases (Idris et al., 2017; Zamani, 2022). Cross-cultural variations and/or sectoral variations may further challenge the model's generalizability (Im et al., 2011; Simeonova et al., 2014). Given the focus on innovative uses, this study therefore examines personal (personal innovativeness) and organisational (innovation support and facilitation) enablers in the next section.

2.5.3 Innovativeness, Innovative Behaviour and Innovation

As clarified in Section 2.4.2, this study distinguishes between innovation as a realised organisational outcome, innovativeness as an individual propensity, and innovative behaviour as the employee-level enactment of idea generation, championing and application. This distinction is important because the present study does not measure objectively verified innovation outputs, such as patents, new products or formal process innovations. Instead, it focuses on the employee-level pathway through which such outcomes may emerge: tablet-enabled ideation and exploratory use. Extended definitions and level distinctions are further discussed in Appendix C.

Personal Innovativeness in IT (PIIT) captures a domain-specific readiness to try new IT and tolerate uncertainty (Agarwal & Prasad, 1998). It is therefore suited to explain differences in willingness to explore a general-purpose device such as a tablet. High-PIIT employees are more inclined to open menus, test advanced features, probe unfamiliar applications and look for alternative ways of completing work tasks. However, empirical findings show that PIIT is more complex than a uniformly positive “booster” of adoption. Studies report positive, null and even negative associations with core acceptance constructs and usage, suggesting that highly innovative users may also be more critical and more willing to abandon technologies that do not meet their expectations (Agarwal & Karahanna, 2000; Jackson et al., 2013; Lewis et al., 2003; Lu et al., 2005; Rosen, 2005).

IT-enabled Innovative Behaviour (ITIB), by contrast, captures the behavioural and ideational expression of this propensity in relation to a specific digital artefact. In this study, ITIB refers to employees' self-reported perception that tablet use helps them generate, develop and try out

novel or improved ways of performing their work tasks. ITIB therefore represents the ideation and exploratory-use stage of innovative work practice, rather than a direct measure of realised organisational innovation. This operationalisation is consistent with research that shifted attention from generic creativity to how IT use helps employees create and try out novel ideas in their tasks (e.g., Torkzadeh & Doll, 1999; Torkzadeh et al., 2005).

This distinction also separates ITIB from extended usage. Extended usage refers to using a larger proportion of a system's existing features, whereas ITIB concerns emergent use: the employee's attempt to appropriate the technology in ways that may improve, adapt or reconfigure work practices. Drawing on Adaptive Structuration Theory (DeSanctis & Poole, 1994) and the concept of reinvention, ITIB can be understood as the user's active role in reshaping structures of use, for example by configuring workflows, combining applications, or introducing new practices that change how work is performed.

Historically, ITIB sits alongside two adjacent streams: 'exploration with IT' and 'trying to innovate with IT'. These streams variously emphasise searching/experimenting, intention to try, or emergent/novel use; over time, they converged on post-adoption use and sometimes served as proxies for each other (e.g., "emergent use"). Against this backdrop, ITIB is the stream whose measurement most cleanly captures ideation with IT, making it the closest behavioural conduit in mandated post-adoption contexts where tablets are already deployed. summarises these streams. Appendix C summarises these related streams.

This trait-behaviour pairing aligns with prior distinctions between predisposition and enacted behaviour (de Jong & den Hartog, 2010). It also connects with creativity research showing that individuals' dispositions (e.g., openness, playfulness, tolerance for ambiguity) provide a fertile ground for idea generation, but that actual creative performance depends on situational affordances and constraints (Amabile & Pratt, 2016; Mumford, 2003).

In the study's continuance framing, experience-updated beliefs—Performance Expectancy (PE) and Effort Expectancy (EE)—and a stabilising Attitude are expected to shape both ITIB and Continuance Intention in a mandated SME setting. PIIT is positioned as an upstream trait shaping employees' propensity to experiment, while ITIB represents the immediate, tablet-enabled expression of innovative behaviour. Chapter 7 revisits this trait-behaviour linkage, showing how different combinations of PIIT, ITIB and organisational conditions help to explain the second-level digital divide in tablet value realisation across SMEs.

2.5.4 Overview

The aim of this research is to explore the adoption and continued use of tablet devices by employees within Hungarian small and medium-sized enterprises (SMEs).

Organisational-level models provide insights into external and internal pressures that influence SME-level ICT adoption. However, their limited focus on individual agency renders them less suitable for studies centred on employees.

Among individual-level models, UTAUT emerge as dominant. TAM emphasises perceived usefulness and ease of use, while UTAUT expands this by redefining performance expectancy, effort expectancy, social influence, and facilitating conditions, moderated by gender, age, experience, and voluntariness. UTAUT is widely validated, including in SME contexts. UTAUT is also used successfully in continuance situations and therefore forms the core of this study's conceptual model. The post-adoption approach focuses on SMEs where tablet devices have been provisioned and used at least for 3 months.

Drawing upon UTAUT as the primary individual-level framework, this study incorporates individual characteristics such as personal innovativeness and motivation, as well as organisational support factors. This theoretical integration addresses a critical gap in existing literature: while many studies emphasise initial technology adoption, fewer investigate the sustained and effective use of ICT tools, especially in SMEs and post-transition economies like Hungary. By situating the research in a continued-use context and incorporating constructs from employee-driven innovation and technology continuance models, the study offers a view of how tablet technology is adopted and maintained within everyday business practices. The conceptual model emerging from this framework links individual beliefs and usage patterns with organisational conditions and guides the empirical analysis of continuance and IT-enabled innovative behaviour.

While UTAUT explains post-adoption behaviour at the individual level, from the SME point of view tablet usage unfolds within the DASAT organisational cycle. The next section details the theoretical and conceptual framework and connects it to DASAT.

2.6 Theoretical and Conceptual Framework

2.6.1 Model Development

This section develops the individual-level framework that links beliefs, affect, traits and organisational conditions to post-adoption tablet use in Hungarian SMEs. UTAUT provides the backbone of the model and is adapted to a mandated, post-deployment context by reinstating

Attitude as an affective appraisal, foregrounding IT-enabled Innovative Behaviour (ITIB) as a mechanism for deeper value realisation, and incorporating Personal Innovativeness in IT (PIIT) together with two organisational enablers—Innovation Support (IS) and Involvement Facilitation (IF)—as upstream conditions shaping innovative use and continuance (Figure 2.5).

In line with the post-deployment setting, the model retains UTAUT's core cognitive beliefs—Performance Expectancy (PE) and Effort Expectancy (EE)—as the main belief antecedents. These constructs capture employees' experience-based assessments of whether tablets help them perform their work more effectively and how easy they are to use. Because tablets are general-purpose devices, PE implicitly incorporates the logic of Task–Technology Fit (see Section 2.5.2) and reflects on users' dominant work tasks.

Studies indicate that in a continuance situation, attitude is one of the most commonly used and stable constructs (Liao et al., 2009; Nabavi et al., 2016). Attitude (ATT) is reinstated as an experience-based evaluation that consolidates these beliefs into an overall stance towards using the tablet for work. In addition, research indicates that in mandatory environments, attitude has a strong correlation with usage behaviour: employees may express positive or negative attitudes towards the given technology by either positively supporting the new technology, or resenting it (Brown et al., 2002). Consequently, in the context of this study, attitude is important and warrants consideration (Yousafzai et al., 2007a). In a TPB meta-analysis study, attitude overall presented the largest correlation with adoption propensity (Weigel et al., 2014). In this study, Attitude is specified as a predictor of both ITIB and Continuance Intention (CI), capturing the distinction between minimal use and engaged, exploratory use.

Two original UTAUT elements are not modelled as direct predictors of CI.

Social Influence is excluded because its effect typically diminishes with experience and when system use is mandated, a well-documented pattern in post-adoption contexts (Bhattacharjee, 2001; Bhattacharjee et al., 2008; Limayem et al., 2007; Venkatesh et al., 2003). Social Influence (SI) in low-voluntariness contexts may also be confounded with formal role expectations and managerial pressure (Clayton & Van Staden, 2015).

Facilitating Conditions (FC) are not linked directly to CI because FC primarily predict actual use behaviour rather than intention in mature, post-adoption contexts (Venkatesh et al., 2003).

The model introduces IT-enabled Innovative Behaviour (ITIB) as a distinct behavioural mediator between internal states and continuance (Torkzadeh et al., 2005). Rather than treating continuance as a simple “keep using vs stop using” decision, ITIB captures experimentation,

repurposing and extension of tablet features to generate novel or improved work outcomes. It represents the ideation and innovative-use pathway through which cognition and affect translate into deeper value realisation and, in turn, reinforce CI. Referencing more recent research, ITIB effectively operationalises the 'organisational bricolage' described in Section 2.2 at the individual level, capturing how employees repurpose available tools to solve immediate workflow problems (Senyard et al., 2014).

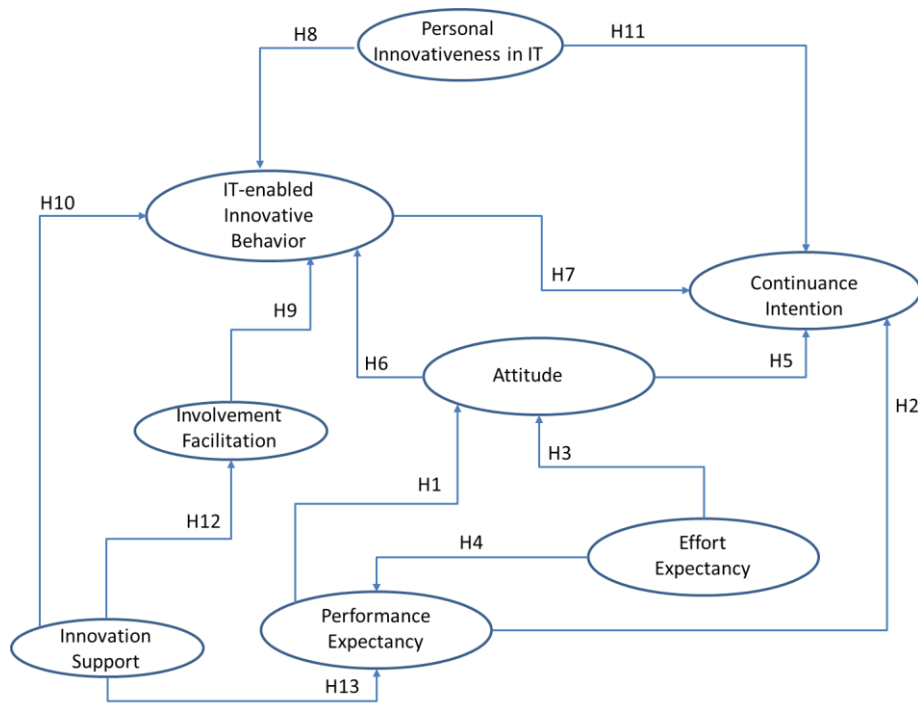
Upstream, three enablers are incorporated.

PIIT (Agarwal & Prasad, 1998) represents a relatively stable, domain-specific trait that shapes individuals' propensity to explore, experiment with and tolerate uncertainty around new IT. It is modelled as an antecedent of both ITIB and CI, leaving open the possibility that, in constrained or immature ecosystems, high innovativeness may encourage experimentation while also increasing sensitivity to frustration and disappointment.

Innovation Support (IS) and Involvement Facilitation (IF) represent the organisational environment. Organisational support for innovation and experimentation by users help them assess available information outputs, and increase their familiarity with the tablet, allowing for further exploration (McKeen et al., 1994; Tarafdar et al., 2010; Weinert et al., 2020). IS is conceptualised as a climate construct capturing employees' shared perceptions that experimentation and novel uses of technology are encouraged within the organisation. It reflects normative signals such as whether risk-taking is tolerated or whether managers respond constructively to ideas.

IF is conceptualised as the structural capacity of the organisation to translate the supportive climate into concrete opportunities for employees to engage with, shape and extend technology use (Doll & Torkzadeh, 1989; Nelson & Kletke, 1990; Tarafdar et al., 2010). It encompasses the provision of resources (e.g. reward or involvement time). In contrast to IS, which captures the "will" to innovate, IF represents the "way" in which that will is operationalised. IF is also modelled as a formative construct: its indicators represent distinct resource-provisioning mechanisms that are not interchangeable. Chapter 3 and Chapter 4 will further review the formative modelling of these constructs (IS, IF).

Figure 2.5 Conceptual model for continuance and IT-enabled innovative behaviour in SMEs



2.6.2 Construct Definitions

Table 2.3 summarises concise, post-adoption definitions, measurement cues, and each construct's role in the model

Table 2.3 Constructs for conceptual model

Abbrev.	Construct	Concise definition (post-adoption)	Measurement cue (examples)	Role in the model
PE	Performance Expectancy	The degree to which continued tablet use is perceived to improve task performance, efficiency, or outcomes. (Venkatesh et al., 2003)	"Using the tablet improves my work quality / helps me accomplish tasks more quickly."	Cognitive belief → affects ATT and CI (H1–H2); shaped by EE (H4).

Abbrev.	Construct	Concise definition (post-adoption)	Measurement cue (examples)	Role in the model
EE	Effort Expectancy	The perceived ease and clarity associated with using the tablet for routine work tasks. (Venkatesh et al., 2003)	“Learning to use the tablet is easy for me / interacting with it is clear and understandable.”	Cognitive belief → affects ATT (H3) and PE (H4).
ATT	Attitude toward Use	Overall evaluative affect toward using the tablet in job tasks, formed through experience in a mandated setting. (Bhattacharjee & Premkumar, 2004)	“Using the tablet is a good idea / pleasant / beneficial for my work.”	Affective appraisal → drives ITIB (H6) and CI (H5); mediates PE/EE → ITIB (M1–M2).
ITIB	IT-enabled Innovative Behaviour	User behaviours that experiment with, repurpose, or extend tablet features to achieve novel or improved work outcomes. (Trivellas & Santouridis, 2013)	“I try new tablet features to improve my tasks / adapt the tablet to new work needs.”	Behavioural conduit → strengthens CI (H7); mediates trait/organisational effects → CI (M3–M5); part of serial chains (M6–M8).
CI	Continuance Intention	The intention to keep using the tablet for work in the foreseeable future.	“I intend to continue using the tablet / it will remain part of my work.”	Focal outcome influenced by PE , ATT , ITIB , PIIT .

Abbrev.	Construct	Concise definition (post-adoption)	Measurement cue (examples)	Role in the model
		(Bhattacharjee & Premkumar, 2004)		
PIIT	Personal Innovativeness in IT	Stable individual tendency to try out new information technologies and tolerate uncertainty. (Agarwal & Prasad, 1998)	"If I hear about a new IT, I look for ways to try it / I am usually among the first to experiment."	Trait antecedent → boosts ITIB (H8) and directly CI (H11); effect partially mediated by ITIB (M3).
IS	Innovation Support	Organisational climate and mechanisms that encourage experimentation, idea sharing, risk-taking, and provide backing for early ideas. (Tarafdar et al., 2010)	"New ideas are encouraged / time and support are provided to try novel uses."	Context antecedent → increases ITIB (H10) and IF (H12); participates in serial path IS → IF → ITIB → CI (M8).
IF	Involvement Facilitation	Formal opportunities and resources that involve users across the IT lifecycle (trialling, feedback, training, influence on use). (Doll & Torkzadeh, 1989)	"I am involved in trying new uses / my input shapes how the tablet is used / I have access to training."	Context antecedent → increases ITIB (H9); contributes to mediation IF → ITIB → CI (M4).

2.6.3 Hypotheses Development

Consistent with the DASAT cycle, these paths treat continuance as the post-implementation consolidation phase: hands-on experience (DAI) confirms or disconfirms expectations, road-maps adjust (DSR), and routines for measurement/upskilling (DTCI) stabilise beliefs that shape continuance intention.

Grounded in the structure above—cognition → affect → innovative use → continuance, with trait and context shaping ITIB—the following hypotheses specify core continuance links, innovative-use links, trait/organisational enablers, and the corresponding mediations. Grounded in UTAUT adapted for continuance and the SME-tablet context—with Attitude reinstated for post-adoption and IT-enabled Innovative Behaviour (ITIB) explicitly modelled as the ideation pathway—the model links individual traits (PIIT) and organisational enablers (Involvement Facilitation, Innovation Support) to Continuance Intention (CI) through cognitive appraisals (PE, EE), affect (Attitude), and innovative use behaviour (ITIB).

2.6.3.1 H1 Performance Expectancy → Attitude

As defined in Table 2.3, PE represents "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003, p. 447). In post-adoption settings, users develop more nuanced judgments of whether continued use delivers meaningful work improvements, with these efficacy beliefs forming the cognitive foundation for evaluative affect (Venkatesh et al., 2012). UTAUT and TAM continuance studies consistently demonstrate that performance-related beliefs serve as primary anchors for favourable evaluations, particularly after users accumulate substantive experience with the system (Emon & Khan, 2025). As users move beyond initial adoption to sustained usage phases, their attitudes become increasingly influenced by perceived instrumental benefits rather than initial impressions or external recommendations (Ayaz & Yanartaş, 2020). Meta-analytical evidence positions performance expectancy among the strongest predictors of attitude in post-adoption contexts, with this relationship amplified when users receive regular feedback on system outcomes (Ren & Zhou, 2023; Yang et al., 2025); thus the following hypothesis was developed.

Rationale: As post-adoption users experience tangible outcomes, perceived usefulness becomes a primary affective predictor; meta-analytic UTAUT/TAM evidence places PE among the strongest predictors of attitude in usage contexts, amplified by implementation feedback in DASAT's DAI→DSR loop.

H1: Performance Expectancy will have a significant positive effect on Attitude.

2.6.3.2 H2 Performance Expectancy → Continuance Intention

PE is consistently one of the strongest predictors of continuance intention in post-adoption models of technology use (Bhattacharjee & Lin, 2015; Venkatesh et al., 2003). This relationship is supported both by the UTAUT and the ECM, which highlight perceived usefulness (analogous to performance expectancy) as directly reinforcing users' intentions to continue system usage, especially after they have confirmed the technology's value through experience (Bhattacharjee, 2001). This way perceived performance gains operate as a cognitive heuristic for future value assessments, directly strengthening intentions to maintain technology engagement (Bhattacharjee, 2001). Meta-analyses show that performance-related beliefs reliably anchor continuance intentions across technologies and contexts, even when satisfaction is included (Dwivedi et al., 2020; Sleiman et al., 2022; Tam et al., 2020). In mandated organisational settings such as SMEs, the utility calculus is central: higher performance expectancy directly elevates the perceived advantage of maintaining technology use, regardless of the presence or absence of satisfaction constructs (Ambalov, 2018). Parsimony arguments in model comparisons support performance expectancy's direct effect on continuance intention even when satisfaction constructs are present, indicating its fundamental role in continuance decision-making (Bhattacharjee & Lin, 2015). Recent longitudinal studies confirm that performance expectancy maintains predictive strength over time, suggesting stable cognitive processes underlying continuance judgments (Veronika et al., 2025); thus, the following hypothesis was developed.

Rationale: Continuance intention reflects a utility calculus; higher performance expectancy directly elevates the perceived value of ongoing use in mandated SME settings, consistent with UTAUT continuance extensions and confirmation-driven updates from implementation experience.

H2: Performance Expectancy will have a significant positive effect on Continuance Intention.

2.6.3.3 H3 Effort Expectancy → Attitude

Effort expectancy, defined as "the degree of ease associated with the use of the system" (Venkatesh et al., 2012, p. 450), significantly influences affective evaluations by reducing cognitive load and operational frustration during continued technology use. The theoretical foundation for this relationship draws from cognitive load theory, which posits that when systems require excessive mental effort, users experience cognitive strain that negatively impacts their evaluative responses (İbili & Billinghamurst, 2019). The Technology Acceptance Model establishes

that perceived ease of use serves as a key antecedent to attitude formation, with this relationship consistently supported across diverse technology contexts (Davis, 1989; Davis et al., 1989). When tablet systems are perceived as easy to learn and operate, users experience reduced cognitive strain and enhanced psychological comfort, enabling more positive affective responses to continued technology engagement (Lemay et al., 2018). Continuance-oriented UTAUT extensions position effort expectancy as a key antecedent of attitude formation, particularly as users develop stable interaction routines (Camilleri, 2024). Research demonstrates that ease of use perceptions create favorable conditions for attitude development by minimizing the mental effort required for system operation, allowing users to focus cognitive resources on value-generating activities rather than navigating system complexity (Chen et al., 2025). In mandatory organisational settings where users cannot easily discontinue system use, perceptions of required effort fundamentally shape whether technology interaction is experienced as pleasant or burdensome, directly influencing overall evaluative attitudes (Cimperman et al., 2016; Yang et al., 2025).

Rationale: Reduced effort costs improve affective evaluations in stable use phases; as routines form (DTCl), ease of use sustains favourable attitudes even when initial training support recedes.

H3: Effort Expectancy will have a significant positive effect on Attitude.

2.6.3.4 H4 Effort Expectancy → Performance Expectancy

The relationship between effort expectancy and performance expectancy is grounded in cognitive fluency theory, which posits that when cognitive processing becomes more efficient and less demanding, individuals develop enhanced capacity to recognise and appreciate system benefits (Davis, 1989; Venkatesh & Davis, 2000). When tablet systems are perceived as easy to learn and operate, users can allocate greater cognitive resources toward exploring advanced functionality and discovering performance advantages, creating a pathway from reduced effort to enhanced performance perceptions (Kim et al., 2015). The Technology Acceptance Model establishes that perceived ease of use serves as a fundamental antecedent to perceived usefulness, with this cognition-to-cognition relationship consistently supported across diverse technology contexts (Davis, 1989; Venkatesh & Bala, 2008). Empirical evidence from UTAUT studies demonstrates that effort expectancy positively influences performance expectancy, particularly in settings where users progress from basic operational competence to sophisticated value realization (Kim et al., 2015; Camilleri, 2024). The underlying theoretical mechanism involves cognitive load reduction: when operational demands are minimized, users experience enhanced processing fluency that enables deeper engagement with system capabilities and improved recognition of instrumental

benefits (Song, 2020; Esser et al., 2022). This relationship reflects the learning curve phenomenon wherein initial ease of use facilitates sustained exploration and experimentation, ultimately revealing performance advantages that may not be immediately apparent to users struggling with complex interfaces; thus, the following hypothesis was developed.

Rationale: When operation becomes fluent, users can better perceive instrumental benefits; longitudinal studies often observe an EE→PE channel post-adoption as skill gains convert into value recognition.

H4: Effort Expectancy will have a significant positive effect on Performance Expectancy.

2.6.3.5 H5 Attitude → Continuance Intention

Attitude represents a user's overall evaluative judgment toward the system, reflecting accumulated affective responses based on interaction experience (Davis, 1989; Yang & Yoo, 2004). In the context of technology continuance, research consistently demonstrates that a positive attitude is among the most robust and stable predictors of continuance intention (Foroughi et al., 2019). This effect intensifies in post-adoption stages, where attitudes crystallise through sustained system use and are informed by direct experiences of value, ease, or frustration (Thong et al., 2006). The Expectation-Confirmation Model (ECM) and Technology Acceptance Model (TAM) both position attitude as a key affective channel linking cognitive appraisals (such as usefulness and ease) to behavioural intention, and meta-analytical evidence corroborates attitude's centrality in continuance prediction (Bhattacharjee, 2001; Venkatesh et al., 2003). In mandatory use scenarios—such as SME technology implementations—attitude remains predictive even when controlling for satisfaction or habit, underlining its persistent influence as users move from initial trial to routine engagement (Bhattacharjee & Lin, 2015). Accordingly, it is theorised that a favourable attitude significantly raises the likelihood of continuance intention; thus, the following hypothesis is developed.

Rationale: In continuance, attitude is a robust, proximal predictor of intention; satisfaction/confirmation effects from ECM are captured in the evaluative component of attitude and reinforced by DASAT's measurement and improvement routines.

H5: Attitude will have a significant positive effect on Continuance Intention.

2.6.3.6 H6 Attitude → IT-enabled Innovative Behaviour

IT-enabled Innovative Behaviour encompasses ideation, exploratory use, and creative repurposing of technology features beyond routine applications (Torkzadeh & Doll, 1999;

Torkzadeh et al., 2005). Positive affect has been consistently linked to enhanced creativity and innovative performance through several psychological mechanisms: broadened attention, increased cognitive flexibility, and reduced inhibition toward novel approaches (Davis, 2009). Meta-analytical evidence demonstrates that positive affective states facilitate creative ideation by promoting associative thinking, increasing openness to experimentation, and reducing psychological barriers to trying unconventional solutions (Baas et al., 2008). In the technology context, favourable attitudes toward tablet devices should stimulate innovative behavioural exploration by creating psychological conditions conducive to creativity and experimentation (Akbari Chermahini & Hommel, 2012). When users hold positive evaluative attitudes toward technology, they are more likely to engage in playful exploration, seek novel applications, and generate creative workarounds for business challenges; thus, the following hypothesis was developed.

Rationale: Favourable attitudes lower psychological barriers to trying novel features/workarounds, facilitating day-to-day IT-enabled innovative behaviour in SME roles.

H6: Attitude will have a significant positive effect on IT-enabled Innovative Behaviour.

2.6.3.7 H7 IT-enabled Innovative Behaviour → Continuance Intention

When employees successfully discover and implement innovative tablet applications—such as novel problem-solving approaches, enhanced decision support capabilities, or improved productivity methods—they experience enhanced value realisation that significantly strengthens motivation for continued system engagement. Research on post-adoption behaviour suggests that users who engage in innovative technology applications develop a deeper appreciation for system capabilities and stronger intentions to maintain usage (Li et al., 2013a). The theoretical mechanism involves experiential value discovery: innovative use often yields incremental process improvements (better task fit, increased efficiency, enhanced autonomy) that demonstrate expanded utility beyond initial expectations (Khedhaouria et al., 2020; Torkzadeh et al., 2005). This behavioural pathway creates a positive feedback loop wherein creative exploration reinforces continuance intentions through the discovery of personally relevant applications and competitive advantages; thus, the following hypothesis was developed.

Rationale: Innovative use often yields small process gains (fit, speed, autonomy) that reinforce intention to keep using; this aligns with DT→culture support→employee innovation evidence and creates a behavioural pathway to continuance.

H7: IT-enabled Innovative Behaviour will have a significant positive effect on Continuance Intention.

2.6.3.8 H8 Personal Innovativeness in IT → IT-enabled Innovative Behaviour

Personal Innovativeness in IT (PIIT), defined as an individual's willingness to experiment with new information technologies independently of peer influence, is a well-established antecedent of innovative technology-related behaviours (Agarwal & Karahanna, 2000; Agarwal & Prasad, 1998). Individuals high in PIIT are more likely to engage in exploratory, creative, and adaptive system use, seeking novel applications and unique features (Lu, 2014). Empirical research confirms a positive association between PIIT and innovative work behaviour, both directly and through mechanisms such as greater cognitive flexibility and propensity to try new solutions (Wu & Yu, 2022). Extensions of UTAUT and meta-analytical syntheses find that PIIT in general positively predicts behavioural intention and innovative usage by increasing openness to experimentation, risk-taking, and engagement with non-routine IT functions (Dwivedi et al., 2020).

Rationale: Individuals high in Personal Innovativeness in IT tend to experiment more readily, generating emergent uses; PIIT thus serves as an upstream trait antecedent of ITIB (and indirectly of CI).

H8: Personal Innovativeness in IT will have a significant positive effect on IT-enabled Innovative Behaviour.

2.6.3.9 H9 Involvement Facilitation → IT-enabled Innovative Behaviour

Involvement Facilitation—the active engagement and empowerment of end-users during technology implementation and use—plays a pivotal role in fostering innovative behaviour (Magnusson et al., 2003; Ragu-Nathan et al., 2008). User involvement mechanisms (e.g., design feedback, idea workshops, co-creation sessions) have been empirically linked to the generation of more original and valuable ideas, as they empower individuals to experiment and contribute beyond routine use. Practices that emphasise participation, voice, and ownership create psychological conditions favourable for creative thinking and novel problem-solving (Wan et al., 2022). Studies in organisational learning and employee engagement further confirm that when individuals are involved in ICT adoption, they feel more motivated to explore, ideate, and implement innovative solutions within their work roles (Lin, 2017). These findings are echoed in open innovation research, where structured user involvement and cross-functional collaboration are shown to amplify innovative competence and practical creativity in technology settings (Huang & Thomas, 2021).

Rationale: Involvement Facilitation (participation in requirement shaping, pilots, feedback) creates ownership and skill depth, two conditions consistently associated with innovative use at the desk-level.

H9: Involvement Facilitation will have a significant positive effect on IT-enabled Innovative Behaviour.

2.6.3.10 H10 Innovation Support → IT-enabled Innovative Behaviour

Innovation Support encompasses organisational mechanisms that encourage experimentation, idea sharing, risk-taking, and creative problem-solving within technology contexts (Ragu-Nathan et al., 2008; Tarafdar et al., 2007; Tarafdar et al., 2010). Research demonstrates that organisational climates characterised by innovation support create psychological safety and resource availability that enable employees to explore novel applications of technology beyond routine use (Jun & Lee, 2023). Empirical studies confirm that when organisations provide innovation support—including recognition for creative efforts, tolerance for failure, and encouragement for experimentation—employees demonstrate significantly higher levels of innovative work behaviour, including creative technology applications (Al-Taie & Khattak, 2024). The technostress literature specifically identifies innovation support as a key inhibitor that not only reduces technology-related stress but actively promotes exploratory and creative technology behaviours (Estrada Muñoz et al., 2022; Tarafdar et al., 2020; Tarafdar et al., 2010). Meta-analytical evidence further confirms that organisational support mechanisms significantly predict innovative behaviour by reducing psychological barriers to creativity and providing the contextual resources necessary for ideation and implementation (Bogilović et al., 2020; Ng, 2024). However, literature also suggests that climate alone may be insufficient without the operational mechanisms to enact it (Scott & Bruce, 1994). While IS provides the 'permission' to innovate, it may require the tangible resources of Involvement Facilitation (IF) to translate that permission into behaviour. In SME tablet adoption contexts, innovation support creates conditions where employees feel empowered to discover creative applications and experiment with novel uses of technology. Assuming appropriate resources, the following hypothesis was proposed.

Rationale: Visible organisational backing for experimentation (resources, tolerance for trial-and-error, knowledge-sharing) encourages employees to repurpose features, integrate tools, and devise workarounds, manifesting as IT-enabled innovative behaviour.

H10: Innovation Support will have a significant positive effect on IT-enabled Innovative Behaviour.

2.6.3.11 H11 Personal Innovativeness in IT → Continuance Intention

Empirical studies have consistently demonstrated that individuals with higher levels of PIIT are more likely to maintain usage and exhibit stronger continuance intentions toward novel technologies (Lu, 2014). This relationship reflects both a willingness to overcome barriers and a natural inclination to seek out new opportunities for meaningful technology use (Solarz & Adamek, 2023). Meta-analytical reviews and systematic studies confirm that PIIT influences the long-term use of systems, not only in adoption but also in sustained engagement (Jackson et al., 2013; Wang et al., 2023). However, while PIIT is typically associated with positive outcomes, it may also have less favourable consequences in resource-constrained settings: PIIT also produced positive, negative or no effects on key technology acceptance constructs (Agarwal & Karahanna, 2000; Jackson et al., 2013; Lewis et al., 2003; Lu et al., 2005; Rosen, 2005; Tarafdar et al., 2010).

Rationale: Individuals higher in PIIT view ongoing use as less risky and more rewarding, so they are more inclined to continue using the system—especially as updates or new use cases emerge post-implementation.

H11: Personal Innovativeness in IT will have a significant positive effect on Continuance Intention.

2.6.3.12 H12 Innovation Support → Involvement Facilitation

The technostress inhibitor literature explicitly establishes the theoretical and empirical link between innovation support and involvement facilitation, demonstrating that when organisations provide psychological safety for experimentation and reward creative problem-solving, employees become more willing to actively participate in technology adoption and change processes (Kot, 2022; Lanzl, 2023). Research consistently shows that organisational climates characterized by innovation support reduce barriers to participation and encourage bottom-up involvement in ICT implementation, as employees feel empowered to contribute ideas and engage in collaborative technology development (Baroudi et al., 1986; Naujokaitienė et al., 2015). When organisations signal openness to new ideas and provide support for innovative thinking, they simultaneously create conditions where involvement facilitation becomes more effective and meaningful, as employees perceive their contributions as valued and their participation as purposeful (Sanders et al., 2018). This relationship reflects a fundamental organisational dynamic wherein supportive innovation climates naturally enhance participatory mechanisms by reducing psychological barriers to engagement and increasing employee willingness to contribute to technology-related decision-making processes; thus, the following hypothesis was developed.

Rationale: When management provides explicit innovation support (time, recognition, safe-to-try norms), it lowers perceived risk and opens participation channels, thereby increasing end-user involvement in shaping requirements, pilots, and feedback cycles.

H12: Innovation Support will have a significant positive effect on Involvement Facilitation.

2.6.3.13 H13 Innovation Support → Performance Expectancy

Innovation support creates organisational conditions that enhance users' ability to recognise and realize performance benefits from technology adoption (Venkatesh & Bala, 2008). When organisations provide mechanisms that encourage experimentation, risk-taking, and creative problem-solving, they simultaneously increase the visibility and demonstrability of technology performance gains through multiple theoretical pathways identified in TAM2 and TAM3 extensions (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). First, innovation support enhances job relevance by creating contexts where technology applications become more aligned with meaningful work goals and organisational priorities (Kaewsaengon et al., 2022). Second, supportive innovation climates improve result demonstrability by providing resources, training, and managerial encouragement that make performance improvements more tangible and communicable to users and stakeholders. Third, innovation support mechanisms increase output quality visibility by creating feedback systems and recognition processes that highlight successful technology applications and their business impact (Tarafdar et al., 2010; Venkatesh & Bala, 2008). This relationship is consistent with social cognitive theory perspectives, which emphasise that resourceful organisational environments bolster outcome expectations by providing evidence that effort and experimentation yield valued performance results (Bandura, 2001). Empirical research demonstrates that perceived organisational support significantly enhances performance expectations and technology acceptance by creating psychological and structural conditions that facilitate performance recognition and value realisation (Li et al., 2022). When organisations signal support for innovation through resource allocation, training provision, and failure tolerance, users develop stronger beliefs about the technology's potential to improve job performance, as the supportive context makes performance gains more achievable and recognisable; thus, the following hypothesis was developed.

Note: In this context, the question may be posed: why no IF → PE? Involvement Facilitation (IF) in this study indexes general participation practices around technology change (e.g., being invited, having channels to contribute). Performance Expectancy (PE), however, is system-specific—beliefs about this system's impact on performance (tablets). Without items that explicitly capture project-specific involvement with tablets, a direct IF → PE path risks a domain mismatch and

cross-level fallacy: generic involvement practices do not necessarily inform beliefs about the specific performance benefits of tablets. By contrast, Innovation Support (IS) provides resources, training, and managerial encouragement that more plausibly shape PE by making job relevance, result demonstrability, and output quality of the tablet visible. Consequently, this study posits $IS \rightarrow PE$, while modelling IF as acting downstream on behaviour ($IF \rightarrow ITIB$), not on PE.

H13: Innovation Support will have a significant positive effect on Performance Expectancy.

2.6.3.14 Mediation Hypotheses

Attitude-based mediations (affect as proximal predictor):

M1: ATT mediates $PE \rightarrow ITIB$ (partial mediation expected). Higher PE improves evaluative affect, which encourages experimentation and ideation. This affect-based channel captures how perceived performance gains translate into innovative use through ATT in continuance contexts. ($PE \rightarrow ATT$ from H1; $ATT \rightarrow ITIB$ from H6)

M2: ATT mediates $EE \rightarrow ITIB$ (full mediation expected). Perceived ease enhances ATT, and favourable affect motivates exploratory use. Accordingly, EE should influence ITIB indirectly via increased positive attitudes toward the technology. ($EE \rightarrow ATT$ from H3)

Innovative-use mediations (behavioural pathway):

M3: ITIB mediates $PIIT \rightarrow CI$ (partial mediation expected). Trait innovativeness promotes innovative use, which strengthens continuance; however, given evidence for a direct $PIIT \rightarrow CI$ path, the indirect effect via ITIB is expected to be partial rather than full. (H8, H11, H7)

M4: ITIB mediates $IF \rightarrow CI$ (full mediation expected). IF creates opportunities and resources for experimentation; these opportunities manifest as ITIB, which then strengthens CI by uncovering additional value. This positions ITIB as the conduit linking involvement mechanisms to sustained use. (H9, H7)

M5: ITIB mediates $IS \rightarrow CI$ (full mediation expected). Innovation-supportive climates encourage exploratory behaviours; those behaviours, rather than climate per se, deliver value realisation that reinforces continuance. ITIB thus transmits IS's influence to CI. (H10, H7)

M6: PE mediates $IS \rightarrow CI$ (full mediation expected). Innovation-supportive climate increases performance expectancy, and reinforces continuance. IS is not expected to directly impact CI, but through mediation it will support it. (H13, H2)

Serial mediations (cognition $\rightarrow$ affect $\rightarrow$ innovative-use $\rightarrow$ CI):

M7: PE → ATT → ITIB → CI (positive serial mediation). Cognitive beliefs about performance elevate affect; affect facilitates innovative use; innovative use consolidates continuance. This serial chain reflects the cognition → affect → behaviour sequence in continuance. (H1, H6, H7.)

M8: EE → ATT → ITIB → CI (positive serial mediation). Ease improves affect, which promotes innovative behaviours, which in turn bolster continuance. This sequence captures how reducing effort ultimately yields stronger CI via ATT and ITIB. (H3, H6, H7.)

M9: IS → IF → ITIB → CI (positive serial mediation). Supportive climates institutionalise involvement; involvement enables innovative behaviours; innovative behaviours strengthen continuance. This serial mechanism aligns with technostress-inhibitor findings that IS elevates IF, which then enables exploratory use with downstream benefits. (H12, H9, H7.)

M10: EE → PE → ATT → ITIB → CI (positive serial mediation). Effort expectancy or ease of use positively effects beliefs about performance, which in turn joins the cognition → affect → behaviour sequence in continuance. (H4, H1, H6, H7.)

M11: IS → PE → ATT → ITIB → CI (positive serial mediation). Supportive climates elevates performance expectations, which then drives innovative behaviours through attitude; innovative behaviours strengthen continuance. This serial mechanism aligns with technostress-inhibitor findings that IS enables exploratory use with downstream benefits. (H13, H1, H6, H7.)

M12: IS → PE → ATT → CI (positive serial mediation).

Supportive climates increases performance expectations, which then positively enhances attitude towards the given ICT; through ATT, it then strengthens continuance. This serial mechanism similarly aligns with technostress-inhibitor findings that IS enables exploratory use with downstream benefits. (H13, H1, H5.)

Demographic and Organisational Variables

Including demographic and organisational variables helps ensure that observed relationships between the core constructs and tablet use/continuance are not artefacts of differences in the workforce or firm context. The original UTAUT model used four moderators: gender, age, experience and voluntariness (Venkatesh et al., 2003). Due to the mandatory situation, voluntariness is not considered. The existing variables are extended with organisational variables. In line with prior technology-adoption research (e.g., UTAUT and post-adoption variants), the study treats SME size, sector and location, management level, age, gender, and experience as controls.

SME size, sector and location

Organisational context can shape perceived usefulness, facilitating conditions, and adoption norms. Medium SMEs typically have more formalised ICT processes and support, while sectoral differences imply distinct task structures and mobility needs (e.g., field service vs office-based work). In this context, sectors with stronger ICT intensity may show higher performance expectancy / innovative use potential.

Management level

Role seniority affects decision authority, exposure to organisational systems, and the salience of productivity benefits, which can shift performance expectancy.

Age

Age can condition effort perceptions, innovativeness, confidence with new interfaces, and continuity of habits. Older respondents may report lower effort expectancy and slower uptake.

Gender

Gendered patterns in technology use can appear via occupational segregation or social norms; contemporary effects are usually small but worth controlling for.

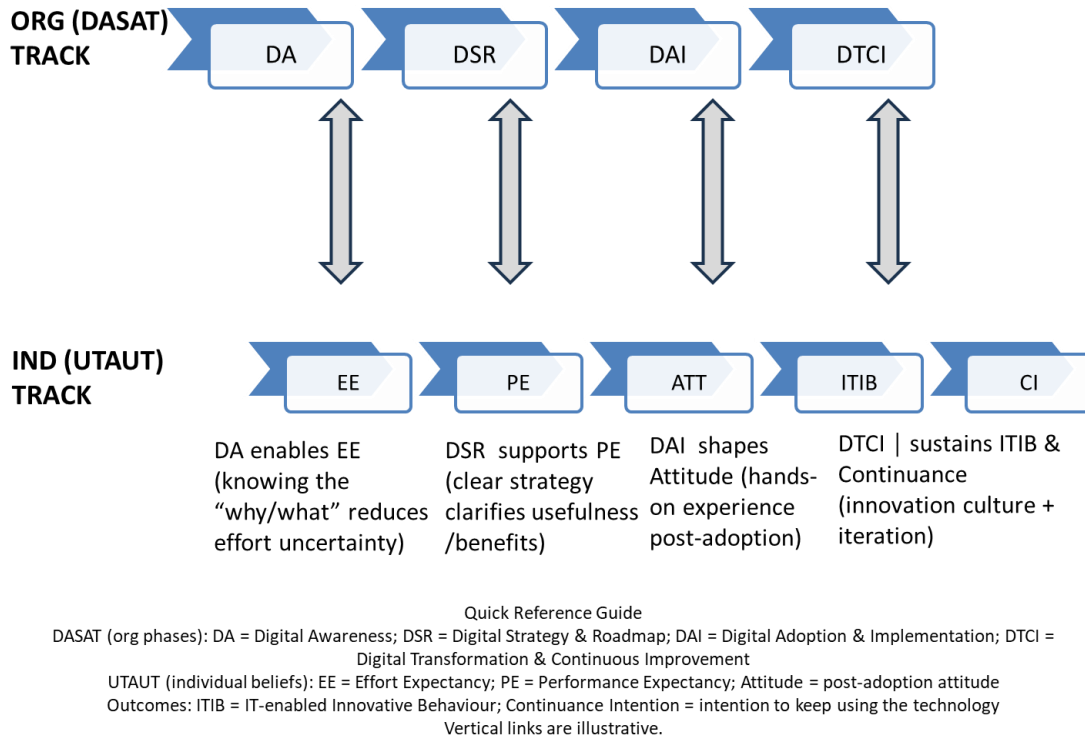
Experience

Experience reduces uncertainty and increases routine fit, shaping effort and facilitating conditions. More experience should lead to lower perceived effort, and possibly easier innovative use approaches. Note:

2.6.4 Mapping the Conceptual Model to the DASAT Cycle

This subsection locates each construct and path of the conceptual model within the DASAT cycle—Digital Awareness (DA) → Digital Strategy & Roadmap (DSR) → Digital Adoption & Implementation (DAI) → Digital Transformation–Continuous Improvement (DTCI)—to make explicit how organisational phases condition individual continuance and IT-enabled innovative behaviour (see Figure 2.6 and Table 2.4).

Figure 2.6 Dual-track mapping: DASAT and UTAUT



Post-adoption continuity is framed using UTAUT beliefs plus Attitude as the evaluative bridge to intention and behaviour. While ECM (expectation–confirmation) and TCM/Habit offer useful background explanations for why attitudes may stabilise and behaviour may routinise over time, Satisfaction or Habit are not modelled in this study. Instead, Attitude is treated as the parsimonious post-adoption carrier of prior experience and evaluative confirmation, consistent with mandated workplace use where social pressures recede and individual value judgements dominate ongoing use and IT-enabled innovative behaviour (ITIB).

The DASAT phases provide a firm-level scaffold for situating individual processes without adding constructs: early deployment clarifies expectations and shapes initial PE/EE, adoption/commitment strengthens evaluative Attitude toward the system, and integration creates stable conditions under which employees can translate beliefs and attitude into continuance and ITIB. Thus, DASAT specifies where organisational progression supports these individual pathways; the model specifies how PE, EE, and Attitude link to continuance and innovative use.

Table 2.4. Conceptual model to DASAT Mapping

DASAT phase	Typical SME activities	Primary model constructs (this study)	Key hypothesised links	Operational cues / data sources
Digital Awareness (DA)	Use-cases, demos, peer examples; basic digital literacy & inclusion; communication of benefits/risks.	PE, EE (formation); Attitude (early signals); PIIT (trait).	Primes H1 (PE→ATT), H3 (EE→ATT), H4 (EE→PE); supports H11 (PIIT→CI) by lowering perceived risk/cost.	Attendance at sessions; comms logs; self-reported literacy; baseline PE/EE.
Digital Strategy & Roadmap (DSR)	Prioritisation; scoping; resourcing & governance; policy for innovation support (IS).	Innovation Support (IS); (Facilitating Conditions operational, not modelled as direct predictor of CI).	H12 (IS→IF), H10 (IS→ITIB); strengthens H2 (PE→CI) by clarifying value realisation path.	Roadmaps; budgets; policy docs; decision memos; resource allocations.
Digital Adoption & Implementation (DAI)	Pilots; training; configuration; involvement workshops; usage monitoring; issue resolution.	Involvement Facilitation (IF); PE, EE (updated via experience); Attitude; ITIB (emergent).	H9 (IF→ITIB), H6 (ATT→ITIB); H1/H3/H4 updated by experience; enables H5 (ATT→CI).	Pilot logs; training records; feature-usage; support tickets; post-pilot reviews.
Digital Transformation Continuous	Measurement & review; upskilling; knowledge-sharing;	Attitude (stabilisation); CI;	Reinforces H7 (ITIB→CI) and H10 (IS→ITIB)	KPI dashboards; retrospectives;

DASAT phase	Typical SME activities	Primary model constructs (this study)	Key hypothesised links	Operational cues / data sources
Improvement (DTCI)	iterative enhancements; diffusion to peers.	ITIB (institutionalised).	via routines; provides conditions supporting H11 (PIIT→CI).	CoP notes; refresher training; improvement backlog.

Note: Facilitating Conditions (FC) are treated as an organisational support context primarily set in DSR and reinforced in DTCI; consistent with the continuance focus, FC is not modelled as a direct predictor of Continuance Intention, but its operational presence is acknowledged in this mapping.

2.7 Chapter Summary and Conclusion

This chapter situated tablet devices within the SME economic context (EU-28/EU-27 and Hungary), defined the focal artefact and its affordances, and traced the theoretical grounding from digital inequality and diffusion to ICT adoption in SMEs. It highlighted both the promise of mobile ICT for process efficiency and innovation and the persistent barriers that SMEs - particularly in Hungary - face in financing, skills and organisational readiness. The longitudinal nature of adoption was clarified, distinguishing pre-adoption, adoption and post-adoption behaviours relevant to continuance.

Building on this review, the chapter motivated an individual-centric lens for post-adoption use. UTAUT was adopted as the backbone and adapted for continuance by reinstating Attitude, and by exposing IT-enabled Innovative Behaviour (ITIB) as the pathway by which traits and context translate into sustained tablet use. Firm-level models (e.g., TOE, Institutional Theory) informed the setting, but were not primary, given the focus on employee behaviour in mandatory-use environments. The conceptual model integrates Performance Expectancy, Effort Expectancy, Attitude, Continuance Intention, Personal Innovativeness in IT, and two organisational enablers - Innovation Support and Involvement Facilitation. Testable hypotheses are articulated linking these constructs together. Demographic and organisational variables (SME size/sector, management level, age, gender and experience) were specified as controls for robustness.

Overall, the literature points to a gap between device provision and innovative everyday use in SMEs. By modelling how individual differences and perceived organisational support foster ITIB and continuance, the study aims to explain how general-purpose tablets become embedded as sources of work improvement in resource-constrained firms.

3 RESEARCH METHODOLOGY

3.1 Introduction

This chapter details the research methodology underpinning this study. The chapter has two main aims. First, it clarifies the philosophical and design choices. Second, it documents the specific quantitative and qualitative procedures used in this study.

The chapter proceeds as follows. Section 3.2 establishes the philosophical foundations, adopting a dual-paradigm stance (positivist for the quantitative strand; interpretivist for the qualitative strand) and clarifying the strand-specific logics for its components. Next, Section 3.3 explains the overall research design and approach, justifying the mixed-methods, explanatory-sequential logic (survey → interviews). Sections 3.4 and 3.5 then discuss methodological strategies and the time horizon. Building on these, Section 3.6 presents the selected methodology in detail. Implementation follows in Sections 3.7 (quantitative strand) and 3.8 (qualitative strand). Finally, Section 3.9 summarises the research plan and the integration of both strands.

3.2 Research Methodology Framework

3.2.1 Introduction

Determining an appropriate research methodology is a key element of any study, because it sets out a forward-looking plan from philosophical stance to data collection, analysis and evaluation (Remenyi et al., 2003). Methodology, in this sense, frames the overall approach to the inquiry and operationalises how the research problem should be addressed (Collis & Hussey, 2009). A review of business PhDs highlights the importance of clearly identifying methodological choices (McManus et al., 2017).

This study's core aim—to predict innovative technology use and explain the mechanisms behind adoption patterns—requires both breadth and depth. The research seeks not merely to confirm theory but to produce warranted, actionable knowledge that SME managers can use to improve technology implementation. The inquiry is problem-centred: it aims to predict employees' innovative technology use and continuance in SMEs and to explain the mechanisms behind these patterns.

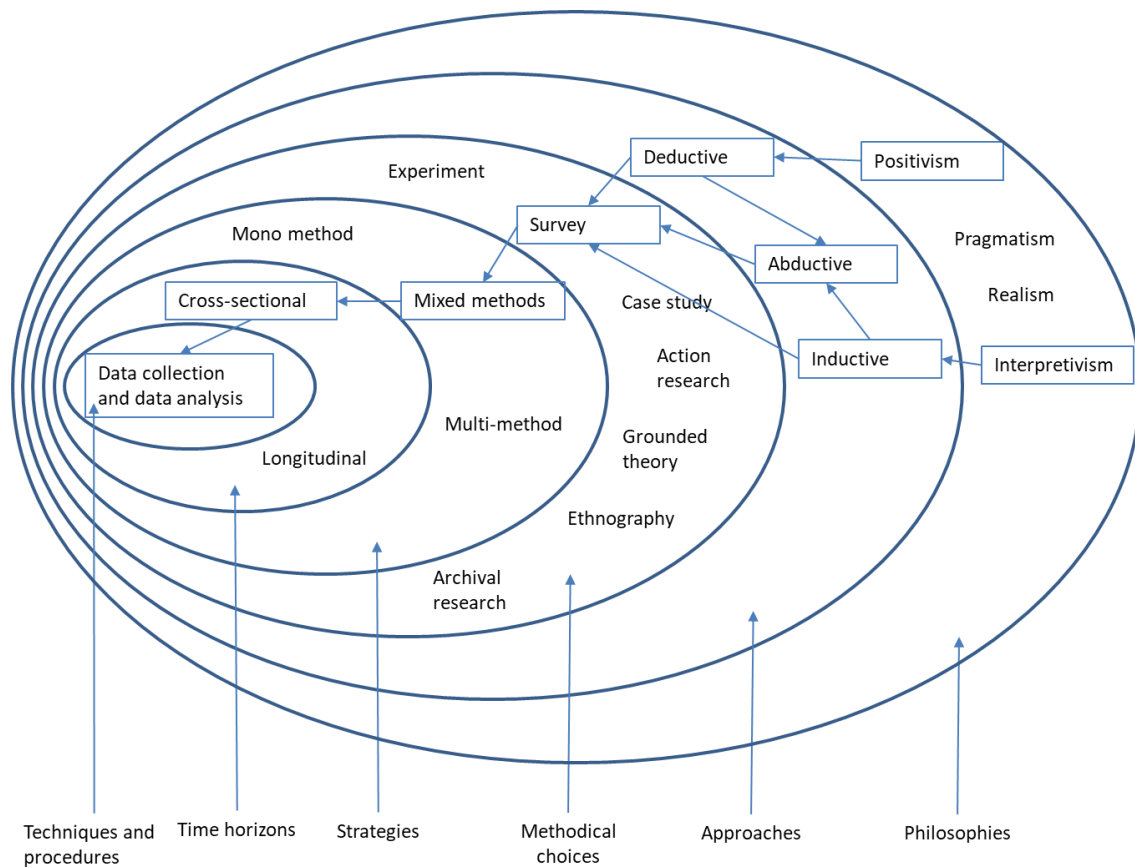
To address these aims, the thesis adopts a dual-paradigm mixed-methods stance. The quantitative strand is grounded in a positivist logic focused on measurement, model testing and prediction. The qualitative strand is grounded in an interpretivist logic that prioritises meaning,

context and lived experience. Rather than forcing both strands into a single philosophical position, the study treats them as complementary and integrates their findings at key points in the design.

Following Crotty (1998), the layers can be stated succinctly: Philosophy—dual-paradigm (positivist and interpretivist); Theoretical perspectives—positivist (quantitative) and interpretivist (qualitative); Methodological choice—mixed methods; Methods—structural equation modelling and semi-structured interviews.

The long-standing paradigm debates have been considered, and a summary is presented in the Appendix F (e.g., Guba & Lincoln’s mappings of positivist, constructivist and critical traditions). Given that ontology and epistemology are intimately related (Kroeze, 2011), rather than attempting to disentangle this complex relationship, the review section will follow the classification of the Research Methodology Onion (Saunders et al., 2019). The chapter setup follows the Research Onion (Saunders et al., 2019): the visual plan is presented first, followed by the detailed rationale for each layer (Figure 3.1).

Figure 3.1. Research Methodology Onion (adapted from Saunders et al., 2019)



3.2.2 Philosophies

3.2.2.1 Introduction

This section clarifies the philosophical foundations that inform this study's design choices. Contemporary reviews of research paradigms in information systems and business studies commonly distinguish between positivist (or post-positivist), interpretivist, critical realist, and pragmatist traditions (Adam, 2014; Avison & Fitzgerald, 2012; Kankam, 2019; Thapa & Haj-Bolouri, 2023). Within this landscape, the present study adopts a dual-paradigm stance. The quantitative strand draws on a positivist tradition that emphasises structured measurement, hypothesis testing and statistical generalisation. The qualitative strand draws on an interpretivist tradition that emphasises contextual meaning and participants' lived experience. Critical realism and pragmatism are acknowledged as influential alternatives in information systems research, but they are not adopted as the primary philosophical anchors here.

A more detailed comparison of the philosophies noted above is provided in Appendix F; a short comparative table is added here (Table 3.1).

Table 3.1 Philosophy Overview

Dimension	Positivism / Post-positivism	Interpretivism / Constructivism	Critical / Transformative	Pragmatism
Core aim	Explanation, prediction, law-like generalisations	Understanding meaning, context, lived experience	Critique, emancipation, change	Problem-solving; actionable knowledge
Ontology	Single reality; knowable (imperfectly under post-positivism)	Multiple, socially constructed realities	Reality shaped by power/ideology; historical	Reality is what works for the inquiry at hand; plural and provisional
Epistemology	Objective/modified-objective; researcher as neutral tester	Subjective/co-constructed; researcher as instrument	Reflexive, standpoint-aware;	Knowledge as warranted assertibility—useful,

Dimension	Positivism / Post-positivism	Interpretivism / Constructivism	Critical / Transformative	Pragmatism
			researcher as change agent	justified, and revisable; strand-specific logics integrated under frame
Axiology	Value-neutral ideals; minimise bias	Values are inherent and made explicit	Values/power central; aim at justice	Values acknowledged ; “fitness-for-purpose” governs choices
Causality	Regularities, (quasi)-causal models	Contextual, idiographic explanations	Causality is linked to structures and power	Causality judged by utility (prediction + credible mechanism)
Theory role	Test theory; deduction	Build/substantiate theory; induction	Critique/transform theory	Use/extend theory pragmatically; abduction links strands

A concise summary follows:

3.2.2.2 *Positivism*

Emphasises measurement, hypothesis testing and generalisation; post-positivism recognises fallibilism and uses falsification, making it the natural home for model testing with structured instruments (Bryman, 2016; Creswell & Creswell, 2018). In this study, positivism underpins the

quantitative strand: several SMEs can be evaluated, and the findings can be generalised cautiously to similar contexts.

3.2.2.3 Interpretivism

Prioritises meaning, context and lived experience; it is well-suited to eliciting mechanisms and sense-making around quantitative patterns (Bryman, 2016; Saunders et al., 2019). In this study, interpretivism underpins the qualitative strand: quantitative results are further evaluated and underlying mechanisms explored through participants' accounts.

3.2.2.4 Realism

Assumes a mind-independent reality, but access is theory-laden. Critical realism distinguishes between three key domains: the real (underlying generative mechanisms and structures), the actual (events that occur whether or not they are observed), and the empirical (events as they are experienced or measured) (Mingers et al., 2013). Within this view, statistical regularities—correlations, path coefficients—are viewed as empirical patterns that require explanation rather than as generative mechanisms themselves (Rao et al., 2025; Stutchbury, 2022). The core task of research is to move from surface regularities towards deeper explanatory accounts (Bhaskar, 1978). Critical realism, therefore, treats quantitative methods primarily as descriptive rather than inferential in the causal sense.

Critical realism is attractive for studies of technology use because it offers ontological depth and encourages researchers to search for hidden mechanisms that generate adoption patterns (Wynn & Williams, 2012). Its central mode of inference, retrodution, requires researchers to move from empirical observations (survey responses, interview accounts) through the actual domain (events that truly occurred, independently of observation) to the real domain (underlying generative mechanisms) (Mingers et al., 2013).

However, critical realism is not adopted as the primary philosophical anchor for this study. There are three main reasons:

First, a fully retroductive design would require deep, sustained organisational access—prolonged observation, repeated data collection and engagement across multiple organisational levels—to surface the mechanisms generating tablet-enabled innovativeness in Hungarian SMEs. Given the limited financial, skills and time resources of these firms, such intensive involvement was not feasible.

Second, this research employs a cross-sectional design, chosen in light of rapid technological change, constrained SME access and likely attrition. This design is well-suited to structural equation modelling and prediction, but it does not provide the longitudinal depth that retroductive analysis typically demands to distinguish surface events from enduring mechanisms.

Third, the heterogeneity of Hungarian SMEs (sector, size, culture, digital maturity) means that mechanisms identified in one firm may not readily generalise to others; conducting retroductive case-based analysis across a sufficiently large and varied sample would require resources beyond the scope of this project.

3.2.2.5 Pragmatism

Pragmatism is a problem-centred philosophy that evaluates knowledge claims by their practical consequences and utility for action. Pragmatism treats truth as warranted assertability: conclusions are provisional, tested against experience, and retained while they remain useful for explanation and prediction (Choo, 2016; Ormerod, 2021). According to Dewey's view, knowledge claims must be defensible and justified through systematic inquiry rather than representing fixed, absolute truths (Boyles, 2006). Pragmatism is a particularly appropriate stance for organisational research where contexts evolve, and recommendations must remain adaptable (Kelly & Cordeiro, 2020; Tashakkori & Teddlie, 2010). In social research, contemporary pragmatists argue that methods are tools selected for fitness-for-purpose rather than for allegiance to a single ontology or epistemology (Johnson et al., 2007; Tashakkori & Teddlie, 2010). At the same time, pragmatist studies frequently take the form of action research or other interventionist designs, and a common critique is that pragmatism can devolve into a “paradigm of convenience”, permitting unconstrained method selection without sufficient philosophical discipline (Hampson & McKinley, 2023).

For the present study, pragmatism is therefore not adopted as the overarching philosophical stance. First, the research design is not action research or interventionist: it does not involve cycles of planning, acting and reflecting within SMEs, but rather an explanatory-sequential design combining a survey with follow-up interviews. Second, the central inferential goals of this study—testing a structural model and explaining observed patterns—are already well served by an explicit dual-paradigm configuration (positivist quantitative; interpretivist qualitative). Invoking pragmatism in addition could blur these commitments by shifting emphasis away from clearly articulated ontological and epistemological positions towards a primarily instrumental view of methods. Finally, given the critique that pragmatism can function as a “paradigm of convenience”,

an explicit dual-paradigm stance is preferable here because it maintains strand-specific philosophical integrity while still allowing purposeful integration.

3.2.2.6 Conclusion

The aims of this study are breadth, prediction and practical feasibility: to test theorised relationships (e.g. Performance Expectancy → Continuance Intention) and to offer predictive guidance on which factors are most likely to drive continued tablet use in Hungarian SMEs. These inferential goals align with a positivist logic of measurement and model testing, complemented by an interpretivist strand that explores mechanisms and sense-making through interviews. Accordingly, neither critical realism nor pragmatism is adopted as the primary philosophical anchor. Instead, the thesis adopts a dual-paradigm, explanatory-sequential mixed-methods stance, described in more detail below.

Dual-paradigm and dialectical stance

A dual-paradigm stance recognises that different phases of a mixed-methods study may legitimately be underpinned by different philosophical assumptions (McChesney & Aldridge, 2019). In this thesis, the quantitative strand is primarily positivist: it assumes a mind-independent reality, employs structured instruments and statistical modelling, and evaluates knowledge claims in terms of explanatory and predictive adequacy (Bryman, 2016; Creswell & Plano Clark, 2018). The qualitative strand is interpretivist: it assumes that social reality is co-constructed through meaning, and it seeks to understand how participants make sense of tablet use and organisational support in context (Saunders et al., 2019).

Rather than treating these strands as incommensurable, the thesis follows a dialectical logic (Johnson, 2017) in which differences between paradigms are used productively. Quantitative findings provide broad patterns and tests of theorised relationships; qualitative findings probe mechanisms, boundary conditions and contextual nuances. Where strands converge, confidence in the explanation increases; where they diverge, the differences become prompts for deeper theorising (Venkatesh et al., 2013).

This dual-paradigm configuration maintains philosophical integrity at the strand level while still supporting an integrated mixed-methods design. It avoids the risks of an a-paradigmatic stance (ignoring philosophical issues) and of forcing all methods into a single paradigm. Instead, it treats paradigm differences as a resource for richer explanation, provided that the integration strategy is explicit and transparent (Fetters & Tajima, 2022; Shannon-Baker, 2016).

In summary, this thesis adopts a dual-paradigm, explanatory-sequential mixed-methods stance: positivist for the survey-based structural model, interpretivist for the interview-based thematic analysis, with purposeful integration via sampling, joint displays and meta-inferences.

A single-paradigm approach would be insufficient for this inquiry.

- Positivism alone, while enabling measurement and generalisation, cannot access the contextually situated meanings and mechanisms that explain adoption patterns in Hungarian SMEs. Survey data may identify that organisational support predicts continuance, but cannot explain how and why this relationship unfolds in practice.
- Interpretivism alone, while rich in contextual detail, cannot provide the breadth of evidence or predictive models needed for generalisable recommendations across the heterogeneous SME population.

The research questions demand both predictive relationships and explanatory mechanisms, as well as statistical patterns and lived experience.

Therefore, methods are not mixed arbitrarily; they are purposefully selected and integrated to produce meta-inferences that unify findings across strands. The design specifies explicit integration principles:

- a) strand-specific logics are maintained (positivist for measurement, interpretivist for meaning),
- b) integration occurs at planned points (sampling and interpretation),
- c) joint displays systematically align quantitative patterns with qualitative mechanisms, and
- d) inference quality is evaluated against transparent criteria.

This design also guards against reproducing 'positivism in disguise' by treating qualitative findings as coequal during interpretation (Gobo, 2023). Interviews are not used merely to illustrate quantitative results but to interrogate, expand, and—where appropriate—challenge them. Divergences between strands were explicitly surfaced and theorised as boundary conditions rather than suppressed. The Gioia-style thematic analysis (see Section 3.8) maintains interpretivist commitments to participant voice and emergent meaning.

Once the core philosophical stance (dual-paradigm mixed methods) is clarified, the Research Onion proceeds to the review of different approaches: deduction, induction and abduction.

3.2.3 Deduction

Five steps are used to describe the stages of deduction (Robson, 2002):

1. Deducing a testable hypothesis from the theory.
2. Operationalising the hypothesis.
3. Testing the hypothesis.
4. Comparison of the results with existing theory.
5. Modifying or confirming the existing theory.

Consequently, deductive reasoning moves towards hypothesis testing, after which the principle is confirmed, refuted or modified; if necessary, the process is repeated. These hypotheses present an assertion about a number of concepts that attempt to explain the relationship between them. Concepts themselves are abstract ideas that form the building blocks of hypotheses and theories (Gray, 2014). The deductive approach requires a highly structured methodology to enable replication. In addition, reductionism plays a strong role in the operational formulation of the hypothesis, as even the simplest possible elements have to be clearly defined. Finally, the comparison of results with the existing theory presupposes a level of generalisation. The deductive approach is closely associated with the positivist framework (Saunders et al., 2019) and was part of the quantitative strand.

3.2.4 Induction

Induction focuses on deriving general statements from an experience involving a number of concrete data points or observations (Saunders et al., 2019). In very general terms, a researcher uses induction to discover new principles; however, the researcher does not set out with the mindset of proving or falsifying a theory. Rather, a variety of different data collection methods are applied to identify patterns or particular meanings (Gray, 2014). In this research, the analysis of the interview method followed an induction-based approach, clarifying patterns in the data.

3.2.5 Abduction

Abduction is an inferential logic that explains surprising results by iterating between data and theory to form the most plausible account. In this thesis, abduction bridges the quantitative→qualitative sequence: unexpected or extreme quantitative patterns guide interview sampling; emergent themes then inform revised explanations that are checked back against the model. Unlike deduction (testing) or induction (building), abduction emphasises plausibility and usefulness. The aim is to produce integrated meta-inferences that reconcile numerical regularities with lived mechanisms and that are fit-for-purpose in addressing the research question.

(Tashakkori & Teddlie, 2010). Integration is made explicit via joint displays that align coefficients/patterns with representative quotations, supporting clear meta-inferences.

3.2.6 Overview

In sum, a dual-paradigm mixed-methods stance best fits the aims here: the positivist strand provides breadth and predictive tests of theorised relationships; the interpretivist strand provides depth and contextual meaning. Together they offer a more valid account of tablet-enabled innovative behaviour in Hungarian SMEs than either could achieve alone.

The explanatory-sequential design (further details in 3.3.3) connects strands at sampling (extremes/contradictions from the structural equation model guide interviews) and integrates them at interpretation via joint displays to form meta-inferences. This avoids running two parallel studies and ensures philosophical coherence. Methodologically, this complementarity is operationalised through a mixed-methods, sequential explanatory logic with between-method triangulation. Quantitative findings from the survey phase guide focused qualitative inquiry, and the interview phase is then used to corroborate, clarify, or qualify model-based results. This sequencing is consistent with the Research Methodology Onion's alignment of philosophy, approach, and method. This study plan is further detailed in the next section (3.3) (cross-sectional survey followed by an interpretive summative interview phase for triangulation).

Regarding reasoning modes, this study employs all three reasoning approaches, with abduction as the bridge:

- Deduction (quantitative). Theory-derived structural relations are specified a priori and tested via structural equation modelling on survey data.
- Induction (qualitative). Semi-structured interviews are analysed thematically to surface second-order themes about enablers, barriers and mechanisms.
- Abduction (integration). Abduction serves as the integrative logic bridging the quantitative→qualitative sequence. Unlike deduction (testing fixed hypotheses) or induction (building from data), abduction explains surprising results by iterating between evidence and theory to form the most plausible account. In this study, unexpected quantitative patterns (e.g., high attitude but low continuance, contradictory moderator effects) guided purposive interview sampling; emergent qualitative themes then resulted in revised explanations (which were then checked back against the model). This abductive process yields integrated meta-inferences that reconcile numerical regularities with lived

mechanisms, producing explanations that are both empirically grounded and contextually credible.

3.3 Methodical Choices

3.3.1 Quantitative Methods

Quantitative research methods focus not only on conceptual variables and theoretical models, but also emphasise objective measurements (Creswell, 2014; Saunders et al., 2019). The data for these measurements are collected by questionnaires and surveys (primary data source) or by working with pre-existing statistical data (secondary data source).

Using the available numerical data and applying statistical methods, quantitative research attempts to explain a particular phenomenon and generalise conclusions across specific populations, based on a sample. Theoretical models include conceptual variables and structural relationships: in practice, they form equations and hypotheses with measurable items, which are tested using the corresponding datasets (Bollen, 2002).

In terms of the main quantitative method designs, the following options are noted (Creswell, 2014; Saunders et al., 2019):

- **Descriptive research** focuses on the current status of an identified variable. Typically, the research starts by observing and collecting data about a particular phenomenon. Hypotheses are developed after the data collection. In the case of this study, the UTAUT model is an existing model; thus, hypotheses are developed before data collection. The descriptive research method would not allow for progress far enough based on the existing theoretical background.
- **Correlational research** expands upon descriptive research by attempting to determine relationships among variables using statistical data and methods. Similar to descriptive research, variables are typically not manipulated. The researched phenomenon is observed and studied: data is identified, collected and analysed as it occurs in a natural setting. Correlational research also stops short of structural equation modelling: this method is a key approach to understanding the interacting constructs.
- **Non-experimental predictive modelling (also called associational or relational research)** goes further by testing theory-driven structural relationships among multiple constructs simultaneously (Shmueli, 2010). This approach uses techniques such as Structural Equation Modelling (SEM) to estimate path coefficients, assess mediation, and produce predictive models (Hastie et al., 2009). Crucially, because this design lacks

random assignment to conditions and does not manipulate independent variables, it cannot establish definitive causality. Instead, it tests theorised associations and evaluates their predictive validity—whether the model can forecast outcomes (e.g., continuance intention) based on antecedents (e.g., Performance Expectancy, Attitude). Specifically in information systems, Shmueli and Koppius (2011) argue that integrating predictive analytics complements theory testing, improves external validity, and enables practically useful artefacts (e.g., policy guidelines or risk scores). Causal claims require additional evidence (e.g., longitudinal data, experimental manipulation) (Breiman, 2001; Kass, 2021). This study follows a non-experimental predictive approach: it uses SEM to test theorised UTAUT relationships and to provide predictive, generalizable models for SME practice. The design is non-experimental because tablet adoption and use occur naturally in SMEs; the research observes and models existing patterns rather than manipulating conditions (causality and inference will be discussed in 3.3.4).

- **Experimental research** focuses on following the scientific method to establish and test causal relationships. In practice, this means that the researcher identifies and controls all variables except one independent variable. That specific independent variable is manipulated to evaluate the effect on the dependent variables. Participants are randomly assigned to conditions to ensure equivalence at baseline. In practice, creating such experiments in SMEs with live subjects is not appropriate or feasible. Experimental research would require randomly assigning employees to different tablet conditions (e.g., providing tablets vs. withholding them, or manipulating organisational support levels), which is ethically questionable, operationally infeasible, and outside the scope of resources available for this study.

In conclusion, this research uses a non-experimental, cross-sectional survey design with SEM to test theorised relationships and produce predictive models. The approach prioritises breadth, generalizability, and practical applicability over experimental control. Causal claims are appropriately limited: this study establishes predictive associations and uses qualitative interviews to explore mechanisms that contextualise and explain quantitative patterns.

Consequently, a short review of qualitative methods follows.

3.3.2 Qualitative Methods

Qualitative research investigates meanings, experiences and social processes in their natural contexts (Denzin & Lincoln, 2017). It is typically grounded in interpretivist assumptions, prioritising depth, nuance and situated understanding over measurement and prediction. Designs are flexible

and iterative, with the researcher engaging with participants, typically generating rich accounts of practice. Sampling is usually small and purposive, selecting cases for their relevance to the phenomenon, and emphasising contextual detail to understand mechanisms and variation. Qualitative research focuses on providing a deeper understanding of people's opinions, attitudes and decisions compared to quantitative methods (Creswell, 2014). Common methods include semi-structured or narrative interviews, focus groups, observations (including ethnographic approaches) and document or artefact analysis. Typically, the collected data and the results are not strictly numerical. The qualitative research report usually has a flexible structure compared to the quantitative report, since the focus is on the importance of interpreting the complexity of the studied problem (Creswell, 2014).

This study employed the qualitative lens through interviews to further explain and detail quantitative results, and also to discover nuances and mechanisms.

3.3.3 Mixed Methods

Mixed methods specifically advocate the usage of qualitative and quantitative data within the same research framework (Creswell, 2014; McChesney & Aldridge, 2019). The main aim is that by combining qualitative and quantitative methods, the mixed methods approach benefits from the strengths of both methods and minimises their weaknesses (Creswell, 2014). There are typically three major streams for mixed methods design (Creswell & Plano Clark, 2018):

- **Convergent parallel:** compares quantitative and qualitative data to provide different perspectives;
- **Explanatory sequential:** attempts to explain quantitative results with qualitative data, providing a more in-depth understanding;
- **Exploratory sequential:** develops better quantitative instruments based on qualitative data.

In this research, as noted, the research model is primarily quantitative-focused, but there are elements which would be well served by a deeper drill-down. As most latent constructs in this research are well tested and have proven to work within the SME environment, the best approach is presented by the mixed methods explanatory sequential design. The convergent parallel approach would not be feasible for trying to complete both research phases at several SMEs at the same time. The exploratory sequential approach would not use (or would limit) the theory building available from existing UTAUT studies.

The use of the mixed methods approach has grown considerably over the past years, resulting in extensive debates related to the paradigmatic stance and triangulation options, which are summarised below.

3.3.3.1 Mixed methods: Paradigmatic Stance

For mixed methods specifically, there are a number of paradigmatic alternatives: a-paradigmatic, dual-paradigm/dialectical, and single-paradigm. These paradigmatic alternatives are acknowledged in the Appendix F, but the present design relies on methodological pluralism. Within a dual-paradigm approach, the quantitative strand uses a positivist logic for measurement and hypothesis testing, and the qualitative strand uses an interpretivist logic for meaning-centred explanation. As noted, these paradigms are treated as strand-specific logics and are integrated through abductive reasoning and joint displays to generate warranted, useful conclusions (Venkatesh et al., 2013).

3.3.3.2 Mixed methods: Triangulation

Triangulation refers to the purposeful use of multiple data sources, methods, investigators and/or theoretical lenses to enhance the breadth, depth and credibility of findings (Denzin, 2009). Early arguments framed triangulation as a response to the limits of any single method (no one approach can capture a complex social reality), while later work cautioned that the aim is not only corroboration: divergence can be theoretically productive and should be examined rather than smoothed away.

Denzin's widely cited typology distinguishes four forms: data triangulation (e.g., time, space, person), investigator triangulation (multiple researchers), theory triangulation (multiple interpretive frames), and methodological triangulation (using more than one method) (Denzin, 2009). This study primarily employs methodological triangulation in a between-method sense (Creswell & Plano Clark, 2018), by combining quantitative survey data and qualitative interview data on overlapping aspects of tablet use, innovativeness and contextual constraints in Hungarian SMEs. It also applied data triangulation by using the secondary data to form the questions that were used in practice. Finally, investigator triangulation was also utilised because some of the participants from the quantitative phase were used for the qualitative phase.

Within the explanatory sequential design outlined above, triangulation is implemented by using the qualitative phase to engage with patterns and results identified in the quantitative phase. The structural equation model provides estimates of relationships and group differences, while follow-up interviews with selected SMEs are used to confirm, nuance or challenge these statistical

patterns and to explore underlying mechanisms and boundary conditions. Because this is an explanatory design, SMEs are purposively selected based on quantitative patterns from the original sample.

Areas of convergence across strands increase confidence in the inferences, whereas well-documented divergences indicate limits to generalisability or suggest refinements to the model. In this way, between-method methodological triangulation is used not only for corroboration, but also to generate richer explanations of tablet-enabled innovation in Hungarian SMEs.

3.3.4 Causality and Inference

A common question in non-experimental research concerns the nature of causal claims. Because this study uses a cross-sectional, non-experimental design, definitive causal inferences are not warranted.

Why causality requires more than association:

1. Randomisation: Experimental designs randomly assign participants to conditions, ensuring that groups are equivalent at baseline and that any post-intervention differences can be attributed to the treatment. This study does not randomise; participants self-select into their natural SME contexts.
2. Manipulation: Experiments manipulate independent variables (e.g., providing vs. withholding organisational support) to isolate causal effects. This study observes naturally occurring variation; it does not manipulate conditions.
3. Temporal ordering: Longitudinal designs establish that causes precede effects over time. This study is cross-sectional; all variables are measured at one time point, limiting temporal inference.

Without these features, causal language is inappropriate. Instead, this study makes predictive claims: the SEM model identifies which factors predict continued tablet use and estimates the strength and direction of associations. These associations are theory-driven (grounded in UTAUT) and empirically tested (path coefficients, R^2 , predictive relevance Q^2), but they remain predictive, not causal. This distinction is critical: this study establishes what predicts continuance and how strongly, but does not claim that manipulating these factors would cause changes in isolation from other contextual influences.

How this study strengthens inference beyond simple correlation:

1. Theory-driven hypotheses: Relationships are specified a priori based on UTAUT, not explored post-hoc.
2. Multivariate modelling: PLS-SEM simultaneously estimates multiple paths, accounting for confounding and mediating relationships.
3. Qualitative triangulation: Semi-structured interviews explore mechanisms—the "how" and "why" behind quantitative patterns. While qualitative data cannot definitively establish causality, they provide plausibility checks and contextual evidence that strengthen the coherence of claims.
4. Robustness checks: Sensitivity analyses (e.g., outlier removal, nonresponse bias tests) enhance the credibility of associations.

From a mixed-methods perspective, this study's aim is not to establish universal causal laws but to produce warranted, actionable knowledge for SME contexts. Managers and policymakers need predictive models (what factors drive continued use?) and contextual mechanisms (how do these factors work in practice?). The combination of predictive SEM and explanatory interviews provides sufficient warrant for practical recommendations, even without experimental proof of causality.

3.3.5 Overview

A methodological review of IS research emphasised that quantitative researchers, rooted in technological foundations, tend to lean toward the quantitative research method Warfield (2010). In contrast, several researchers originating from the behavioural sciences prefer the qualitative research method. The author also noted that "mixed methods research has illustrated that combining computer science and human behaviour requires the use of both methodologies practically to advance the knowledge" in this area (Warfield, 2010). As this research connects IS and human behaviour, it is therefore appropriate to focus on a mixed methods approach, specifically a sequential explanatory design. Because the strands run in different phases, a dual-paradigm configuration with strand-specific logics (positivist quantitative; interpretivist qualitative) addresses the usual concerns about mixing worldviews while preserving philosophical coherence at the strand level.

The justification for adopting a mixed-methods design must go beyond a general appeal to combining qualitative and quantitative strengths. Venkatesh, Brown and Bala (2013) highlight that mixed methods should be guided by a clear purpose, an explicit integration strategy, and a commitment to producing meta-inferences that unify findings across strands. In this study, the purpose of the explanatory sequential design is twofold: first, to corroborate the quantitative findings from the structural model by providing contextual detail, and second, to expand the

explanatory power of the model by capturing nuanced employee perceptions of innovativeness and organisational support.

Integration is a critical element of mixed methods research quality, and this study embeds integration at two stages:

- a) sampling, where participants for qualitative interviews are purposively selected based on patterns observed in the quantitative survey (e.g., extreme scores on certain innovativeness constructs), and
- b) interpretation, where quantitative results and qualitative narratives are jointly analysed to identify convergent, divergent, and complementary insights.

This ensures that the two strands are not treated as parallel, isolated studies, but as interconnected phases that inform and enrich each other.

A further step beyond strand-level reporting is the development of meta-inferences, defined as overarching theoretical conclusions that synthesise both quantitative and qualitative evidence into a coherent whole (Venkatesh et al., 2013). For example, survey results may establish significant predictors of continued tablet use, while interviews illuminate why employees perceive certain factors as barriers or enablers. The integration of these strands yielded meta-inferences that both validate statistical relationships and generate richer theoretical and practical implications for SME contexts. The ultimate product of this mixed-methods inquiry is meta-inferences—overarching conclusions that synthesise quantitative and qualitative evidence into a coherent whole. For example, the survey may establish that organisational support predicts continued use ($\beta = X$, $p < .05$), while interviews illuminate which specific support practices employees experience as enabling or constraining and why these matter in the SME context. The meta-inference integrates both: 'Organisational support predicts continuance; specifically, managers who provide X and Y create conditions where employees perceive autonomy and efficacy, thereby sustaining use'. Such integrative conclusions are more useful for practice than either strand alone.

The two paradigms are applied sequentially (positivist for the quantitative strand, interpretivist for the qualitative strand), with integration at the inference stage. Integration weaves the quantitative and qualitative findings together in the discussion rather than being presented as parallel strands.

Finally, following Venkatesh et al.'s framework (2013), inference quality in this study was evaluated across three dimensions: design quality (rigour in survey instrument development and interview protocols), explanation quality (credibility, reliability, and transferability of findings), and integration quality (coherence and validity of the meta-inferences). This tri-partite evaluation

ensures that the mixed-methods design serves as a rigorous framework rather than a convenience.

This dual-paradigm, explanatory-sequential mixed-methods design therefore provides a coherent, rigorous framework for combining structural equation modelling and hypothesis testing with interview-based explanation to produce actionable knowledge for the Hungarian SME context. Consequently, this thesis adopts a dual-paradigm stance: the quantitative component uses a positivist logic, the qualitative component an interpretivist logic, and integration produces warranted, useful conclusions.

3.4 Research Strategies

These research strategies may be used for different paradigms, depending on the approach they may be supporting an exploratory, descriptive or explanatory research (Saunders et al., 2019; Yin, 2013). However, they are not exclusive strategies: a combination may be the most appropriate considering the research questions, available time and resources, and philosophical underpinnings.

3.4.1 Experiment

An experiment is a well-designed study for evaluating or discovering causal links: the aim is to evaluate how a change in an independent variable may change the dependent variable (Saunders et al., 2019). In its classic form, it requires establishing an experimental and a control group to study the planned intervention. Consequently, the process of designing an experiment requires a) definition of a theoretical hypothesis, b) sample selection, c) establishing the experimental and control groups, d) executing the planned intervention, e) measuring the required variables, and f) controlling all other variables (Saunders et al., 2019). In many studies, establishing control and experimental groups while controlling all variables except the focus of the study may become very difficult (Saunders et al., 2019), and this is applicable to Hungarian SMEs planned for this study as well. Experiments in this environment are not feasible unless a researcher has the full support of the SME management and agreement of the employees for a considerable time period.

3.4.2 Survey research

Survey research exists to answer questions that have been raised, to solve problems or to establish baselines: in general, to obtain answers for the who, what, where, how much and how many questions (Glasow, 2005; Saunders et al., 2019). Common overarching features of survey research are:

- a) quantitatively or qualitatively describe specific aspects;
- b) data collection from people and
- c) using a selected portion of a given population (Glasow, 2005; Leeuw et al., 2008).

The main drawback of survey research is linked to issues related to participant responsiveness, sampling issues or quality of survey completion (Saunders et al., 2019).

Thus, key definitions to be discussed in survey research include target population (the set of elements one desires to apply the findings of the study), the unit of analysis (the major entity being analyzed), and the sample, which is a subset of the target population (Leeuw et al., 2008).

Commonly noted cornerstones of survey research are coverage, sampling, response, and measurement (Leeuw et al., 2008). In reality, the cornerstones may introduce a variety of errors into the final output, and researchers should be aware of them. Coverage error occurs when some members of the population have zero chance of being included in the survey sample, while sampling error follows as only a subset is used to find an answer to the proposed research questions. Nonresponse errors occur as some of the sampled units may not answer, and finally, measurement error stems from the fact that respondents' answers may be inaccurate. A perfect survey research would minimise all these errors, but in practice, there are several limiting factors in real-world data collection (Leeuw et al., 2008; Saunders et al., 2019).

Surveys can be divided into two broad categories: the questionnaire and the interview.

- **Questionnaires** are usually online or paper-and-pencil instruments based on closed or open-ended questions. Closed questions have a limited number of response options, while open-ended questions typically collect data in a short essay format. The popularity of questionnaires may be linked to the ease of collecting a large amount of data from the selected population in an expedient and cost-effective form. However, there is a practical limit to the number of questions included in a survey. While open-ended questions may allow individual variations and responses, the possibility to drill down into individual viewpoints is limited.
- **Interviews** are completed by the interviewer based on what the respondent says. In research, an interview is a purposeful conversation that privileges the participant's perspective while enabling clarification and probing. Depending on the aim and stage of inquiry, interviews may be unstructured, semi-structured, or structured. Unstructured interviews are open-ended and conversational, allowing participants to shape the agenda and introduce new themes. Semi-structured interviews follow a flexible guide of core topics

and prompts; the interviewer adapts wording and order, using follow-up questions to explore meanings, examples, and contradictions. Structured interviews use a standardised set of questions asked in a fixed order to maximise comparability across respondents and reduce interviewer effects. Across formats, interviews are typically conducted one-to-one, in a quiet, private setting (face to face or online), with informed consent obtained for note-taking and, where appropriate, audio recording. In certain research situations, focus groups may also be used, though several issues may arise in such an environment (e.g., groupthink). In practice, the interviewer should practice active listening and neutral prompts to ensure accuracy and minimise bias. Data are transcribed and thematically coded; structured responses may also be summarised descriptively. The choice of format depends on research objectives, required depth, and the need for standardisation.

The survey method lends itself to data collection, and both questionnaires and interviews were used in this study. The quantitative and qualitative strategies are further discussed in Sections 3.7 and 3.8.

3.4.3 Case Study

A generic definition of case study describes it as “a strategy for doing research which involves an empirical investigation of a particular contemporary phenomenon within its real life context using multiple sources of evidence” (Robson, 2002 p. 178). A very important element of case study research is that it takes place in a real (uncontrolled) environment and provides a very rich environment for understanding the given phenomena, particularly focusing on questions like ‘why’ or ‘how’ (Saunders et al., 2019). A case study may use a variety of data collection methodologies; however, generalising from a single case study may be difficult, and therefore, this method is not applicable to this study. At the same time, challenging or further exploring an existing theory in a particular context is a well-suited task for case study research (Saunders et al., 2019; Yin, 2013). A case study would give a very detailed insight into one (or a few) SMEs, but generalisability would not be part of the approach.

3.4.4 Action Research

Action research has been interpreted in a number of different ways in the literature, but four key themes can be listed as a generic guideline for action research (Saunders et al., 2019):

- Action research implies that the focus is on research in action, rather than research about action

- Action research implies a collaborative, equal partnership between practitioners and researchers
- Action research is iterative and may be represented as a spiral along the diagnosing, planning, taking action, and evaluating steps
- Action research should bring results that are applicable in different contexts.

Action research generally includes the sponsor (company representative), the researcher (frequently as a consultant) and the practitioners (members of an organisation), who participate in the research. There is a clear focus on the actual action implemented within the organisation (unlike in many other research strategies), and thus it is particularly appropriate for answering 'how' questions (Saunders et al., 2019). Action research would be a great follow-up to a fully established model, but again, it would primarily focus on a limited number of SMEs.

3.4.5 Grounded Theory

Grounded theory is a research method that aims to develop a theory that is based on data systematically gathered and analysed (Urquhart et al., 2010). Four major elements are described as key characteristics of grounded theory (Urquhart et al., 2010):

- The main target of the grounded theory method is theory building;
- The researcher should not rely on preconceived theories or notions, but rather let ideas emerge from the collected data;
- Joint data collection and constant comparison to existing concepts and constructs are providing the path to progress with the theory building; and
- A careful analysis is applied to select different kinds of data providing different views to aid the development of the emerging theory.

Grounded theory focuses on 'theory building', using both deduction and induction in an iterative process, frequently requiring repeated data collection phases and continued referencing of the collected data throughout building the new theory (or theories) (Saunders et al., 2019). While powerful, grounded theory is resource-intensive (requires multiple data-collection waves) and aims to generate new theory rather than explain existing theory-driven findings. This study's qualitative phase does not build a new theory from scratch; it explains and enriches an established UTAUT-based model tested quantitatively. The explanatory sequential design already has a theoretical anchor (UTAUT), making grounded theory's inductive, theory-building logic a mismatch.

3.4.6 Ethnography

Ethnography is a primarily inductive approach, originating from anthropological studies. The main purpose of an ethnographic study is to “describe and explain the social world the research subjects inhabit in the way in which they would describe and explain it” (Saunders et al., 2019 p. 149). Ethnographic studies may provide unique insights into a particular environment, but a full immersion of the researcher in the given environment is a difficult task to achieve (Saunders et al., 2019). Ethnography would require the researcher to become a member of a specific SME and would inform the researcher in detail about that specific organisation, but would not give a generic view of how tablet adoption proceeds in SMEs.

3.4.7 Archival research

Archival research uses existing records - public, organisational and personal - to study social and organisational phenomena over time (Saunders et al., 2019). Researchers appraise provenance, authenticity, credibility and representativeness of documents, and triangulate across datasets to mitigate gaps or institutional bias. Materials include administrative files, minutes, correspondence, policy papers, media, statistics and digital traces. Designs range from historical reconstructions to longitudinal organisational analyses, often combining quantitative counts with qualitative interpretation (Saunders et al., 2019). Unfortunately, documentation about Hungarian SMEs is rather limited – even official statistics are frequently questionable (e.g., number of employees).

3.4.8 Narrative inquiry

Narrative inquiry explores how people make sense of experience through stories, treating narratives as both data and a mode of knowing. Studies collect life histories, written accounts, field texts and conversational narratives, attending to temporality, sociality and place. Analysis may focus on content, structure, performance and context, with attention to voice, audience, and positioning (Saunders et al., 2019). Narrative inquiry may be used in the qualitative phase, but this requires more time allocated for sharing these stories, and many of the SMEs, employees or managers would have problems sharing such stories from their organisation with an external researcher.

3.5 Time Horizons

3.5.1 Cross-sectional

Cross-sectional research observes a population or sample at a single point in time to describe characteristics, test associations, or compare subgroups. It is efficient, relatively low-cost, and

well-suited to prevalence estimates and hypothesis generation. Designs range from surveys to secondary analysis of administrative or organisational datasets. Key limitations include temporal ambiguity (causality cannot be inferred), cohort and selection effects, and vulnerability to common-method bias when data come from the same source. Good practice emphasises clear operationalisation, appropriate sampling and weighting, confounder adjustment, and transparent reporting of design constraints. Findings provide useful snapshots for policy and practice, and can guide subsequent longitudinal studies (Saunders et al., 2019). As a cross-sectional design, causal claims are limited; this is mitigated through theory-driven modelling, robustness checks, and an explanatory interview phase. A cross-sectional approach was feasible and appropriate to manage surveys.

3.5.2 Longitudinal

Longitudinal research follows the same units over multiple time points to examine change, trajectories and temporal ordering. Designs include panel surveys, cohort studies, repeated measures and organisational time-series. Strengths include modelling intra-individual change, identifying lagged effects and improving plausibility. Challenges include attrition, measurement invariance, cohort and period effects, and greater resource demands. Longitudinal evidence clarifies mechanisms, sustainability of interventions and heterogeneity in pathways across people, groups or firms (Saunders et al., 2019). Returning to SMEs and repeating surveys raises a large number of questions – mostly whether they would agree to this approach at all. The changing environment, employees, and technological background would make it nearly impossible to contrast the phases of longitudinal research in the SMEs in this context.

3.6 Selected Research Methodology

3.6.1 Philosophy & methodological choice

A dual-paradigm stance is declared. The quantitative strand follows a positivist logic (measurement and hypothesis testing); the qualitative strand follows an interpretivist logic (meaning-centred explanation). Given the research questions, a mixed-methods design is appropriate (Creswell, 2014; Creswell & Plano Clark, 2018). Integration is planned explicitly at sampling (using notable quantitative cases to inform interviews) and at interpretation (joint displays). For corroboration and insight, this study employs between-method triangulation within a sequential explanatory design. Consequently, if predictive results fail and qualitative mechanisms contradict them in ways I cannot reconcile in the joint display/sensitivity checks, that

would make the integrated claims unwarranted and would represent a rejection of a given hypothesis.

3.6.2 Approach to reasoning

The work primarily operationalises and tests theory—specifically, how attitude influences IT-enabled innovative behaviour and, in turn, continuance of use. Starting from theory and applying Robson's (2002) criteria, a deductive approach is warranted for the quantitative strand; the qualitative strand contributes inductive insights, linked abductively to reconcile surprises and boundary conditions.

3.6.3 Strategies

A structured literature review underpins a conceptual framework, which is tested using a survey and PLS-SEM to examine relationships at scale. Follow-up semi-structured interviews are then used to explain quantitative patterns and deepen understanding in context.

3.6.4 Time horizon

A longitudinal design was not feasible due to rapid changes in tablet technology, SME access constraints, attrition risks, and potential measurement variance across waves. This study is therefore cross-sectional with a planned interpretive interview phase for explanatory triangulation.

3.6.5 Primary and Secondary Data Sources

This study employs two distinct forms of data to address the research questions: primary and secondary data. Primary data refers to original empirical information collected directly by the researcher for the purposes of this study. In this research, primary data comprise two sources: (1) quantitative survey responses collected from 1,040 tablet-using employees across 21 Hungarian SMEs during 2014–15, and (2) qualitative interview transcripts obtained from 18 participants (employees and managers) across nine of those original SMEs during 2021. These primary data constitute the core empirical material through which SRQ1, SRQ2 and SRQ3 are addressed. By contrast, secondary data refers to information originally collected by others for different purposes, which is repurposed for this research. In this study, secondary data comprise peer-reviewed academic literature (e.g. reviews of ICT adoption, innovation and the digital divide in SMEs), prior UTAUT-based measurement scales, and contextual statistics and policy reports on Hungarian and European SMEs. The distinction between primary and secondary sources is important: while secondary sources provide the theoretical scaffolding, measurement foundations

and methodological guidance, primary sources (survey and interview data) provide the empirical evidence needed to test hypotheses and explore mechanisms in the Hungarian SME context.

3.7 Quantitative Data Collection and Data Analysis Tools

3.7.1 Introduction

Quantitative data collection in this study relies on a survey, a structured instrument that gathers standardised responses from many participants to produce numerical evidence. Surveys translate theoretical constructs into measurable items (e.g., Likert-type scales), enabling statistical description, comparison, and hypothesis testing. Administered online, the questionnaire offers efficient reach, consistent delivery, and automated data capture. A cross-sectional design provides a snapshot of attitudes and behaviours at one point in time across firms. Sampling procedures define eligibility and contact routes, while uniform wording and fixed response options enhance reliability and comparability. Attention to anonymity, instructions, and bias controls supports valid, generalisable inferences (Saunders et al., 2019).

3.7.2 Selection of Quantitative Data Analysis Method

Quantitative data analysis proceeds from clear hypotheses and operationalised variables to transparent, reproducible procedures (Creswell, 2014; Saunders et al., 2019). To test the complex theoretical framework developed in this study, which includes multiple interdependent relationships and mediating pathways, Structural Equation Modelling (SEM) was selected as the primary analytical method. The research aims not merely to predict single outcomes, but to simultaneously test a system of 13 hypotheses involving eight latent constructs and multiple, complex mediation pathways. While an alternative approach, such as multilevel regression, could account for the nested structure of the data (i.e., employees within firms), it would be less effective for testing the entire path model (Curran, 2003; Richter et al., 2016). Machine learning models would help with prediction and prediction modelling, but would not support the explanatory modelling (Richter et al., 2016). SEM is uniquely suited to estimating this complete system of relationships at once, while also accounting for the measurement error associated with latent variables (Hair, 2018). SEM is the typical approach in UTAUT research as it allows for the simultaneous estimation of a series of interrelated dependence relationships (Xue et al., 2024).

In structural equation modelling, a critical step is to specify whether a latent construct is modelled reflectively or formatively, as this decision determines both the structure of the measurement model and the appropriate evaluation criteria (Hair et al., 2022; MacKenzie et al., 2011; Roy et al., 2012). In a reflective measurement model, the latent construct is viewed as the common cause

of its indicators: the items are manifestations of the underlying concept, are expected to covary, and can often be interchanged without substantially altering the construct's meaning. Changes in the latent variable should be reflected in consistent changes across all indicators, and the assessment therefore focuses on indicator reliability, internal consistency, and convergent and discriminant validity (Hair et al., 2022; MacKenzie et al., 2011).

In a formative measurement model, by contrast, the indicators are seen as defining or forming the construct: they capture distinct facets that collectively create the latent variable. Indicators need not be highly correlated and are not interchangeable; omitting an indicator may change the conceptual domain of the construct. Evaluation, therefore, emphasises examining multicollinearity among indicators and the significance and relevance of indicator weights, rather than internal consistency (Hair et al., 2022; MacKenzie et al., 2011). Misspecifying formative constructs as reflective (or vice versa) can bias parameter estimates and lead to incorrect substantive conclusions, underlining the importance of careful specification at the design stage (Roy et al., 2012). These measurement considerations influence the choice of the SEM estimator.

The field of SEM is broadly divided into two distinct methods: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM) (Dash & Paul, 2021). To address the heated debate about PLS- vs CB-SEM, the short conclusion is that both methods are appropriate for the right task (Dash & Paul, 2021; Hair et al., 2011; Richter et al., 2016; Sarstedt et al., 2023; Sarstedt et al., 2014). Specifically, Sarstedt et al. (2023) notes that CB-SEM should not be considered as a 'gold standard' against which PLS-SEM need to be measured. Sharma et al. (2022) investigated the use of PLS-SEM in IS and management research, using published UTAUT-based papers. Their findings indicate that "PLS(-SEM) reliably estimates common factor models with zero and weak relationships with marginal differences from CB-SEM" (Sharma et al., 2022). In fact, simulation research has shown that when data are generated by a composite model (i.e., where constructs are represented as weighted composites of their indicators), estimating such models with CB-SEM, which assumes common factors, produces substantial parameter bias (Cho et al., 2022; Sarstedt et al., 2016). Model evaluation with PLS-SEM has progressed to the level of using explanatory and predictive lenses simultaneously (Sarstedt et al., 2023; Sharma et al., 2022) and therefore both PLS-SEM and CB-SEM present valid choices. Therefore, the choice between them must be guided by the specific objectives and characteristics of the study (Dash & Paul, 2021; Hair et al., 2011; Henseler et al., 2014; Richter et al., 2016). The rationale for PLS-SEM is summarised in Table 3.2.

Table 3.2 Rationale for PLS-SEM

Consideration	Rationale for PLS-SEM
A) Research Goal	The primary goal of this research is predictive and explanatory. Beyond testing theoretical relationships (confirmation), this study aims to identify the key predictors of continuance intention and innovative behaviour to provide actionable recommendations for managers. PLS-SEM is optimised for prediction and theory development in this manner, whereas CB-SEM is primarily used for theory confirmation and prioritises overall model fit over predictive power (Dash & Paul, 2021; Sarstedt et al., 2023).
B) Measurement Model Specification	The theoretical model includes both reflective and formative constructs. Specifically, Innovation Support and Involvement Facilitation are specified as formative. PLS-SEM is a composite-based approach that readily accommodates formative measurement models (Sarstedt et al., 2023). Traditional CB-SEM, being factor-based, is focused on reflective measurement models, making it unsuitable for the specified theoretical framework (Hair et al., 2022; Sarstedt et al., 2014). This is a decisive factor in the choice of method.
C) Data Characteristics	The survey data, collected from heterogeneous SMEs, do not conform to a multivariate normal distribution. PLS-SEM is a non-parametric method that is distribution-agnostic, making it inherently robust to violations of normality. While maximum likelihood-based CB-SEM can be robust with large samples, PLS-SEM avoids the need for alternative estimators or data transformations (Sarstedt et al., 2023).
D) Structural Model Complexity	The proposed model is complex, comprising eight constructs and numerous simple and serial mediation pathways. PLS-SEM is well-suited for estimating complex models, as its algorithm estimates path coefficients in a series of individual regressions, thereby avoiding the convergence issues that can arise in CB-SEM when a model is highly complex (Hair et al., 2022).

In conclusion, the selection of PLS-SEM is strongly justified by

- a) Its alignment with this study's predictive goals,
- b) Its unique ability to handle the model's formative constructs,
- c) Its robustness to non-normal data, and
- d) its suitability for complex path models.

3.7.3 Quantitative Data Collection Process

The quantitative data collection in this study follows a two-stage process: an initial pilot study followed by the main survey. This sequential approach aligns with established best practices in survey research and structural equation modelling, where pilot testing plays a critical role in ensuring the feasibility, validity, and reliability of research instruments before full-scale deployment (Hassan et al., 2006; Khanal & Chhetri, 2024; Memon et al., 2017; Teijlingen & Hundley, 2001). Pilot studies serve multiple functions in the research process: testing the feasibility of recruitment and data collection procedures, evaluating the psychometric properties of measurement instruments (reliability, convergent validity, discriminant validity), identifying ambiguities or confusing items that require refinement, assessing completion time and respondent burden, and examining preliminary factorial structure through exploratory factor analysis (Malmqvist et al., 2019).

For this study, the pilot phase specifically targets instrument validation (see details in Table 3.4):

- ensuring that all UTAUT-based and innovation-related constructs demonstrate acceptable internal consistency (Cronbach's $\alpha \geq 0.70$);
- reflective items load appropriately onto their intended factors (loadings ≥ 0.708), and
- formative indicators exhibit adequate content validity and minimal collinearity ($VIF < 3.3$).

Questionnaire validity will be evaluated with the help of 10 experts using Lawshe's method (Almanasreh et al., 2019; Ayre & Scally, 2014; Lawshe, 1975; Romero Jeldres et al., 2023).

The pilot also assessed procedural feasibility, including response rates, data quality (missing data patterns, attention check performance), and the effectiveness of common method variance (CMV) controls (anonymity, randomisation, instructed items). A minimum pilot sample of $n = 100$ was targeted, exceeding conventional pilot thresholds ($n = 50-80$; Viechtbauer et al., 2015). Findings from the pilot inform final instrument refinement, including item rewording, deletion of poorly performing indicators, and adjustment of survey administration protocols (e.g., layout, completion time estimates).

3.7.4 Sampling

3.7.4.1 Introduction

Sampling determines which units are included from a population (Saunders et al., 2019).

- Probability sampling gives each unit a known, non-zero chance and supports statistical generalisation: (1) simple random draws individuals independently; (2) stratified samples within subgroups to ensure representation (e.g., firm size, sector); (3) cluster samples intact groups (e.g., firms) and may use multistage designs; (4) systematic selects every k-th case from an ordered list.
- Non-probability sampling is practical when frames are incomplete: (1) convenience uses available cases; (2) purposive targets information-rich cases; (3) quota fills predefined cells; (4) snowball recruits via referrals.

3.7.4.2 Pilot Study Sample Selection

Prior to the main survey, a pilot study was conducted to test the questionnaire's feasibility, data quality, completion time, and the suitability of demographic items. The pilot employed purposive firm recruitment: one medium-sized ICT SME was selected based on two key criteria.

- First, sample size adequacy: the firm had 201 employees, providing sufficient responses ($n = 100$ targeted, see sample size calculation below) to conduct preliminary psychometric evaluation (reliability, validity, exploratory factor analysis) and trial PLS-SEM analyses.
- Second, representativeness: as most Hungarian SMEs in the sample frame were expected to come from the ICT sector and fall within the medium-size category (50–249 employees), selecting a medium-sized ICT firm ensured that pilot findings would closely approximate the target population's characteristics and challenges.

Within the firm, convenience sampling was used: all employees with tablet access were invited via an internal company email (survey link through Central European University Qualtrics account). This approach balanced practical feasibility (access, cost, time constraints) with methodological rigour (adequate sample size, relevant context).

In terms of sample size, researchers recommend different sample sizes for pilots, ranging from 50 to 80 (Viechtbauer et al., 2015). Specifically for PLS-SEM, the most recent empirical recommendations suggest a minimum sample size of 100, although the more sophisticated inverse square method in general recommends a minimum of 160 (Guenther et al., 2023; Kock & Hadaya, 2018). As the target of the pilot is the evaluation of the basic measurement structure

(instrument validation, reliability testing, and preliminary SEM estimation), a 100 sample was targeted. The pilot yielded a usable response rate of $n=148$.

3.7.4.3 Main Study Sample Selection

This study uses purposive firm recruitment and within-firm convenience sampling. This research was specifically designed to investigate post-adoption behaviours in a mandatory-use context, a phenomenon that requires identifying a very particular subset of Hungarian SMEs. In 2014–2015, the corporate use of tablets was novel and largely confined to the most innovative and technologically forward-thinking firms, even in a Bring Your Own Device form (Disterer & Kleiner, 2014). These firms align with the "early adopter" and "early majority" categories in established technology adoption theories (Rogers, 2003). They are often described in economic literature as 'gazelle' companies—dynamic, high-growth enterprises that are disproportionately responsible for innovation and job creation (Birch, 1987; Vecsenyi, 1999).

A standard probability sampling approach was considered first. The official Hungarian company registry at the time was primarily a list of addresses with limited and often outdated contact information (Papanek, 2010). Hungarian SMEs tend not to participate in surveys: they are reluctant to share company information, even to discuss their successes (Papanek, 2010). Crucially, email contacts, where available, typically belonged to external accountants rather than internal managers, making direct contact with relevant decision-makers for a technology-focused study nearly impossible. Unsolicited approaches through such formal channels would have faced significant gatekeeping and were projected to yield an unworkably low response rate. In such a specific target population, standard probability sampling was rejected as both impractical and inappropriate. A similar problem was noted in the SME innovation research Csonka (2014), and their purposive sampling approach resulted in contacting 230 SMEs and receiving 49 responses. Considering the issues outlined above, and without a proper sampling frame, random and stratified sampling techniques, and the use of a formula to calculate the sample sizes are not considered appropriate (Memon et al., 2017).

Therefore, a multi-stage, non-probability purposive sampling strategy was the most rigorous and effective method to reach this hard-to-access population. The strategy focused on identifying firms where tablet adoption was most likely to occur. Key channels included approaching members of IVSZ (the Association of Information Technology, Telecommunications and Electronics Enterprises), Hungary's leading ICT industry body, and the MKIK (Hungarian Chamber of Commerce and Industry), as well as leveraging professional networks and attendance at ICT-focused conferences. This purposive approach ensured that the research was directed at the

specific firms where the phenomenon of interest—post-adoption tablet use—was actually occurring.

Regarding the sample size, the inverse square method with a significance level of 5% and effect size of 0.2 calculates the minimum sample size to 154 (Kock & Hadaya, 2018). Considering the complexity of the proposed model, it is appropriate to consider the number of latent variables in calculating the sample size. Using model complexity values (effect size small=0.2, number of latent variables 8, observed variables 30) the calculation recommends a sample size of 444 (Christopher Westland, 2010; Soper, 2025). Therefore, a minimum of 500 samples was targeted for the quantitative questionnaire phase.

Through this targeted process, 421 SMEs were identified and contacted. Twenty-one firms consented to participate (SME01–SME21), yielding a multi-site, individual-level dataset (n=1040 usable surveys).

3.7.5 Clustering and Robustness

The multi-site sampling design resulted in a nested data structure, with 1,040 individual employees clustered within 21 SMEs. Employees within the same firm may share exposure to common organisational factors (e.g., management practices, technology implementation strategies), potentially inducing intra-firm correlation that violates independence assumptions. However, PLS-SEM does not natively support multilevel modelling or cluster-robust standard errors (Hair et al., 2022; Hair et al., 2024). To assess the potential influence of firm-level clustering on individual-level parameter estimates, two complementary robustness strategies were planned and executed.

- First, leave-one-firm-out (LOFO) sensitivity analysis was conducted by re-estimating the final structural model 21 times, each time omitting all observations from a single firm. Each time, stability of path coefficients (β), explained variance (R^2), and effect sizes (f^2) were reviewed. Coefficients that remain stable in magnitude and direction across iterations (i.e., no sign changes, shifts < .02) indicate that no single organisation disproportionately drives the findings.
- Second, firm-level heterogeneity testing used multigroup analysis (MGA) to compare structural relations between the two largest firms (SME16, SME19) and all other firms pooled, following MICOM procedures to establish measurement invariance (Henseler et al., 2015). Significant differences after false discovery rate (FDR) correction would indicate

boundary conditions requiring theoretical interpretation; non-significant differences would support the generalizability of individual-level estimates across organisational contexts.

Together, these analyses provided empirical evidence regarding whether clustering materially affects the structural model, without requiring explicit multilevel decomposition. Results of these robustness checks are reported in Chapter 5 (LOFO and MGA).

3.7.6 Common Method Variance

Given this study's cross-sectional, self-report design, it is necessary to address the potential for common method variance (CMV). CMV is the variance attributable to the measurement method itself, rather than to the constructs being measured (e.g. Podsakoff et al., 2024). This is a relevant consideration for this research, as respondents were asked to evaluate their own perceptions and intentions (e.g., performance expectations, attitude, continuance intention) in a single survey. For instance, the very act of completing the survey on the tablet device in question could create a specific measurement context that influences responses. If such an effect systematically inflates or deflates relationships between variables, it leads to common method bias (CMB) (Fuller et al., 2016; Podsakoff et al., 2024).

The academic community holds varied perspectives on this issue; some scholars argue that the effects of CMV are often limited (Bozionelos & Simmering, 2022; Fuller et al., 2016), while others view it as a more serious threat to validity (Podsakoff et al., 2024). Acknowledging this debate, this study adopted a comprehensive, two-pronged strategy to proactively mitigate and retroactively test for CMV, incorporating both preventative ex ante design measures and ex post statistical diagnostics.

The primary and most effective safeguards are procedural remedies implemented before data collection. This study incorporated several such measures, which are detailed with their specific relevance in Table 3.3.

Table 3.3 Procedural remedies for Common Method Bias

Procedural remedy	Relevance to this study
Obtaining measures from different sources.	The constructs in this study (e.g., organisational support perception, effort expectancy) are inherently individual-level perceptions. Therefore, obtaining measures from each individual is a theoretical necessity. However, a significant procedural safeguard is created by the sample's heterogeneity;

Procedural remedy	Relevance to this study
	data were collected from numerous individuals across different organisational levels, age groups, and distinct organisations using various tablet devices. This diversity helps to prevent any single, uniform method effect from systematically biasing the entire dataset (Bliese, 2000; Fuller et al., 2016).
Separate the measurement of the predictor and criterion variables temporally, proximally, or psychologically.	Temporal separation was deemed impractical, as respondents in a Hungarian SME context are unlikely to complete a follow-up survey, and their perceptions could change over time. Instead, proximal and psychological separation were maximised. Using Qualtrics logic, items for different constructs were spread across multiple pages, with the order of both items within pages and the pages themselves randomised for each respondent. This disrupts the cognitive carryover that can occur when related items are grouped together (Podsakoff et al., 2024).
Reducing item social desirability and minimising common scale formats.	To reduce social desirability, all statements were formulated to be as neutral as possible. Crucially, respondent anonymity was guaranteed and emphasised, and the survey link was not directly associated with the respondent's specific organisation, further encouraging candid responses. While using varied scale formats is a known technique (Podsakoff et al., 2024), it was decided that introducing multiple formats would place an unnecessary cognitive burden on respondents. This decision is supported by evidence suggesting that common scale formats do not inherently produce stronger relationships than varied combinations (Podsakoff et al., 2013).

Following these procedural controls, ex post statistical diagnostics were performed. While various options exist, including complex techniques like marker variables or latent method factors, their application can be problematic. For example, adding a marker variable would have increased survey length, risking respondent fatigue. A latent factor may not be uniform across different organisational contexts (Podsakoff et al., 2024). Research also suggests that while complex

methods appear more sophisticated, they do not necessarily provide superior diagnostics, and that simpler, well-established tests are effective for detection at similar levels (Fuller et al., 2016; Podsakoff et al., 2024).

Therefore, two widely accepted diagnostics appropriate for this study's design and analytical method (PLS-SEM) were chosen (Fuller et al., 2016; Kock, 2015; Podsakoff et al., 2024):

- **Harman's Single-Factor Test:** This diagnostic test assumes that if a single factor accounts for the majority of the variance, a substantial CMV issue may be present. The 50% threshold is a generally accepted heuristic for this purpose (Fuller et al., 2016).
- **Full Colinearity Variance Inflation Factors (VIFs):** Specifically for PLS-SEM, a full colinearity test can be used to assess bias. If all variance inflation factors (VIFs) are below a conservative threshold of 3.3, the model can be considered free of common method bias. For formative items, the 3.3 limit was applied directly. For reflective items, values between 3.3 and 5 warranted inspection. Values above 5 are indicative of problematic colinearity that could be symptomatic of CMB, and therefore, they were not accepted (Kock, 2015).

3.7.7 Data Screening

Given that self-report surveys can be susceptible to low-quality or inattentive responses, a rigorous, multi-stage data screening process was implemented to ensure the integrity of the final dataset. Although the assumption is that participants are motivated enough to provide thoughtful responses, this is not guaranteed (Desimone et al., 2014). Therefore, the screening process involved a sequence of direct, archival, and statistical screening methods, as recommended in the literature (Desimone et al., 2014; Saunders et al., 2019).

1. **Direct Screening:** To identify inattentive respondents, instructed items (e.g., "For this item, please select 'Strongly Disagree'") were embedded on each page of the survey. While other methods, like bogus items, were considered, they were avoided to minimise survey length and maintain respondent trust (Desimone et al., 2014). Failures on instructed items were flagged for review.
2. **Archival Screening:** Post-collection, the data were examined for patterns indicative of low-effort responding. This included:
 - **Response Time Analysis:** Based on pilot data, a minimum completion time of 9 minutes was established. Cases with implausibly short completion times were removed.

- **Monotone Responding:** The data was screened for "straight-lining", where respondents select the same answer for all items in a construct or across the entire survey. Cases with long strings of identical responses (e.g., selecting '3' for all items across three or more constructs) were flagged for further inspection of their response variance.
3. **Statistical Screening:** Finally, statistical methods were used to identify multivariate outliers. While the Mahalanobis distance is a common technique, it has been questioned for its sensitivity to the very outliers it seeks to identify. Therefore, this study employed the more robust Minimum Covariance Determinant (MCD) method, which is less influenced by extreme cases (Fauconnier & Haesbroeck, 2009; Leys et al., 2018). The analysis was conducted in R. A conservative chi-square value threshold of $p < .001$ was used to identify outliers. Any case flagged as a multivariate outlier was reviewed (Leys et al., 2018).

3.7.8 Nonresponse Bias

Nonresponse can stem from a variety of sources, including (Toepoel & Schonlau, 2017):

- the inability to contact potential respondents,
- the refusal or lack of cooperation
- language or technical issues.

In this survey, the main concern is that nonresponse is based on a negative feeling towards the tablet, and thus, the survey may not collect data from participants who intend to stop using the tablet. As such, the survey was made available through an external link, so respondents would feel safe to respond freely (Toepoel & Schonlau, 2017).

In addition, post-survey adjustment was implemented as well. To address the potential for nonresponse bias, a time-based analysis was planned, grounded in the continuum-of-resistance perspective (Toepoel & Schonlau, 2017). This theory posits that respondents who answer later in the data collection period are more similar to nonrespondents than those who answer early (Armstrong & Overton, 1977; Groves & Peytcheva, 2008; Rogelberg & Stanton, 2007). The survey administration protocol, which involved an initial invitation followed by four weekly reminders over a five-week period at each SME, creates distinct response waves that are well-suited for this type of analysis.

The assessment was conducted using a multi-step approach:

- Group Formation:** For each participating SME, respondents were ordered by their completion time. "Early" and "Late" respondent groups were formed based on a median

split within each firm (i.e., the first 50% to respond are "Early," and the last 50% are "Late"). This within-firm split controls for differences in the survey timeline across organisations (Duszynski et al., 2022; Lindner et al., 2001).

- B. **Demographic Comparison:** First, the demographic composition of the Early and Late groups was compared on key variables (Gender, Management Level, and Age) using chi-square tests. Cramér's V was used to gauge the practical magnitude of any observed differences. Cramér's V is an effect-size measure for the strength of association between two categorical (nominal) variables, derived from the chi-square statistic (Kearney, 2017; Watson, 2014).
- C. **Structural Model Comparison:** As the primary concern is whether nonresponse could bias this study's substantive findings, a multigroup analysis (MGA) in PLS-SEM was conducted at the aggregate level. This approach formally tested for any statistically significant differences in the path coefficients of the final structural model between the Early and Late respondent groups (Henseler et al., 2015).

This portfolio of tests, examining both sample composition and the stability of the model's structural relationships, provides a comprehensive diagnostic for nonresponse bias. This approach is consistent with modern recommendations to assess its potential impact directly rather than relying on response rates alone (Groves & Peytcheva, 2008).

3.7.9 Scale Discussion

In line with prior UTAUT-based studies, this research employs a five-point Likert scale ranging from Strongly Disagree to Strongly Agree. A five-point format was selected as it provides an appropriate balance between measurement sensitivity and respondent comprehensibility, while avoiding the potential respondent fatigue associated with longer scales (Carifio & Perla, 2007; Dawes, 2008). To enhance clarity and reduce ambiguity, all response options are explicitly anchored (Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree). Anchoring each point has been shown to improve response reliability by minimising misinterpretation of intermediate categories, particularly in heterogeneous respondent groups such as SME employees (Leeuw et al., 2008; Presser et al., 2004). This approach is consistent with the operationalisation of UTAUT constructs in information systems research, where five-point anchored Likert scales have been widely applied to capture technology adoption and use behaviour (Venkatesh et al., 2012; Venkatesh et al., 2003). It therefore supports the consistency required for subsequent statistical procedures, including structural equation modelling and ensures comparability across demographic groups in the dataset (Carifio & Perla, 2007).

The debate regarding the Likert scale in terms of being ordinal or interval data has been ongoing for decades (Sullivan & Artino, 2013). For ordinal data, one cannot assume that the difference between responses is equidistant. In contrast, in the case of interval data, the difference between responses can be calculated.

Regarding the descriptive statistics, such as means and standard deviations, the argument emphasises that they have unclear meanings when applied to Likert scale responses (Jamieson, 2005). As an example, what does the average of “strongly agree” (5) and “disagree” (2) really mean – 3.5 would be higher than neutral (3), but less than agree (4)? Nevertheless, researchers have been treating the Likert scale as interval data. The general assumption is that if there is an adequate sample size (at least 5–10 observations per group) and if the data are normally distributed (or nearly normal), parametric tests can be used with Likert scale ordinal data (Jamieson, 2005).

Therefore, this study will present the distribution of the Likert scale data (kurtosis, skewness) and present both mean and median for descriptive purposes. Descriptive statistics (means, medians, standard deviations) are reported for interpretability, acknowledging the ongoing debate about interval vs. ordinal treatment of Likert scales (Jamieson, 2005; Sullivan & Artino, 2013).

Following best practice for PLS-SEM with Likert data (Henseler et al., 2016), ordinal data type is selected in SmartPLS4 to avoid distributional assumptions.

3.7.10 Measurement and Structural Model Evaluation Protocol

A critical step in SEM is the correct specification and evaluation of the measurement models, as misclassification can lead to flawed theoretical conclusions (MacKenzie et al., 2011; Sarstedt et al., 2023). Following the selection of PLS-SEM, a rigorous two-stage evaluation protocol was followed, adhering to the latest guidelines. SEM requires the researcher to specify whether constructs are reflective or formative, since this decision determines both the measurement model and the evaluation criteria (MacKenzie et al., 2011; Roy et al., 2012). Reflective constructs assume that observed indicators are interchangeable manifestations of an underlying latent factor, while formative constructs assume that indicators jointly form the construct and capture different facets of its domain. Misclassification can lead to biased estimates, incorrect reliability assessments, and flawed theoretical conclusions (Roy et al., 2012).

PLS-SEM requires a two-step approach: a) outer model (measurement model) evaluation and b) inner model (structural model) review (Hair et al., 2022; Hair et al., 2018). Therefore, first the measurement model was assessed.

As an initial step, factorability was tested before progressing with factor analysis. Factorability is the extent to which a set of observed variables shares enough common variance to justify extracting one or more latent factors. In practice, it asks whether the sample correlation matrix departs sufficiently from an identity matrix and exhibits the intercorrelations required for factor extraction. If the data are not factorable, factor analysis yields unstable or trivial solutions (Hair, 2018; Tabachnick & Fidell, 2019).

The Kaiser-Meyer-Olkin (KMO) measure together with Bartlett's test of sphericity remains a widely accepted, transparent screening step prior to factor analysis (Tabachnick & Fidell, 2019). The KMO measure evaluates whether partial correlations among items are small enough to support the presence of underlying common factors. Conceptually, it is the ratio of shared variance to shared and unique variance; values closer to 1 indicate that correlations are largely common rather than idiosyncratic (Tabachnick & Fidell, 2019). Conventional heuristics are: $\geq .90$ "marvellous", $\geq .80$ "meritorious", $\geq .70$ "middling", $\geq .60$ "mediocre" (acceptable), and $< .50$ problematic (Kaiser, 1974; Tabachnick & Fidell, 2019). Bartlett's test of sphericity assesses the null hypothesis that the correlation matrix equals the identity matrix (i.e., variables are uncorrelated) (Tabachnick & Fidell, 2019). As Bartlett's test is sensitive to large samples, Velicer's Minimum Average Partial (MAP) test may also be used for the full sample pre-extraction diagnostic (Garrido et al., 2011; Velicer, 1976). Velicer's MAP tests compare different factor/component structures, computing and minimising the average squared partial correlations among variables (Auerswald & Moshagen, 2019; Velicer, 2000). Consequently, Velicer's MAP was used to check that a factor structure is appearing before proceeding with factor analysis.

Reflective and formative constructs are evaluated using distinct criteria, as summarised in the table below (Hair et al., 2022; Hair et al., 2018; Kock, 2015; Kock & Lynn, 2012; Sarstedt et al., 2023).

Table 3.4 PLS-SEM standards summary table

Construct Type	Reliability	Convergent Validity	Discriminant Validity	Colinearity
Reflective	CR ≥ 0.70 , $\alpha \geq 0.70$	Loadings ≥ 0.708 , AVE ≥ 0.50	HTMT < 0.90	VIF < 5.0
Formative	Not applicable	Content validity & Outer weights (bootstrapped)	N/A	VIF < 3.3

Second, once the reliability and validity of the measurement models have been established, the structural model was evaluated by examining its explanatory and predictive power. This involves assessing the R^2 values of the endogenous constructs, the size and significance of the path coefficients (via bootstrapping), the effect sizes (f^2), and the model's out-of-sample predictive power (Q^2) (Hair et al., 2018; Sarstedt et al., 2023). Specifically for bootstrapping, the increased 10000 sample was used (Sarstedt et al., 2023). While PLS-SEM prioritises predictive relevance (Q^2) and explanatory power (R^2) over global fit indices, the Standardised Root Mean Square Residual (SRMR) is reported as a supplementary measure of approximate model fit, with values <0.09 considered acceptable (Henseler et al., 2016).

3.8 Qualitative Data Collection and Data Analysis Tools

3.8.1 Introduction

Interviews are a qualitative data collection method that provides rich, contextual accounts of participants' experiences. For this research, semi-structured interviews were developed to balance comparability with flexibility (Creswell, 2014; Saunders et al., 2019). A clear protocol defines purpose, sampling (e.g., purposive selection from quantitative extremes/contradictions), opening prompts, and follow-up probes. Ethical practice includes informed consent, confidentiality, and secure recording. Sessions were audio-recorded (with participant consent), transcribed verbatim, and de-identified.

In this study, interviews serve an explanatory function within the mixed-methods design: they are used to contextualise, expand, and interrogate quantitative PLS-SEM findings by exploring the meanings, mechanisms, and boundary conditions behind statistical patterns (e.g., high attitude but low continuance, role of organisational support). This positions the qualitative strand as interpretivist in logic, co-equal with the quantitative strand during interpretation, and integrated via joint displays and meta-inferences.

3.8.2 Selection of Qualitative Data Analysis Method

3.8.2.1 Introduction

Given the explanatory sequential purpose—using interviews to illuminate mechanisms and meanings behind quantitative patterns—the choice of qualitative analysis method must align with this aim (Bowen et al., 2017). Several qualitative analysis methods were considered. Grounded theory, and other broad research strategy options (discussed in Section 3.4) were rejected because this study's qualitative phase explains an established UTAUT model rather than building

new theory inductively. Two specific methods relevant to interview analysis—content analysis and thematic analysis—are compared below.

3.8.2.2 *Content Analysis*

Content Analysis (CA) focuses on systematically describing and quantifying what is present in the data: categories, frequencies, co-occurrences of words/phrases (Bengtsson, 2016). It is optimal for descriptive tasks (e.g., "How often do employees mention 'lack of training'?") but less suited to interpretive, meaning-centered inquiry (e.g., "Why does lack of training matter in this SME context? What underlying assumptions shape employees' perceptions?"). CA's strength lies in its structured, often quantitative approach (frequencies, correlations), which is valuable for hypothesis verification but not for mechanism exploration (Nicmanis, 2024). In this study, the qualitative aim is not to count occurrences but to explain and contextualize statistical relationships—a task CA is not optimized for (Bowen et al., 2017).

3.8.2.3 *Thematic Analysis*

Thematic Analysis (TA), by contrast, is explicitly designed to identify, analyze, and interpret patterns of meaning ("themes") across a dataset to explain experiences, mechanisms, or assumptions (Braun & Clarke, 2022). Unlike CA (which describes content), TA is flexible, accessible, and fit-for-purpose for explanatory work (Bowen et al., 2017). It allows researchers to move between data and theory abductively—using theory to sensitize coding while remaining open to emergent insights. This aligns perfectly with the explanatory sequential design: quantitative findings guide interview sampling (e.g., contradictory cases, extreme values), and thematic analysis surfaces mechanisms that explain those patterns (Bowen et al., 2017).

Crucially, TA is compatible with multiple epistemologies (Braun & Clarke, 2022). This study employs an interpretivist logic for the qualitative strand (prioritizing participant meaning-making, contextual depth). TA's flexibility supports this stance and it is aligned with this study's aims.

In summary, thematic analysis is selected because it:

- Focuses on patterns of meaning (themes) rather than frequency (CA);
- Supports explanatory, mechanism-focused inquiry aligned with this study's sequential design;
- Allows abductive reasoning—moving between UTAUT theory and emergent participant accounts;
- Is epistemologically flexible, supporting interpretivist qualitative analysis within a mixed-methods frame.

Consequently, for this study TA was selected as an overall method, and the next section looks at key approaches in TA.

3.8.3 Thematic Analysis Methods

Thematic analysis is not a monolith; it encompasses several variants that differ in structure, flexibility, and epistemological commitments (Kiger & Varpio, 2020). The two most established are:

3.8.3.1 *Reflexive Thematic Analysis*

Reflexive TA emphasises researcher subjectivity as a resource, not a threat (Braun & Clarke, 2012, 2022). Themes are meaning-based interpretive stories constructed through deep, iterative engagement with data, not pre-identified topics. Reflexive TA rejects codebooks, inter-coder reliability, and positivist notions of researcher bias. The reflexive approach prioritises organic, creative theme development grounded in the researcher's theoretical and contextual lens. It is strongly aligned with "Big Q" qualitative research—interpretivist, subjective, context-sensitive (Braun & Clarke, 2006, 2012, 2022).

3.8.3.2 *Codebook/Template Thematic Analysis*

Template TA (including approaches like Gioia methodology) strikes a middle ground: it is more systematic than reflexive TA (using structured coding procedures, data structure diagrams), but still allows themes to emerge inductively. Codebook TA often uses iterative coding levels (e.g., first-order codes → second-order themes → aggregate dimensions) to build from participant terms toward theoretical constructs, with an audit trail to enhance credibility (Gioia et al., 2022; Magnani & Gioia, 2023). This variant is particularly well-suited to theory-informed but exploratory work, where the researcher has a theoretical lens (e.g., UTAUT) but seeks to understand how it manifests in a specific context (e.g., Hungarian SMEs).

For this study, a Gioia-style inductive thematic analysis is selected for four reasons:

- **Systematic rigor with flexibility:** The Gioia methodology provides a clear, auditable structure (three-level coding, data structure diagram) that enhances transparency and credibility—critical for a mixed-methods thesis where qualitative rigor must match quantitative rigor. Unlike reflexive TA (which rejects systematic templates), Gioia offers a reproducible process that examiners can follow (Gioia, 2021; Gioia et al., 2013).
- **Theory-informed but open to emergence:** This study begins with UTAUT constructs (PE, ATT, IS, ITIB) from the quantitative phase, but qualitative analysis must remain open to

unexpected mechanisms, boundary conditions, and participant-defined meanings that the survey could not capture. Gioia methodology supports this balance: first-order concepts capture informant-centric terms (e.g., "manager doesn't get it," "tablet slows me down"); second-order themes interpret these through a theoretical lens (e.g., lack of managerial understanding as a barrier to organisational support); aggregate dimensions connect themes to UTAUT constructs or surface new mechanisms (Magnani & Gioia, 2023).

- Alignment with explanatory sequential design: The Gioia approach explicitly links raw data → emergent themes → higher-level constructs/mechanisms, producing a data structure figure that transparently shows how evidence supports each analytical level. This structure is ideal for joint displays in mixed methods: quantitative paths (e.g., $IS \rightarrow ITIB, \beta = X$) can be paired with qualitative mechanisms (second-order themes explaining how support enables innovation), creating meta-inferences that integrate both strands (Bowen et al., 2017; Creswell & Plano Clark, 2018).
- Abductive reasoning: Gioia methodology is explicitly abductive (not purely inductive). Researchers engage with theory to refine explanations while remaining open to novel insights. This contrasts with reflexive TA (which may de-emphasise systematic structure) (Bowen et al., 2017; Creswell & Plano Clark, 2018).

Importantly, the Gioia methodology aligns with social constructionism: it assumes that organisational realities (e.g., "organisational support," "innovation") are actively constructed through social interaction and interpretation, not objective entities to be discovered (Magnani & Gioia, 2023). This interpretivist stance honors participant meaning-making while driving toward theoretically useful constructs—exactly what an explanatory sequential design requires.

Finally, this study acknowledges the debate on the use of templates (Balachandran Nair, 2021; Denzin, 2009; Mees-Buss et al., 2020). However, templates – including the ones for the Gioia methodology – are simply modern recipes for the researcher to use them appropriately (Balachandran Nair, 2021). It is the responsibility of the researcher to keep the emerging new threads in mind while reading the interviews and apply sense-making, rather than getting lost in the numbering sequence of the paragraphs (Balachandran Nair, 2021).

3.8.4 Gioia Methodology: Implementation

The Gioia methodology is an inductive, rigor-oriented qualitative analysis approach (Gioia et al., 2013; Magnani & Gioia, 2023). The methodology explicitly links raw interview accounts to emergent theory through a three-level coding architecture: first-order concepts (informant-centric

terms), second-order themes (researcher-centric interpretations), and aggregate dimensions that express higher-level constructs and mechanisms (Gioia, 2021).

- First-order concepts (informant-centric terms): Captures participant language and categories in vivo (e.g., "tablet is too slow," "no one showed me how to use this feature," "I just figured it out myself"). These preserve participant voice and avoid premature theoretical imposition.
- Second-order themes (researcher-centric interpretations): Groups first-order concepts into analytically meaningful themes by interpreting them through a theoretical lens (e.g., grouping "no training," "manager doesn't understand tablets," "no time allocated for learning" under a second-order theme: Inadequate managerial facilitation of learning).
- Aggregate dimensions: Higher-level constructs that express mechanisms, processes, or theoretical insights (e.g., grouping several second-order themes under Organisational Barriers to Innovative Use).

Analysts move iteratively between data and concepts (constant comparison, memoing) with the aim of building a transparent data structure figure. This figure shows how evidence supports each level, and maintains an audit trail/codebook to enhance credibility and dependability. Although often described as "inductive," the approach is best seen as abductive: researchers remain open to novel insights while engaging with theory (in this case, UTAUT) to refine explanations.

The methodology captures informants' lived meanings while driving toward theoretically useful constructs and testable propositions (Gioia, 2021; Gioia et al., 2013). In practice, the Gioia approach is well-suited to processual, context-rich phenomena, such as the post-adoption ICT use in SMEs. Reporting typically includes a data-structure diagram, illustrative quotes by theme, and a narrative that explains how the dimensions interrelate (Gioia, 2021; Gioia et al., 2013; Magnani & Gioia, 2023). Credibility was supported by:

1. audit trail—detailed codebook documenting all coding decisions, iterative refinement, and analytical choices;
2. peer debriefing—regular discussions with peers challenging interpretations and surfacing blind spots;
3. reflexive memos—explicit documentation of researcher positionality and interpretive choices to enhance transparency; and
4. deviant-case analysis—systematic examination of contradictory cases to refine theoretical boundaries rather than suppress negative evidence.

Together, these mechanisms address the classic credibility concerns of bias, interpretation drift, and premature closure in qualitative analysis. Note: Transcripts were coded manually using MS Excel to support the three-level Gioia structure (first-order concepts, second-order themes, aggregate dimensions). This approach, while more time-intensive than NVivo or MAXQDA, ensures deep researcher engagement with data and transparent audit trail documentation.

3.8.5 Interview Protocol and Sampling

3.8.5.1 Overview

Following the explanatory-sequential design (Section 3.3.3), Phase 2 interview participants were purposively sampled from the Phase 1 quantitative survey using theoretically informative selection criteria (Palinkas et al., 2015; Patton, 2015).

The aim is to interview employees or managers who:

- Participated in the Phase 1 survey and reported tablet use ≥ 3 months,
- Exhibit extreme, contradictory, or theoretically interesting patterns on key UTAUT constructs (ATT, PE, EE, IS, ITIB, CI), and
- Can provide explanatory accounts of quantitative relationships identified in Chapter 5.

This sampling strategy aligns with Integration Point A (Section 3.9.3): drawing informants from configurations that challenge, refine, or elaborate statistical findings rather than merely illustrating them (Creswell & Plano Clark, 2018; Venkatesh et al., 2013).

3.8.5.2 Recruitment Strategy: Gatekeeper-Mediated Access

Given the explanatory-sequential aim—connecting quantitative patterns to qualitative explanations within the same population—interview participants must be drawn from the original survey cohort (Creswell & Plano Clark, 2018). Three recruitment approaches were considered:

Alternative 1: Direct contact with original survey respondents

This would require collecting participant email addresses during Phase 1 (survey). However, this approach was rejected during pilot testing (Chapter 4) for three reasons:

- Anonymity concerns: Expert validators recommended against collecting contact information to enhance anonymity, minimize social desirability bias, and maximise response rates (employees might self-censor if aware of future contact).
- SME confidentiality norms: Many Hungarian SMEs restrict sharing employee contact lists with external researchers, citing data protection and organisational secrecy concerns.

- Low retrospective response rates: Even if contact lists existed, cold-emailing participants 6+ years post-survey ("Do you remember completing a tablet survey? Please respond if interested") would likely yield response rates <5% and introduce severe self-selection bias (only highly motivated or dissatisfied users respond, missing "routine continuance" majority).

Alternative 2: Random sampling from new SMEs or new employees

This would involve recruiting participants from different firms or new hires who did not participate in Phase 1. This approach violates the explanatory-sequential integration logic: quantitative patterns (e.g., High IS → Low ITIB in Firm X; High ATT → Low CI in Firm Y) cannot be explained by informants who were not part of those configurations (Creswell & Plano Clark, 2018; Venkatesh et al., 2013). Joint displays comparing survey coefficients with interview themes require same-firm contexts to establish credibility. Random sampling from new SMEs would produce a parallel qualitative study, not an integrated explanatory follow-up.

Alternative 3: Longitudinal panel tracking

A true panel design—where survey respondents self-opt into future contact—was not embedded in Phase 1 (due to anonymity and feasibility constraints). Retrospectively tracking individuals via professional networks (e.g., LinkedIn) poses ethical issues (contacting individuals without prior consent violates GDPR Article 6) and practical challenges (turnover in Hungarian SMEs averages 15–20% annually; panel attrition would be prohibitive).

Selected Approach: Gatekeeper-Mediated Recruitment

Given these constraints, gatekeeper-mediated recruitment was employed: organisational contacts who facilitated Phase 1 (managers, HR coordinators, IT champions) were recontacted and asked to identify employees who participated in the original survey and remain with the firm. This strategy is optimal for four reasons:

- Feasibility: Gatekeepers have institutional knowledge of which employees participated in Phase 1 and remain employed, enabling targeted recruitment.
- Legitimacy and response rate: Gatekeeper endorsement signals legitimacy to potential interviewees, particularly in SME contexts where employees may be skeptical of unsolicited external requests (Silverman, 2024). Internal forwarding (gatekeeper → employee) is expected to yield response rates 40–60%, far exceeding cold-contact alternatives.

- Theoretical alignment: The approach preserves explanatory-sequential integration by ensuring interviewees are drawn from the same firms and cohort where quantitative patterns were observed, enabling direct triangulation (Creswell & Plano Clark, 2018).
- Ethical appropriateness: Gatekeeper-mediated recruitment respects employee privacy (no direct tracking) while maintaining voluntary participation (gatekeepers forward invitations; employees self-select whether to respond). This aligns with informed consent principles (Section 3.9.7).

Limitations and Mitigation

This approach introduces two potential biases:

Bias 1: Gatekeeper filtering (success story bias)

Gatekeepers may selectively nominate "positive" cases. Mitigation: Gatekeepers were explicitly instructed to identify diverse cases, including "employees who stopped using tablets or expressed dissatisfaction." The multi-lens sampling framework prioritises contradictory configurations (e.g., High IS → Low ITIB) rather than uniformly positive cases.

Bias 2: Survivorship bias

Employees who left the firm (turnover) and firms that closed (attrition) are unobservable. Mitigation: Where organisational change is known (e.g., restructuring, gatekeeper turnover), this context was documented. Findings were explicitly bounded to "employees who remained at adopting SMEs," limiting transferability claims to stable organisational contexts.

The implemented recruitment procedures, actual response rates, and reflections on bias mitigation are documented in Chapter 6.

3.8.5.3 Selection Criteria Framework

To identify interview sites and informants, a multi-lens purposive sampling framework was applied:

- Extreme/Deviant Cases (Flyvbjerg, 2006; Patton, 2015): SMEs or individuals with unusually high or low scores on focal constructs (e.g., very high organisational support but low innovative use, or vice versa). Extreme cases illuminate mechanisms that typical cases obscure.
- Contradictory Configurations (Miles et al., 2014; Seawright & Gerring, 2008): Participants exhibiting theoretically unexpected patterns (e.g., high attitude → low continuance intention; high innovation support → low innovative behaviour). These configurations

reveal boundary conditions or suppressor mechanisms that quantitative models cannot surface.

- Maximum Variation (Patton, 2015): Coverage across key dimensions—sector (Manufacturing, Services, ICT), location (Capital, Urban, Rural), firm size (Small vs. Medium), and roles (managers, frontline employees)—to ensure findings reflect diverse SME contexts rather than a single homogeneous population.
- Climate Homogeneity vs. Fragmentation (Miles et al., 2014): Selection included SMEs with low within-firm variance (indicating shared organisational climate) and high within-firm variance (indicating contested or fragmented climates) on ITIB and CI. This contrast reveals how organisational culture moderates technology adoption dynamics.

Operationally, firm-level profiles were constructed by averaging employee responses on UTAUT constructs and computing standardized scores (z-scores) relative to the distribution of firm means. Cases were ranked on multivariate deviation (e.g., Euclidean distance from the sample centroid) to identify outliers. Within-firm dispersion (standard deviation) was calculated to flag fragmentation. Contradictory configurations were identified using theoretically motivated thresholds (e.g., High ATT & Low CI = $z\_ATT > +0.5\text{ SD}$, $z\_CI < -0.5\text{ SD}$). SMEs satisfying multiple lenses simultaneously (e.g., an outlier and a contradictory configuration) were prioritised.

The specific firms selected, participant profiles, and recruitment outcomes are documented in Chapter 6.

3.8.5.4 Interview Protocol Design

Semi-structured interviews balance comparability (core prompts aligned with UTAUT constructs and quantitative findings) with flexibility (open probes to surface emergent themes). The protocol includes:

Core prompts addressing UTAUT constructs (e.g., "Tell me about how organisational support influenced your use of tablets for new tasks") and quantitative anomalies (e.g., for High ATT → Low CI cases: "You indicated positive attitudes in the survey—what prevented continued use?").

Open probes to elicit emergent themes (e.g., "What surprised you about using tablets?" "What barriers have you faced?").

Retrospective-prospective framing: Participants reflected on 2014–2015 adoption experiences (Phase 1 survey period) and discuss current use patterns, enabling longitudinal process tracing.

Interviews were conducted in Hungarian, audio-recorded (with consent), transcribed verbatim (where possible). A pilot interview (n=2) tested the protocol for clarity and timing before full deployment (with two colleagues). Ethical approval covers informed consent, confidentiality, data security, and the right to withdraw.

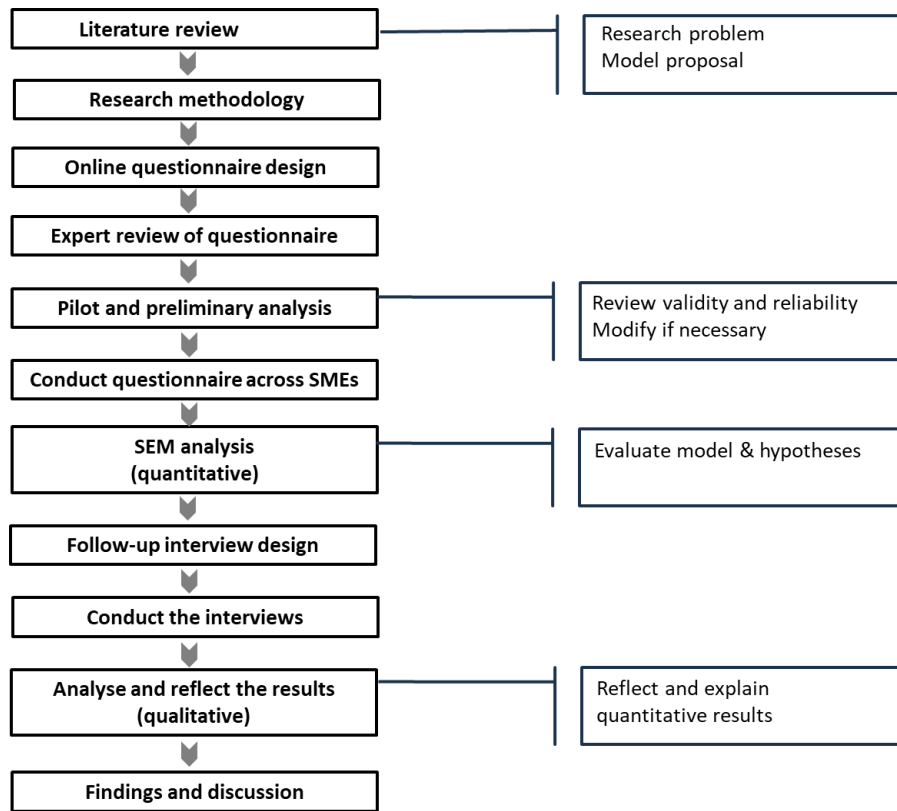
The final interview protocol and data collection procedures are documented in Chapter 6. In addition, the implementation of this sampling and recruitment strategy, including specific firm selection, participant profiles, achieved sample characteristics, and reflections on methodological challenges, can also be found Chapter 6.

3.9 Research Plan

3.9.1 Design and purpose

This study follows a mixed methods, explanatory sequential design (quantitative → qualitative) to (i) corroborate model-based quantitative findings with contextual evidence and (ii) expand explanatory depth around innovativeness, organisational support, attitude and continued use in Hungarian SMEs. Integration occurs by connecting strands at sampling (using survey results to select interviewees) and weaving findings at interpretation/reporting to produce meta-inferences that synthesise both strands (Figure 3.2).

Figure 3.2 Research plan



3.9.2 Phase 1 – Quantitative survey (primary strand)

Population & sampling

Employees in Hungarian SMEs using tablets. Firm-level access via purposive recruitment (partners/associations); within-firm participation is voluntary (convenience/self-selection). Nonresponse bias was assessed via wave-analysis (early vs late responders).

Instrument & administration

Online questionnaire with validated multi-item reflective measures for UTAUT-based constructs and study extensions (e.g., personal innovativeness, organisational support, innovative use, attitude, continuance).

Analysis

Data screening (missingness, outliers, design effects), descriptives, and correlations precede PLS-SEM for theory testing/prediction. Structural results report path coefficients, 95% CIs, f^2 , adjusted R^2 , Q^2 , and PLSpredict. Given employee clustering within firms, robustness checks were applied.

3.9.3 Integration point A – Connecting to Phase 2

The quantitative phase did not simply precede the qualitative phase chronologically; it actively shaped the qualitative strand through two concrete mechanisms: purposive sampling and interview protocol design. Together, these mechanisms ensured that the qualitative phase was structurally connected to the quantitative findings rather than operating as a parallel or independent inquiry (Creswell & Plano Clark, 2018; Venkatesh et al., 2013).

Mechanism 1: Purposive sampling from quantitative configurations. Interview sites were selected from the original 21-SME Phase 1 cohort using firm-level composite scores on key constructs (ATT, PE, EE, IS, IF, PIIT, ITIB, CI); informants were then recruited within those selected sites through the gatekeeper process. Firms were ranked by their z-scores relative to the sample centroid, and four theoretically motivated selection lenses were applied:

- extreme/deviant cases: firms with unusually high or low scores on focal constructs, which illuminate boundary conditions invisible in average-case analysis;
- unexpected configurations: firms exhibiting theoretically unexpected patterns (e.g., high ATT paired with low CI, or high PIIT paired with low ITIB), which reveal suppressor mechanisms the structural model cannot surface;
- within-firm dispersion of ITIB and CI: firms with low versus high within-firm variance on these constructs, allowing examination of how organisational climate may affect appropriation dynamics; and
- maximum variation across sector and location: firms were also selected to retain variation across Manufacturing, Services and ICT, and across Capital, City and Rural locations, so that the qualitative phase did not over-represent one organisational or geographical context.

SMEs satisfying multiple lenses simultaneously were prioritised. This sampling strategy meant that every interview site was selected because of its quantitative profile and theoretical relevance, not independently of the Phase 1 findings (Palinkas et al., 2015; Patton, 2015). See Section 3.8.5.3 for full operationalisation and Appendix K1 (Table 9.105) for firm z-scores. Each site was selected on the basis of its 2014–15 quantitative profile; firm conditions may have evolved during the temporal gap between phases, but the interviews focused on theoretically stable mechanisms rather than period-specific conditions.

Mechanism 2: Interview protocol designed around quantitative anomalies. The semi-structured interview protocol was not a generic technology-use guide; it was constructed to probe the specific

paths and relationships that the Phase 1 model flagged as surprising or theoretically under-explained. Core prompts were directly linked to quantitative constructs and unexpected findings. For instance, the finding that the effect of Innovation Support on ITIB operated primarily through Involvement Facilitation prompted interview questions about the gap between symbolic organisational encouragement and the concrete resources employees need to innovate. The competitive mediation of PIIT (positive indirect, negative direct path to CI) prompted questions distinguishing exploration-driven enthusiasm from frustration-driven discontinuance. Open probes were added to allow emergent themes to surface that the model had not anticipated (see Section 3.8.5.4 and Appendix K2 (Table 9.106) for the full protocol). This ensured that the interview guide operationalised the research question for the qualitative phase (Section 6.2.1) as a direct extension of the quantitative model's unresolved questions, not as a free-standing topic list.

Together, these two mechanisms operationalised the explanatory-sequential logic: the qualitative phase was designed principally to explain how and why the quantitative patterns emerged, while remaining open to confirming, qualifying, or extending them — and it pursued that goal through informants drawn from the organisational contexts in which those patterns had been observed.

3.9.4 Phase 2 – Qualitative interviews (follow-up strand)

Sampling & data collection

Semi-structured interviews with selected employees (and, where access permits, managers for triangulation) until analytical saturation (anticipated ~15–25 interviews, contingent on heterogeneity). A protocol defines prompts around perceived enablers/barriers to innovative use, role of organisational support and control/autonomy, perceived risks, and narratives that explain the quantitative patterns.

Analysis

Transcripts are anonymised and analysed using thematic analysis with a Gioia-style structure (first-order terms → second-order themes → aggregate dimensions) to surface mechanisms that explain and contextualise the modelled relationships. Credibility is supported by an audit trail, peer debriefs, reflexive memos, and, where feasible, brief member checks on emergent interpretations.

3.9.5 Integration point B – Interpretation & meta-inferences

Results are integrated using joint displays (linking coefficients/patterns to representative quotations and themes) and woven narrative in the Discussion. The goal is to produce meta-

inferences—coherent, theory-consistent conclusions that (i) validate statistical relationships, (ii) explain divergences, and (iii) generate implications for SME practice and policy.

3.9.6 Inference quality and rigor

Following mixed-methods guidance, rigor is addressed on three fronts (Venkatesh et al., 2013):

- Design quality: validated measures and transparent PLS-SEM reporting; explicit, criteria-based interview sampling and a documented qualitative protocol.
- Explanation quality: quantitative validity (reliability, discriminant validity, predictive relevance) and qualitative credibility (coherence, confirmability, transferability via rich context).
- Integration quality: planned connection of strands, joint displays, and consistency of meta-inferences with theory and evidence.

3.9.7 Ethics and governance

All participants provide informed consent; confidentiality and secure data handling are ensured. Participation is voluntary; no identifiable data appear in reports. Any firm-level sensitivities are respected through aggregated reporting and paraphrased quotations where necessary. Survey organisations are labelled under pseudonyms (SME01, SME02, etc). Interview organisations and participants are also assigned independent pseudonyms (Company A, A-01; Company B, B-01, B-02). The mapping between survey and interview identifiers is retained in an encrypted file accessible only to the researcher and is not disclosed in this thesis. Descriptors (industry, size, role) are reported in generalised form to minimise deductive disclosure. Ethical approval: CEU: No. 1/2012/13; CEU: No. 2/2013/14; Social Sciences Arts and Humanities ECDA Minute 134; UH ECDA BUS/PGT/UH/04934. Participants gave informed consent and could withdraw without penalty. Data handling complied with GDPR.

3.9.8 Limitations and contingencies

Cross-sectional timing limits causal claims; this is mitigated through theory-driven modelling, robustness checks, and explanatory interviews. Access constraints in SMEs may affect coverage: transparent reporting addresses generalisability concerns. Rapid device/feature evolution is acknowledged in the Discussion as a boundary condition.

All three Attitude (ATT) items are positively keyed ("Using a tablet at work is a good idea"; "Using the tablet device would be beneficial to my job"; "Overall, I have a positive attitude toward using tablets in my job"). While this follows standard UTAUT-based operationalisation (Bhattacharjee &

Premkumar, 2004; Venkatesh et al., 2003), it introduces a directional constraint: the scale captures the degree to which respondents endorse positive evaluation, but it does not separately measure ambivalence, negative affect, or resentment toward the technology. This limitation is especially relevant in mandated-use contexts, where employees may comply with technology use while holding mixed or negative views about it (Brown et al., 2002). More broadly, positive keying applies across all constructs in this study, as the single reverse-coded item in the pilot produced unreliable responses and was rephrased. The implications of this uniform positive framing for the structural model, and the partial mitigation achieved through the qualitative phase, are discussed in Section 8.2.7.

4 PILOT TEST AND FINAL SURVEY DEVELOPMENT

4.1 Introduction

This chapter documents the pilot survey conducted to validate the research instrument and test data collection procedures ahead of the main study. Specifically, this pilot phase targeted four key objectives: first, to validate the research instrument by assessing the reliability and validity of all UTAUT-based and innovation-related constructs; second, to test the procedural feasibility of the online survey administration and data collection workflow; third, to examine the preliminary factorial structure of the measurement model through appropriate exploratory techniques; and fourth, to identify any problematic items or ambiguities in wording that might require revision before main study deployment.

These objectives align with the two-stage quantitative data collection process established in Chapter 3, ensuring that the pilot provides both psychometric validation and operational feasibility testing before full-scale implementation across multiple Hungarian SMEs. The pilot results, detailed analysis, and instrument refinements are presented in the subsequent sections of this chapter. For statistical analysis, XLSTAT 2024 (Addinsoft, 2024) and SmartPLS4 (Ringle et al., 2024) is used.

4.2 Pilot Survey Questionnaire Development

Surveys were introduced in Chapter 3: a more detailed overview follows as part of the questionnaire development. Online surveys have become a widely adopted method for data collection in management and social science research due to their cost-effectiveness, scalability, and flexibility. They allow researchers to reach large and diverse populations quickly, which is particularly useful in contexts where respondents are geographically dispersed, such as SMEs operating across different regions. Online platforms (e.g., Qualtrics, SurveyMonkey: this research will use Qualtrics) support sophisticated design features (e.g., branching logic, randomization or mobile-friendly interfaces), ensuring accessibility and improved response experiences (Leeuw et al., 2008). Furthermore, online surveys reduce administrative burdens by automating data entry, minimizing transcription errors, and facilitating immediate export of datasets for statistical analysis (Presser et al., 2004).

However, these benefits come with important caveats that must be carefully managed. One major concern is sampling bias, as online surveys often rely on non-probabilistic sampling strategies. This raises questions about representativeness and limits the generalizability of findings. Self-

selection bias occurs when individuals with stronger opinions or higher digital literacy are more likely to participate, potentially skewing results. Another limitation is the issue of response quality: inattentive respondents may engage in satisficing, such as speeding through questions, straight-lining responses, or providing inconsistent answers (Presser et al., 2004). While tools such as attention checks or time filters can mitigate this risk, they do not eliminate it entirely. Consequently, pretesting through pilot surveys is strongly recommended, as it enables researchers to identify problematic items, assess completion times, and refine survey flow before full-scale distribution (Teijlingen & Hundley, 2001).

Technological barriers are also frequently highlighted in the literature, as they may affect participation. However, considering that the respondents will be tablet users, this is not expected to be a major problem. Privacy and data security concerns can also deter participation if respondents fear that their answers may be traced or misused: this concern is particularly relevant in the Hungarian context, where high power distance and a culture of organisational secrecy can heighten respondent reluctance (Bánó, 2014). Finally, while online surveys support anonymity, the lack of interviewer presence means researchers cannot clarify misunderstandings or probe deeper into responses, limiting the richness of data compared to qualitative approaches.

Overall, online surveys represent an efficient and practical data collection method for the study of ICT adoption in SMEs, provided their limitations are acknowledged and mitigated through careful design, piloting, and transparent reporting.

The following guideline list was compiled based on key recommendations in the literature (Leeuw et al., 2008; Presser et al., 2004; Teijlingen & Hundley, 2001):

- Clarity of wording – Use short, precise, and unambiguous language. Avoid jargon, double negatives, and double-barrelled questions.
- Logical structure – Organise questions in a natural flow, beginning with easier and less sensitive items before moving to more complex or personal topics.
- Consistency in scales – Keep rating scales (e.g., Likert) consistent in direction and labeling throughout the survey to reduce respondent error.
- Length and timing – Keep surveys concise to avoid fatigue. Ideally, completion time should not exceed 15–20 minutes.
- Pilot testing – Pretest the instrument with a small group to identify unclear questions, technical issues, or survey fatigue before full deployment.

- Mobile and device compatibility – Ensure that the survey is accessible on multiple devices (desktop, tablet, smartphone) to maximise reach, particularly important in workplace contexts.
- Anonymity and confidentiality – Clearly communicate data protection measures and reassure respondents about the anonymity of their answers.
- Engagement features – Use progress bars, simple navigation, and clear instructions to sustain motivation and prevent dropouts.

These principles were applied in the design of the questionnaire, leading to three sections: a) demographics, b) core UTAUT constructs and c) innovative behaviour-related constructs. The UTAUT model, along with other technology acceptance models, was published and introduced into the Hungarian research scene in detail in 2016 (Keszey & Zsukk, 2017). While individual papers, university notes and conference papers were published in Hungarian about technology acceptance models in the early 2010s, this was the first official publication in a leading Hungarian research journal providing an overview of the various technology acceptance models. Following the official introduction, UTAUT (or other extensions of the model) were applied in the Hungarian context, specifically in the higher education context (Halász & Kenesei, 2022; Koteczki & Balassa, 2025). Consequently, for the development of the questionnaire, the English version of the instrument was completed first. Subsequently, it was translated into Hungarian by a fully bilingual faculty and graduate assistants. A fully bilingual individual who was not involved with the initial translation then translated the Hungarian version back into English. The two versions were compared, and minor adjustments related to the choice of words were made. The final pilot survey in English can be found in Appendix H.

4.3 Development of Questionnaire

4.3.1 Introduction

This section deals with the development of the questionnaire items. A short version of the constructs and the definitions is inserted below (Table 4.1). The original table is in Chapter 2 (Table 2.3).

Table 4.1 Constructs for the conceptual model

Abbrev.	Construct	Concise definition (post-adoption)	Role in the model
PE	Performance Expectancy	The degree to which continued tablet use is perceived to improve task	Cognitive belief → affects ATT and CI

Abbrev.	Construct	Concise definition (post-adoption)	Role in the model
		performance, efficiency, or outcomes. (Venkatesh et al., 2003)	(H1–H2); shaped by EE (H4).
EE	Effort Expectancy	The perceived ease and clarity associated with using the tablet for routine work tasks. (Venkatesh et al., 2003)	Cognitive belief → affects ATT (H3) and PE (H4).
ATT	Attitude toward Use	Overall evaluative affect toward using the tablet in job tasks, formed through experience in a mandated setting. (Bhattacharjee & Premkumar, 2004)	Affective appraisal → drives ITIB (H6) and CI (H5); mediates PE/EE → ITIB (M1–M2).
ITIB	IT-enabled Innovative Behaviour	User behaviours that experiment with, repurpose, or extend tablet features to achieve novel or improved work outcomes. (Trivellas & Santouridis, 2013)	Behavioural conduit → strengthens CI (H7); mediates trait/organisational effects → CI (M3–M5); part of serial chains (M6–M8).
CI	Continuance Intention	The intention to keep using the tablet for work in the foreseeable future. (Bhattacharjee & Premkumar, 2004)	Focal outcome influenced by PE , ATT , ITIB , PIIT .
PIIT	Personal Innovativeness in IT	Stable individual tendency to try out new information technologies and tolerate uncertainty. (Agarwal & Prasad, 1998)	Trait antecedent → boosts ITIB (H8) and directly CI (H11); effect partially mediated by ITIB (M3).
IS	Innovation Support	Organisational climate and mechanisms that encourage experimentation, idea sharing, risk-	Context antecedent → increases ITIB (H10) and IF (H12);

Abbrev.	Construct	Concise definition (post-adoption)	Role in the model
		taking, and provide backing for early ideas. (Tarafdar et al., 2010)	participates in serial path IS → IF → ITIB → CI (M8).
IF	Involvement Facilitation	Formal opportunities and resources that involve users across the IT lifecycle (trailing, feedback, training, influence on use). (Doll & Torkzadeh, 1989)	Context antecedent → increases ITIB (H9); contributes to mediation IF → ITIB → CI (M4).

4.3.2 Core UTAUT constructs

The core UTAUT constructs (Effort Expectancy, Performance Expectancy, Continued Use) were adapted from the UTAUT studies (Venkatesh et al., 2003; Venkatesh et al., 2011). All these constructs are reflective.

Attitude Construct

In terms of attitude, three types of items are typically used in this reflective construct (Bagozzi et al., 1992; Davis et al., 1989; Venkatesh & Davis, 2000; Venkatesh et al., 2012; Venkatesh et al., 2011):

General evaluation

- Using [the system/technology] is a good idea.
- I like the idea of using [the system/technology].
- Using [the system/technology] is a wise decision.

Affective evaluation

- I find using [the system/technology] to be enjoyable.
- I feel positive about using [the system/technology].
- I have a generally favourable attitude towards using [the system/technology].

Work-related benefits

- Using [the system/technology] would be beneficial to my job.
- I think using [the system/technology] improves the quality of my work.

Finally, three items were put forward to measure attitude, based on the assumption that these items would be balanced and cover general evaluation, affective enjoyment, favourable orientation, and perceived benefit.

- Using a tablet at work is a good idea.
- Using a tablet helps me perform my work more effectively.
- Overall, I have a positive attitude toward using tablets in my job.

4.3.3 Innovative Behaviour-Related Constructs

Personal Innovativeness in IT

PIIT is measured using 4 Likert items, adapted from the original study (Agarwal & Prasad, 1998). This is a reflective construct, and one item is reverse-coded; items were adapted from the literature.

- If I heard about a new information technology, I would look for ways to experiment with it.
- Among my peers, I am usually the first to explore new information technologies.
- I like to experiment with new information technologies.
- In general, I am hesitant to try out new information technologies.

IT-Enabled Innovative Behaviour

Three Likert items were adapted from the literature as a reflective construct (Torkzadeh & Doll, 1999; Torkzadeh et al., 2005).

- This tablet device helps me to identify innovative ways of doing my job.
- This tablet device helps me to come up with new ideas relating to my job.
- This tablet device helps me to try out innovative ideas.

Innovation Support

Innovation support was historically operationalised using 5 items as a reflective construct (Tarafdar et al., 2010). The items are as follows:

- We have a very open communications environment.
- Employees and managers are supportive of each other.
- Employees at all levels are rewarded for learning new skills.
- Experimental mind-sets and risk taking is encouraged.
- New ideas are easy to be implemented.

As discussed in Chapter 3, a critical step in SEM is to correctly specify whether constructs are reflective or formative (MacKenzie et al., 2011; Roy et al., 2012). For this reason, each construct in the study was carefully reviewed against theoretical definitions and item content before deciding on its measurement model.

The construct Innovation Support was originally identified in the literature as reflective. However, upon closer inspection of the survey items, it became evident that a formative specification is more appropriate. The measurement items (e.g., open communications, supportive relations between employees and managers, rewards for learning new skills, encouragement of experimental mind-sets, and ease of implementing new ideas) represent distinct organisational practices that together define the broader domain of innovation support. These indicators are not interchangeable manifestations of a single underlying factor: for instance, an SME may strongly reward skill development, but still lack an open communication environment. Dropping one indicator would narrow the conceptual meaning of the construct, which is a defining feature of formative measurement. Moreover, the expectation of high inter-item correlations is not theoretically justified, making traditional reliability measures such as Cronbach's alpha inappropriate.

In summary:

- Low redundancy: The items capture different dimensions (communication, support, rewards, risk-taking, implementation).
- Different outcomes: Changing one does not necessarily change the others.
- Conceptual breadth: The meaning of innovation support depends on all of them together. Dropping one would narrow the construct.

Accordingly, Innovation Support is modelled as a formative construct in this thesis. The methodological implications are twofold: (1) emphasis is placed on establishing content validity by ensuring that the set of indicators comprehensively represents the construct domain, and (2) formative indicators are assessed for colinearity (via variance inflation factor, VIF) and their relative contribution (indicator weights and significance) to the construct. This approach aligns with established guidelines for formative measurement in partial least squares structural equation modelling (PLS-SEM) (Hair, Hult, Ringle & Sarstedt, 2017; Sarstedt, Hair, Ringle, Thiele & Gudergan, 2016).

Involvement Facilitation

Involvement Facilitation (IF) or end-user involvement was adopted from studies as a 4-item construct, reflecting on how the user engages in adoption and post-adoption processes (Doll & Torkzadeh, 1989; Tarafdar et al., 2010). The items are as follows:

- Employees are encouraged to try out new technologies.
- Employees are rewarded for using new technologies.
- Employees are consulted before the introduction of new technology.
- Employees are involved in technology change and/or implementation.

Following the same logic as for the innovation support, the items capture different dimensions, including rewards (1 item), encouragement (1 item) and consultation/involvement (2 items). Consequently, in this study, the Involvement Facilitation construct will be modelled as formative, where the items jointly define involvement facilitation.

4.3.4 Scale Discussion

For the UTAUT statements, 5-point Likert statements are used (Strongly Disagree, Disagree, Neutral, Agree, Strongly Agree). As discussed in Chapter 3, descriptive statistics (means, medians, standard deviations) are reported for interpretability, acknowledging the ongoing debate about interval vs. ordinal treatment of Likert scales (Jamieson, 2005; Sullivan & Artino, 2013). Following best practices for PLS-SEM with Likert data (Henseler et al., 2016), constructs are modelled using the ordinal data type setting in SmartPLS4 to avoid distributional assumptions. This approach is consistent with the data treatment protocol specified in Chapter 3.

4.4 Content Validation

Content validity represents the degree to which a questionnaire accurately measures all relevant aspects of the intended construct. For UTAUT-based questionnaires, establishing content validity through expert evaluation ensures that the instrument comprehensively captures the theoretical dimensions of technology acceptance and use. A common solution is Lawshe's method (Almanasreh et al., 2019; Ayre & Scally, 2014; Lawshe, 1975; Romero Jeldres et al., 2023). Following this method, 10 experts were recruited (Table 4.2), and they received a cover letter explaining the study purpose, the questionnaire in both languages with a theoretical framework explanation and the content validity assessment forms with clear rating instructions. Note: as the UTAUT model and the constructs have not been translated officially to English, both the original statements and the Hungarian statements were provided. Based on the replies, using Lawshe's CVR with a critical value of 0.80 (Ayre & Scally, 2014), all 30 UTAUT and organisational support items achieved $CVR \geq 0.80$ ($I-CVI \geq 0.90$). In contrast, several demographic or contextual items

(Functionality, SME sector, size, location, education, work area, experience) fell below this threshold and were either removed or made optional, in line with the experts' qualitative comments (see the Lawshe CVR table in Appendix G for details).

Table 4.2. Expert Panel

	Participant	Mother tongue	Level of Hungarian	Level of English	Area of Expertise
Academic Researchers	A	English	Good	Fluent	Information technology
	B	English	Good	Fluent	Cognitive science
	C	Hungarian	Fluent	Fluent	Quantitative methods
	D	Hungarian	Fluent	Fluent	Organisational behaviour
	E	Hungarian	Fluent	Fluent	Biorobotics, information technology
Industry Specialist / SME Employee / Researchers	F	Hungarian	Fluent	Good	SME Manager / Corporate Training
	G	Hungarian	Fluent	Good	SME Manager / Architect & Designer
	H	Hungarian	Fluent	Good	SME Manager / Professional Translator / Interpreter
	I	Hungarian	Fluent	Good	IT Project Leader
	J	English	Fluent	Fluent	IT project Leader

The following recommendations were given by the expert panel (sample text from the responses):

SME Sector / Location / Size question: *“Do not include the sector / location / size – ask the SME before the survey and record it once. The survey is already long, took me 15 minutes to complete.”* (8 experts with similar opinions)

Tablet Functionality question: *“Its okay to include, but probably everybody will just tick everything. It’s unlikely that it will be useful for the analysis. In addition, people will be worried to select ‘Playing Games’. Better not start this, SME managers may feel bad that there is no dedicated app in their organisation.”* (6 experts with similar opinions)

Level of Education question: *“Remove this, its unlikely to impact anything, and Hungarian people may not feel comfortable fully with this. Also, because of the systemic changes in 1995, some of your respondents completed 5 years university studies and yet they don’t have a Master degree or may not understand what you are asking.”* (6 experts with similar opinions)

Work Area question: *“In SMEs, roles generally overlap. I wear many hats. And respondents may react negatively, thinking that they can be identified if they identify the work area. It can be left in, but make it optional.”* (6 experts with similar opinions)

Experience (with tablets, in years/months): *“I do not recommend this. They will either skip this question at the end, or will impact / bias their responses if you put it at beginning. Some of them will be thinking oh, I don’t have a year experience, I am not good at this. You already have enough questions. You already said its post-adoption.”* (6 experts with similar opinions)

Following these recommendations, the Company Sector, Tablet Functionality, Education, Work Area and Experience fields were removed.

Age question: initially, the year of birth had to be selected. Experts recommended that respondents may feel more comfortable selecting an age group (e.g. 20-30, or 30-40, etc.), as in SMEs (particularly at higher management levels), the age may identify the individual

All Industry / SME experts commented on the fact that some of the questions may feel as critique towards the employer (IS, IF) and therefore it is imperative that the survey is provided through an external link (Qualtrics). In addition, the experts noted that in Hungarian SMEs ‘manager’ is a very fluid term. In some cases, employees will be managers not because they are in a managerial role, but because it’s a higher prestige work profile. It was considered to simply ask the question employee/manager, rather than refer to different management levels, but the junior/mid-level/senior levels were retained. Finally, as individuals may feel that they can be identified through demographics in an SME, six experts recommended leaving all demographics questions as optional. These recommendations were followed.

The survey is displayed over five short pages, and questions are separated and randomised by the Qualtrics system. On every page, an attention check is done by a single item (Please select Strongly Agree for this line). Qualtrics stores the time spent on the survey/screens. All items are mandatory, except the demographics.

4.5 Pilot Test: Analysis and Findings

4.5.1 Sampling and Sample Size

This approach follows the sampling framework outlined in Chapter 3, employing purposive firm-level selection and within-firm convenience sampling. At the firm level, purposive sampling was used to select one medium-sized ICT SME based on two criteria:

- I. adequate sample size—the firm employed 201 individuals, providing a sufficiently large pool to achieve the chosen pilot sample sizes of 100 participants for instrument validation and reliability testing (Viechtbauer et al., 2015); and
- II. contextual representativeness—the majority of SMEs in the main study were expected to be ICT firms of medium size (50–249 employees), making this firm an appropriate proxy for the target population in terms of technological sophistication, organisational structure, and employee characteristics. The selected SME employees at the time of survey distribution had been provided with tablets by the organisation.

At the individual level, convenience sampling was used. The SME did not agree to share employee email addresses; therefore, distribution relied on an internal company contact forwarding the survey (organisational gatekeeper).

The questionnaire was delivered online via the Central European University Qualtrics platform. Completion time was two weeks. Employees received a single email invitation with the survey link, followed by reminders after one week and one day before closure. A total of 177 responses were received (response rate: 88%). After removing incomplete or problematic responses (e.g., straight-lining, attention check failures, excessive completion time), 148 responses were retained for analysis.

While the inverse square method recommends $n=154$ – 160 for the full structural model (Kock & Hadaya, 2018), the pilot's primary objective is instrument validation and preliminary psychometric evaluation rather than definitive hypothesis testing. Therefore, $n=148$ is considered adequate for pilot purposes, with the understanding that the full study will achieve the larger sample required for robust inference.

4.5.2 Demographics and Descriptive Statistics

The pilot sample comprised 148 valid responses from a single medium-sized Hungarian ICT SME with 201 employees. Demographic characteristics are presented in Table 4.3. The sample was predominantly male (65%, $n=96$), with 62% aged 20–29 years. Most participants were operational staff (76%, $n=112$), with smaller proportions in junior management (13%), mid-level management (5%), and senior management (6%). The average survey completion time was 17 minutes 25 seconds (median: 16 minutes 42 seconds), closely approximating the 15-minute target and indicating appropriate questionnaire length without excessive respondent burden (minimum: 9 min 48 seconds).

Table 4.3 Pilot demographics data

Categories	Subcategories	Frequency (N)	Percent (%)
Gender	Male	96	65%
	Female	52	35%
Age	20 – 29 years	92	62%
	30 – 39 years	34	23%
	40 – 49 years	12	8%
	50 & above years	10	7%
Org Level	Employee	112	76%
	Junior mgr	19	13%
	Mid-level mgr	8	5%
	Senior mgr	9	6%

Descriptive statistics for all survey items are summarised in Table 4.4 (detailed results in Appendix G). Reflective constructs showed mean scores ranging from 2.99 to 3.88 on the 5-point scale, with Effort Expectancy highest ($M=3.43\text{--}3.84$) and Personal Innovativeness displaying the widest variability ($SD=1.02\text{--}1.14$). Formative constructs ranged from $M=2.99$ to 3.81, with comparable variation ($SD=0.74\text{--}1.05$). Skewness and kurtosis values were within acceptable ranges ($|skewness| < 2$, $|kurtosis| < 7$), confirming suitability for PLS-SEM analysis. Overall, the data demonstrate meaningful variation across constructs and items, validating the utility of the pilot dataset for psychometric evaluation (Hair et al., 2018).

Table 4.4 Pilot descriptive statistics

Construct	N Items	Mean Range	SD Range
PIIT	4	3.06–3.75	1.02–1.14
EE	4	3.43–3.84	0.93–1.08
PE	4	3.42–3.66	0.97–1.11
ATT	3	3.74–3.88	0.70–0.95
ITIB	3	3.47–3.68	0.74–0.81

Construct	N Items	Mean Range	SD Range
CI	3	3.56–3.65	0.91–0.94
IF	4	3.32–3.81	0.85–1.05
IS	5	2.99–3.68	0.74–0.99

4.5.3 Common Method Variance

Chapter 3 includes a detailed discussion and protocol on common method variance (CMV). As noted, the best safeguards are procedural: assure anonymity, use clear scale formats and anchors, separate predictors and outcomes psychologically or temporally, randomise item order, and avoid leading or double-barreled items. These items were implemented in the questionnaire, including spreading the corresponding items across five pages and randomising the survey items. As Fuller et al. (2016) notes, the most commonly used post-hoc approach (Harman's one-factor test) can detect biasing levels of CMV under conditions typical in survey-based marketing research. Consequently, Harman's one-factor test was calculated across the pilot data. The first factor (eigenvalue 5.673) only explained 18.911% of the total variance. Following the discussion in Chapter 3, VIF values were also reviewed (Kock, 2015). All formative items had $VIF < 3.3$. All reflective items (except $PE2=3.736$) were below 3.3 as well. The PE2 item correlated with other PE values and, as a historically tested UTAUT item, was kept in the item set. Together, these values show that CMV is not a concern with the dataset.

4.5.4 Latent Factor Analysis

In the pilot, the multi-item constructs are evaluated against their latent variables—unobserved traits reflected by patterns in the observed items (indicators). Model building proceeds in stages: (i) assess multicollinearity and factorability (e.g., Kaiser-Meyer-Olkin (KMO), Bartlett), (ii) choose the extraction solution, and (iii) refine the item set by retaining strongly loading, non-redundant indicators (e.g., salient pattern loadings, minimal cross-loadings, adequate communalities) to achieve a clean structure. The resulting EFA solution provides an empirically grounded measurement model for the constructs used later in the thesis.

4.5.4.1 Multicollinearity

As a first step, a multicollinearity test is performed to assess any high correlations among the independent variables, because such high correlations may influence the results from the model estimation. If the VIF (variance inflation factor) value reaches five and tolerance values are less than 0.1, multicollinearity can be recognised (Hair et al., 2022). The greatest VIF in the pilot study

was 3.736, which is within the acceptable limits. In addition, the tolerance value was within the permitted range (0.1 and 1). Therefore, it can be confirmed that multicollinearity was not present in the dataset (see Appendix G).

4.5.4.2 Factorability

The next step was to review the KMO Value Interpretation Rules:

- values below 0.5: unacceptable for factor analysis.
- 0.50–0.59: "miserable"—barely acceptable; consider revising data or removing problematic variables.
- 0.60–0.69: "mediocre"—minimally acceptable.
- 0.70–0.79: "middling"—adequate and suitable for analysis.
- 0.80–0.89: "meritorious"—good for factor analysis.
- Above 0.90: "marvellous"—excellent sampling adequacy.

For robust factor analysis, a KMO value of at least 0.6 is recommended, but values above 0.8 are considered optimal. In the pilot phase, values above 0.50 are acceptable.

The statistic applies both to the overall dataset and individually to each variable; variables with KMO below 0.5 should be considered for removal. The test is frequently paired with Bartlett's test of sphericity, which should also be significant ($p < 0.05$) before proceeding with factor analysis. Results are shown in Appendix G. All items have KMO values above 0.50 (overall value 0.767), and Bartlett's test is significant. Consequently, for the pilot, KMO yielded a value of 0.767, indicating good suitability for factor analysis. Bartlett's test of sphericity was also significant ($p < 0.001$), confirming that the correlation matrix significantly differs from an identity matrix and that meaningful correlations exist between variables.

4.5.4.3 Exploratory Factor Analysis vs Principal Component Analysis

At this point, the difference between the formative and reflective items has to be emphasised. Exploratory Factor Analysis (EFA) and Principal Component Analysis (PCA) are both techniques for reducing data dimensionality, but they differ in purpose and methodology. EFA is a modelling approach aimed at discovering underlying latent factors that explain the shared variance among observed variables, assuming that each item's variance can be partitioned into common (shared by the factor) and unique (specific/error) components. PCA, in contrast, is a descriptive technique that transforms the original variables into a new set of uncorrelated components, maximising the total variance explained, without distinguishing between shared and unique variance or assuming underlying causal relationships. In summary, EFA is typically used for identifying and modelling

latent constructs, while PCA is primarily for data reduction and summarisation. Factor analysis (EFA) and its associated diagnostics, like KMO, are designed for reflective models, where the correlations between items are caused by a common underlying factor. EFA is suitable for analysing items that are conceptually reflective, i.e., they are indicators of a latent variable. In this approach, each item is assumed to be a consequence of the underlying construct. Formative indicators are not expected to be highly intercorrelated, since each item represents a unique aspect of the construct. Including formative items in EFA can produce misleading results because EFA expects items to be manifestations (reflections) of a latent variable, not contributors to it. In formative models, items are not expected to be intercorrelated, since they represent different aspects contributing to a construct. Calculating KMO for formative items is both conceptually and statistically inappropriate, as formative indicators do not share variance explained by a latent variable. Consequently, the pilot review separates the formative and reflective data sets at this point. First, the reflective items (PIIT, EE, PE, ATT, ITIB, CI) will be reviewed and interpreted using EFA and associated procedures; then, the remaining data (IS and IF) will be evaluated using Principal Component Analysis (PCA) (Fleuren et al., 2018).

Thus, it is correct to partition the data: use EFA for reflective items and PCA for formative items. PCA treats all observed variance as meaningful, aiming to reduce the dataset into principal components without assuming an underlying latent construct. This approach is widely endorsed in measurement theory and psychometrics, where the direction of causality between items and constructs determines the choice of analysis.

4.5.4.4 Reflective Constructs and EFA

For the reflective constructs and factor analysis process, the sample adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) measure. For the pilot, KMO yielded a value of 0.813, indicating good suitability for factor analysis. Bartlett's test of sphericity was also significant ($p < 0.001$), confirming that the correlation matrix significantly differs from an identity matrix and that meaningful correlations exist between variables.

Exploratory Factor Analysis (EFA) using principal factor analysis (also called principal-axis factoring) was used to extract common variance among items. It is an iterative method which enables the communalities to be gradually converged. The calculations are stopped when the maximum change in the communalities is below a given threshold or when a maximum number of iterations is reached. Maximum likelihood was discarded because it requires the input variables to follow a normal distribution. As the theoretical constructs are likely correlated, an oblique rotation was used. The oblique rotation methods offered by XLSTAT are Quartimin and Oblimin.

The Promax method, also offered by XLSTAT, is a mixed procedure since it consists initially of a Varimax rotation followed by an oblique rotation so that the high factor loadings and low factor loadings are the same, but with the low values even lower. The Promax rotation was used, with Kaiser normalisation to stabilise the rotation (power=4). This combination typically yields interpretable, simple-structure pattern matrices while allowing factors to co-vary.

In terms of critical values, a short overview follows:

- For primary loadings ≥ 0.50 preferred, but ≥ 0.40 acceptable in early/exploratory work;
- Cross-loadings: a difference of ≥ 0.20 between the target loading and the next highest is a common rule. If an item loads ≥ 0.30 on two factors and the gap is < 0.20 , consider dropping or revising the item.
- Communalities (h^2): ≥ 0.40 on retained items
- Items per factor: keep ≥ 3 well-loading items per factor.
- Factor intercorrelations: with oblique rotation, correlations < 0.85 help reassure discriminant validity.

The factor structure is displayed in the Appendix G. The problematic items are as follows (will be discussed in detail later):

- PIIT4 is borderline with 0.449
- EE1 is borderline with .372
- ATT2 cross-loads on Effort Expectancy (.240) and Attitude (.343)

4.5.4.5 *Formative Constructs and PCA*

As discussed, principal component analysis (PCA) is a statistical technique for dimensionality reduction that transforms a large set of potentially correlated variables into a smaller set of uncorrelated components, known as principal components, while retaining as much of the original information as possible. By maximising the variance explained along successive orthogonal axes, PCA simplifies complex datasets, enhances interpretability, and is commonly used to aid data visualisation, feature extraction, noise reduction, and preprocessing for machine learning algorithms. For consistency, and due to possible correlations, Promax rotation was used, with Kaiser normalisation to stabilise the rotation (power=4).

For formative constructs, IF and IS are separated appropriately and will be entered into the modelling phase (see Appendix G for weights). As is typical for formative constructs, indicators

are not dropped because of low weights—each item may capture a unique facet. Thus, the items are kept on content validity grounds.

4.5.5 Measurement Model Results

The measurement model evaluation follows the rigorous protocol established in Chapter 3. The table is reproduced here (Table 4.5):

Table 4.5 PLS-SEM standards summary table

Construct Type	Reliability	Convergent Validity	Discriminant Validity	Colinearity
Reflective	CR $\geq$ 0.70, $\alpha \geq$ 0.70	Loadings $\geq$ 0.708, AVE $\geq$ 0.50	HTMT < 0.90	VIF < 5.0
Formative	Not applicable	Content validity & Outer weights (bootstrapped)	N/A	VIF < 3.3

For the pilot model run, PIIT4 and EE1 were removed. Although ATT2 cross-loads, to avoid a two-item construct, ATT2 was left in the model.

4.5.5.1 Analysis of the Measurement Model

Convergent validity and reliability

The results obtained from the analysis of the measurement model are shown in the table below (Table 4.6): Cronbach's alpha (CA) scores above 0.70, and composite reliability (CR) values over 0.70 were used to determine construct reliability (Hair et al., 2019). The construct reliability was established because all of the latent variables' Cronbach's alpha values and all of the CR values were above 0.70. Factor loading (FL) values (reflective) should be above 0.70, though in a pilot study, values above 0.40 may be accepted. Average variance extracted (AVE) with a value of more than 0.50 is used to determine convergent validity (Hair et al., 2019). The only problematic factor is PIIT, after the removal of the reverse-coded item. For the pilot, this item was retained on content-validity grounds (PIIT overall AVE and reliability are acceptable), with its performance monitored again in the main study. Apart from PIIT, all factor loadings are above 0.70. Furthermore, an AVE of 0.50 or higher indicates that the latent construct is responsible for 50% or more of the variance in the observable variables, on average.

Table 4.6 Pilot validity and reliability

	FL	CA	CR	AVE
ATT1	0.753	0.723	0.842	0.640
ATT2	0.830			
ATT3	0.816			
CI1	0.797	0.754	0.859	0.670
CI2	0.867			
CI3	0.789			
EE2	0.863	0.798	0.880	0.711
EE3	0.834			
EE4	0.831			
ITIB1	0.856	0.768	0.866	0.683
ITIB2	0.826			
ITIB3	0.796			
PE1	0.847	0.872	0.912	0.721
PE2	0.872			
PE3	0.855			
PE4	0.823			
PIIT1	0.664	0.729	0.737	0.516
PIIT2	0.364			
PIIT3	0.987			

Discriminant validity

Discriminant validity ensures that each latent variable is unique and different from other latent variables. Discriminant validity was investigated by comparing the correlation coefficients of the constructs with the corresponding square root of AVE values. According to Fornell and Larcker (Fornell & Larcker, 1981), the square root of AVE should be greater than the correlations to achieve adequate discriminant validity. As illustrated in the table below, all the square roots of AVE values (diagonal elements in italic) were higher than the inter-construct correlation coefficients (off-diagonal elements) (Table 4.7).

Table 4.7 Pilot discriminant validity

Latent variables	ATT	CI	EE	ITIB	PE	PIIT
ATT	<i>0.800</i>					
CI	0.493	<i>0.819</i>				
EE	0.421	0.321	<i>0.843</i>			
ITIB	0.277	0.458	0.221	<i>0.826</i>		
PE	0.516	0.232	0.430	0.213	<i>0.849</i>	

Latent variables	ATT	CI	EE	ITIB	PE	PIIT
PIIT	0.014	0.014	-0.157	0.237	-0.005	<i>0.718</i>

Heterotrait-Monotrait Ratio (HTMT) measures the real correlations across components, and it is a measure of discriminant validity (less than 0.90) in the PLS-SEM approach (Hair et al., 2019). In this pilot, all values were below 0.90, and this suggests that all the latent variables are unique and thus, discriminant validity is ensured (Table 4.8).

Table 4.8 Pilot HTMT analysis

Latent variables	ATT	CI	EE	ITIB	PE	PIIT
ATT						
CI	0.659					
EE	0.531	0.407				
ITIB	0.359	0.591	0.278			
PE	0.618	0.269	0.493	0.254		
PIIT	0.153	0.115	0.299	0.249	0.076	

4.6 Pilot Conclusions

The pilot study achieved its primary objectives. First, it confirmed the feasibility of the online survey procedures (Qualtrics administration, completion time, and response quality) in an SME environment. Second, psychometric evaluation demonstrated acceptable reliability and convergent/discriminant validity for the core UTAUT, IT-enabled innovative behaviour and continuance constructs, with only a small number of items requiring refinement. Third, exploratory factor analysis and multicollinearity diagnostics supported the viability of the proposed measurement model, and common method variance checks indicated that CMV is unlikely to pose a major threat in the main survey.

Measurement quality was generally sound (reliability and convergent/discriminant validity met). Based on the pilot diagnostics, PIIT4 (reverse-coded) and EE1 were rephrased, and ATT2 was revised to avoid overlap and cross-loading:

PIIT4

PIIT is measured using 4 items. The last item is reverse-coded and proved to be borderline in the loadings (Item: In general, I am hesitant to try out new information technologies.). A more detailed analysis of the data showed that on several occasions, all three other items (PIIT1-PIIT3) were ranked opposite to PIIT4. One can postulate that respondents are not reading the surveys carefully enough, and the reversed phrasing is skipped. Some researchers remove this reverse-coded item (e.g. Wang et al., 2013), while others change the coding (e.g. Lu, 2014). It was decided to reverse the phrasing of the PIIT4 item: In general, I am eager to try out new information technologies.

ATT2

Attitude is measured by 3 items, ATT2 is given as: Using a tablet helps me perform my work more effectively. It may be that the effective /efficient words are confusing for the respondents (PE has an item that is given as Using this tablet device enhances my effectiveness in my work). In conclusion, this item should be changed: a replacement is recommended: Using the tablet device would be beneficial to my job.

EE1

EE1 is a more difficult item: it is given as I find it easy to use this tablet device in my work. Participants may have interpreted this as a reference to finding appropriate software for their tablets (which may be more difficult). Finally, a rephrasing was recommended for this item as well: I find the tablet device easy to interact with.

All these changes were communicated to the expert panel, and they agreed to these modifications.

4.7 Chapter Summary

The pilot phase validated the online questionnaire's feasibility and psychometric foundations in an SME context. Data quality checks (CMV, VIF/tolerance, KMO/Bartlett) were satisfactory, and the reflective/formative partitioning guided the correct use of EFA and PCA. Minor wording changes (PIIT4, EE1, ATT2) were identified and approved, improving the measurement model ahead of full deployment. With these refinements, the study is positioned to proceed to the final

survey across multiple Hungarian SMEs (Chapter 5), followed by PLS-SEM estimation of the hypothesised relationships and the subsequent qualitative analysis with interviews (Chapter 6) as outlined in the thesis design (Chapter 3).

5 QUANTITATIVE ANALYSIS AND FINDINGS

5.1 Introduction

This chapter presents the quantitative findings in five main sections. The central argument of this chapter is not merely about predicting tablet use; it is about uncovering a complex, multi-layered mechanism that helps to explain continued tablet use. By incorporating the concept of innovative use, this study examines individual traits, user perceptions, and organisational context. The analysis reveals a dynamic interplay between cognitive antecedents (Performance Expectancy), affective responses (Attitude), behavioural outcomes (IT-enabled Innovative Behaviour), and crucial organisational enablers (Innovation Support, Involvement Facilitation).

Section 5.2 establishes the representativeness of the sample and the quality of the data. The next step is to reveal the core architecture, and Section 5.3 focuses on this task. Sections 5.3.1-5.3.2 evaluate measurement model validity for both reflective and formative constructs. Section 5.3.3 describes the structural model (baseline model).

However, unpacking the explanatory mechanisms requires moving ‘under the hood’ of the model. This is the role of the three-stage model development process: the baseline model, the augmented (mediation) model, and the final model (Section 5.4). The model’s boundaries are tested in Section 5.5. This section not only examines heterogeneity via multigroup analysis, but also asks: where, for whom, and under what conditions these predictive pathways are strongest. Translating theory into action, Section 5.6 identifies practical priorities through Importance-Performance Map Analysis (IPMA). The chapter concludes with a synthesis of key findings that will inform the qualitative phase.

For reference, two tables are included with the construct names, abbreviations, and a figure with the core hypotheses (H1-H13) (Table 5.1, Table 5.2 and Figure 5.1, see further details in Chapter 2).

Table 5.1 Construct names and abbreviations

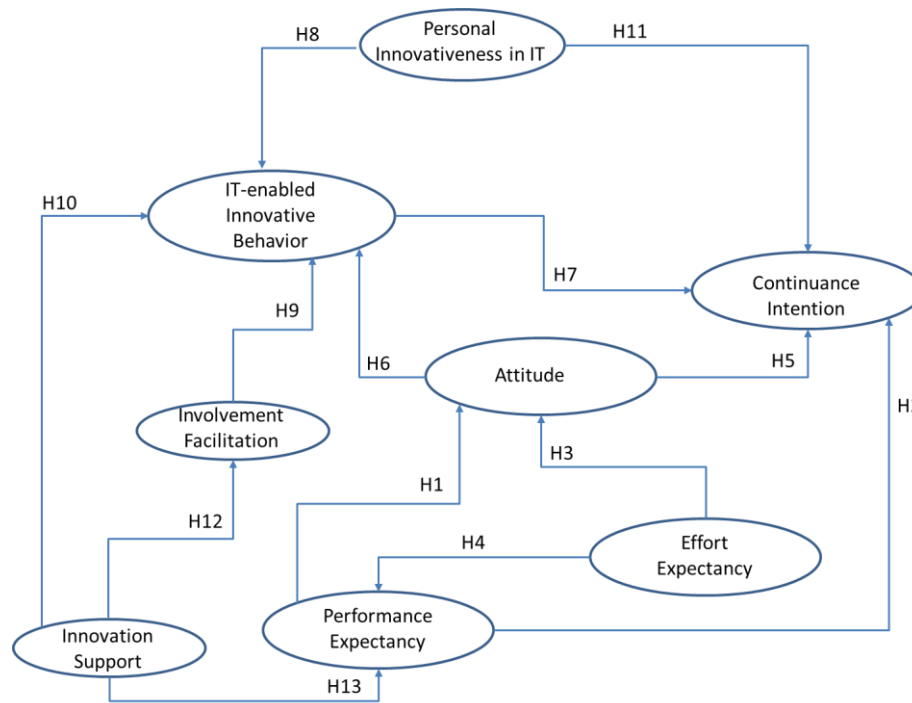
Abbrev.	Construct name
PE	Performance Expectancy
EE	Effort Expectancy
ATT	Attitude

Abbrev.	Construct name
ITIB	IT-enabled Innovative Behaviour
CI	Continuance Intention
PIIT	Personal Innovativeness in IT
IF	Involvement Facilitation
IS	Innovation Support

Table 5.2 Summary of initial H1-H13 hypotheses

H#	Path (direction only)	Expected sign
H1	PE → ATT	+
H2	PE → CI	+
H3	EE → ATT	+
H4	EE → PE	+
H5	ATT → CI	+
H6	ATT → ITIB	+
H7	ITIB → CI	+
H8	PIIT → ITIB	+
H9	IF → ITIB	+
H10	IS → ITIB	+
H11	PIIT → CI	+
H12	IS → IF	+
H13	IS → PE	+

Figure 5.1 Conceptual model for continuance and IT-enabled innovative behaviour in SMEs



5.2 Data Collection and Demographics

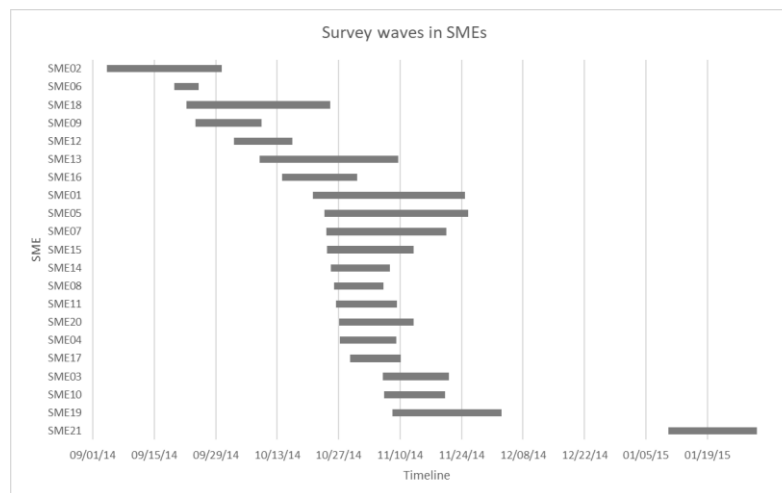
5.2.1 Sampling

The data for this chapter were collected from employees across 21 Hungarian SMEs. As detailed in the methodology chapter (Chapter 3), a multi-stage, non-probability purposive sampling strategy was employed. This approach was necessary to identify and access a specific, hard-to-reach population: SMEs that were "early adopters" of mandated tablet technology in 2014–2015. Given the novelty of corporate tablet use at the time and the practical limitations of standard probability sampling in the Hungarian context, this targeted method ensured that data were collected from firms where the post-adoption phenomena under investigation were actively occurring. In total 421 firms were identified and contacted. Of the 421 firms contacted, 21 agreed to participate (firm-level response rate: 5.0%), reflecting the challenges of accessing SMEs for academic research and the specialised nature of the target population (tablet-adopting firms in 2014–2015). The final multi-site dataset was drawn from these 21 participating organisations (SME01-SME21). Of the 21 participating SMEs, 20 qualify as medium-sized enterprises (50–249 employees) and one as a small enterprise (10–49 employees) under the EU headcount criterion (European Commission, 2005; Appendix B1).

As discussed in chapter 3, sample size for PLS-SEM may be calculated based on the number of latent variables: this calculation provides a minimum of 116, but to detect the small effects, recommends a sample size of 444 (effect size small=0.2, number of latent variables 8, observed variables 30) (Christopher Westland, 2010; Kock & Hadaya, 2018; Soper, 2025). Therefore, a minimum of 500 samples was targeted for the quantitative questionnaire phase.

Data were collected online via Qualtrics between 1 July and 28 November 2014 (primary window), with late entries planned until 31 Mar 2015. The actual data collection required careful discussions with each SME. The SMEs did not provide a full email list of their employees: instead, a neutral email address was set up (e.g. survey@business.hu), and the survey invitation and reminder emails were sent from this email address. According to the protocol outlined in Chapter 3, the survey was open in each SME for 5 weeks: reminders were sent at the beginning of each week (one invitation + 4 reminders in total). The first SME started the survey 4th September, 2014; the last survey was closed at SME 21 on 14th February, 2015. The Gantt chart shows the starting date at each SME and the last response received from the SME (Figure 5.2). SMEs were actively responding (completing the questionnaires) for an average of 19 days (median=17).

Figure 5.2 Gantt chart with survey waves in SMEs



The instrument used validated reflective and formative scales. The survey instrument was refined through a pilot study (documented in Chapter 4), which confirmed the reflective/formative split of constructs, validated item wording, and established preliminary psychometric properties. The survey was administered online, and participation was voluntary. Ethical approvals, consent, and anonymisation procedures are detailed in Chapter 3. Analyses were conducted in SmartPLS (Ringle et al., 2024), using R code and XLSTAT (Addinsoft, 2024).

5.2.2 Data screening and exclusions

Survey invitations (n=2,709) yielded 1,551 starts (a 57% start rate); 1,040 responses (67%) were deemed usable for the final analysis. To ensure data quality, all responses were screened prior to analysis using a multi-stage sequence of direct, archival, and statistical checks (Desimone et al., 2014) as detailed in Chapter 3:

- **Incomplete responses:** All core model items were mandatory. Partial responses occurred only when participants left the 5-page survey prematurely. Cases missing an entire set of items (n=489) were removed. Demographic items were optional, and any missingness on these variables was handled via listwise deletion (only where a specific analysis required it).
- **Inattentive Responding:** An attention-check item (e.g., "Select 'Strongly Disagree' in this row") was embedded on each page (Desimone et al., 2014). Failures were reviewed individually in the context of page completion times and response patterns, and cases demonstrating clear non-attentive behaviour (n=12) were excluded.
- **Low-Effort Responding:** Speeding and low-effort responses were flagged using multiple indicators, including monotone response strings (e.g. as "all 1s/3s/5s"), near-zero within-person variance, and implausibly short completion times (Desimone et al., 2014). Based on pilot data, cases completed in under 9 minutes were removed (n=10). After all exclusions, the final sample's completion times ranged from 9 minutes 36 seconds to 54 minutes 55 seconds (mean: 18 minutes 6 seconds; median: 14 minutes 43 seconds), confirming that rushed responses were successfully filtered out.
- **Multivariate Outliers:** Finally, statistical screening was conducted using the robust Minimum Covariance Determinant (MCD) method, which is less susceptible to the masking effects of extreme cases than traditional methods (Desimone et al., 2014; Fauconnier & Haesbroeck, 2009; Leys et al., 2018). Using the recommended conservative chi-square threshold of $p < .001$ (Leys et al., 2018), this procedure flagged 14 cases for review. Manual inspection revealed these cases typically represented respondents with an extreme score on one construct (e.g., very low Perceived Expectancy) but moderate scores on others. Because these patterns could represent valid, albeit uncommon, experiences, a sensitivity analysis was performed. The final structural model was estimated with and without these 14 cases, which confirmed that their inclusion did not alter the path coefficients or the study's overall conclusions (see Section 5.5.8 for details). Therefore, to preserve the natural variance within the sample, these cases were retained.

Screening completed; the next section reports the data's central tendency and variation.

5.2.3 Data Normality

Across the 1,040 responses, item means range from 2.73 to 3.88, and medians are typically at 3 or 4 (1–5 Likert scale). Standard deviations are centred around 0.90–1.10. There is no evidence of floor/ceiling effects with a full range of 1–5 observed for each item. Overall, the data display moderate dispersion (see Table 9.22).

Highlighting some of the key trends, Effort Expectancy shows the highest central tendency (EE2 $M=3.88$), and Attitude is generally positive (ATT1 $M=3.79$) – which is expected for tablet devices (Quade & Leimstoll, 2017). Involvement Facilitation (IF2) is the lowest ($M=2.73$), with several Innovation Support items also lower (IS3–IS5 $M\approx 2.87$ – 3.02). Personal Innovativeness in IT averages are mid-scale (PIIT $M\approx 2.95$ – 3.71), and Performance Expectancy items are consistently above the midpoint (PE $M\approx 3.53$ – 3.61).

Turning to distribution shape, distributions are approximately symmetric to mildly left-skewed (most skewness values between -0.72 and $+0.15$). The data is predominantly platykurtic (kurtosis near zero and negative). The data support the assumption of approximate normality for large-sample analyses (Ghasemi & Zahediasl, 2012). This provides greater confidence in the descriptive profiles of the variables (Knief & Forstmeier, 2021). This concludes the initial data overview; the next step is to examine the sampling frame.

5.2.4 Participants and sampling frame

The final dataset included 1,040 valid responses from SMEs distributed across three geographic settings: Capital ($n = 680$; 65.4%), City ($n = 261$; 25.1%), and Rural ($n = 99$; 9.5%). In terms of sectoral representation, ICT comprised 60.0% of the sample ($n = 624$), Services represented 26.2% ($n = 272$), and Manufacturing accounted for 13.8% ($n = 144$).

Building on the overall distribution, sectoral composition showed significant variation across geographic locations, as illustrated in Figure 5.3 and Table 5.3. Specifically, the Capital setting was predominantly represented by ICT enterprises (78.7%), the City setting by Services (55.2%), and the Rural setting by Manufacturing (73.7%). There were no ICT respondents from rural areas in this dataset. From a sectoral perspective, ICT enterprises were concentrated in metropolitan areas (85.7% in the Capital, 14.3% in the City, 0% in Rural areas). The Services sector was distributed across Capital (37.5%), City (52.9%), and Rural (9.6%) settings. Manufacturing enterprises were most prevalent in rural areas (50.7% Rural, 29.9% Capital, 19.4% City).

Table 5.3 Location and sector

	Capital	City	Rural	Total
ICT	535 (78.7%)	89 (34.1%)	0 (0.0%)	624 (60.0)
Services	102 (15.0%)	144 (55.2%)	26 (26.3%)	272 (26.2)
Manufacturing	43 (6.3%)	28 (10.7%)	73 (73.7%)	144 (13.8)
Grand total	680 (65.4%)	261 (25.1%)	99 (9.5%)	1040 (100.0)

Figure 5.3 Sector composition by location



Organisational roles

Most respondents were non-managerial employees ($n = 717$; 68.9%), while managers comprised 25.9%: junior ($n = 118$; 11.3%), mid-level ($n = 108$; 10.4%), and senior ($n = 48$; 4.6%). Roles not reported accounted for 4.7% ($n = 49$).

Role composition differed by sector (Table 5.4). For example, in ICT ($n = 624$), employees accounted for 73.4% ($n = 458$), while junior, mid-level, and senior managers accounted for 9.9%, 8.0%, and 1.9%, respectively (role blank 6.7%). In Services ($n = 272$), employees were 63.6%, with junior, mid-level, and senior managers at 13.2%, 16.2%, and 6.6% (blank 0.4%). In Manufacturing ($n = 144$), employees accounted for 59.7%, while junior, mid-level, and senior managers comprised 13.9%, 9.7%, and 12.5%, respectively (blank 4.2%).

Table 5.4 Organisational role by sector (n, column % within sector)

	ICT	Services	Manufacturing	Total
Employee	458 (73.4%)	173 (63.6%)	86 (59.7%)	717 (68.9)
Junior manager	62 (9.9%)	36 (13.2%)	20 (13.9%)	118 (11.3)
Mid-level manager	50 (8.0%)	44 (16.2%)	14 (9.7%)	108 (10.4)
Senior manager	12 (1.9%)	18 (6.6%)	18 (12.5%)	48 (4.6)
Role blank	42 (6.7%)	1 (0.4%)	6 (4.2%)	49 (4.7)
Column totals	624 (100.0%)	272 (100.0%)	144 (100.0%)	1040 (100.0)

Gender and age

The gender distribution was 31.1% female (n = 323), 67.3% male (n = 700), with 1.6% (n = 17) not reporting gender (Table 5.5). Age was concentrated in the younger and mid-career bands: 31–40 (n = 415; 39.9%) and 18–30 (n = 379; 36.4%). The remaining participants were 41–50 (n = 155; 14.9%), 51–60 (n = 49; 4.7%), 61–70 (n = 9; 0.9%), and ≥71 (n = 2; 0.2%), with age not reported for 3.0% (n = 31). Among women (n = 323), 18–30 and 31–40 accounted for 40.6% and 39.3%, respectively; among men (n = 700), 31–40 was the largest band (40.3%), followed by 18–30 (34.9%).

Table 5.5 Age × gender distribution (n, % of total)

	Female	Male	Gender blank	Total
18–30	131 (12.6%)	244 (23.5%)	4 (0.4%)	379 (36.4%)
31–40	127 (12.2%)	282 (27.1%)	6 (0.6%)	415 (39.9%)
41–50	39 (3.8%)	112 (10.8%)	4 (0.4%)	155 (14.9%)
51–60	14 (1.3%)	35 (3.4%)	0 (0.0%)	49 (4.7%)
61–70	1 (0.1%)	8 (0.8%)	0 (0.0%)	9 (0.9%)

	Female	Male	Gender blank	Total
71+	0 (0.0%)	2 (0.2%)	0 (0.0%)	2 (0.2%)
Age blank	11 (1.1%)	17 (1.6%)	3 (0.3%)	31 (3.0%)
Total	323 (31.1%)	700 (67.3%)	17 (1.6%)	1040 (100.0%)

Missingness and reporting notes

Missingness on mandatory constructs was not accepted. Exclusions were due to missing data across constructs, attention-check failures, and quality filters.

Demographic items were optional by design. Missingness was modest: role 4.7%, gender 1.6%, age 3.0%. All tables present counts and percentages: Table 5.3 shows column percentages within location, while Table 5.4 shows column percentages within sector. This distinction reflects the structural composition relevant to subsequent analyses. Because of pronounced differences in sectoral make-up across locations, both location and sector are included in the boundary analysis (Section 5.5).

By EU size bands, the achieved frame included one small and twenty medium enterprises. No micro firms participated. Therefore, findings are most applicable to small and medium firms, particularly medium-sized ones. Micro-firms in Hungary are generally under-represented in research, as many are dormant or shell companies (Győri, 2013). The achieved sample over-represents medium enterprises (95.2% vs. 85.9% nationally) and ICT sector firms (60% vs. 6% economy-wide) (Csonka, 2014; Mester & Tóth, 2015; Mezei et al., 2016).

This reflects the purposive sampling of tablet-adopting organisations. As noted, this profile matches with technology early-adopter demographics (Rogers, 2003) and is suitable for exploring post-adoption behaviours. However, findings may not generalise to micro firms or non-digital sectors without tablet mandates.

Finally, post-stratification weights were not applied. The accessible population is a programme-specific subpopulation (firms piloting/mandating tablets), for which credible population margins (by sector, size, and location) are not available. Applying coarse national SME margins could introduce model dependence and inflate variance without demonstrably reducing bias. Therefore, the study reports unweighted estimates

5.2.5 Common Method Variance

As discussed in detail in Chapter 3, it is important to consider common method variance (CMV) in a self-report survey. CMV refers to the variance that is attributable to the measurement method rather than to the constructs the measures represent (e.g. Fuller et al., 2016). When this effect systematically inflates or deflates the relationships between variables, this phenomenon is referred to as Common Method Bias (Bozionelos & Simmering, 2022; Fuller et al., 2016; Podsakoff et al., 2024).

This study included ex ante procedural remedies and ex post statistical diagnostics (see Chapter 3 for details).

For ex ante remedies, the instrument and protocol incorporated procedural controls such as: (i) anonymity and confidentiality statements on the cover page; (ii) neutral wording; (iii) randomised item order (Bozionelos & Simmering, 2022; Fuller et al., 2016; Podsakoff et al., 2024).

For ex post statistical diagnostics, the following complementary tests were completed:

- Unrotated single-factor (Harman) test. An exploratory single-factor solution accounted for 30.689% of the total variance—well below the conventional 50% limit—suggesting no dominant common factor (Fuller et al., 2016).
- Full colinearity Variance Inflation Factors (VIFs). Following Kock's recommendation (Kock, 2015), full colinearity VIFs were < 3.3, except for the PE and CI construct. There were two PE indicators and one CI indicator, with values of ~4 (CI2=3.821; PE2=4.396; PE4=4.544). These values remain within the 5.0 threshold and do not indicate problematic inflation (Hair et al., 2022; Kock & Lynn, 2012). The indicators were retained because both PE and CI are reflective and theoretically central to the model. Sensitivity checks did not show material changes in path significance when either indicator was removed (see Appendix Table 9.21 for VIF results).

Taken together, the procedural controls and diagnostics indicate that CMV is unlikely to explain the observed structural relationships.

5.2.6 Nonresponse Bias

Following the protocol outlined in Chapter 3, potential nonresponse bias was examined using an early–late comparison. For each SME, cases were ordered by completion time and split at the within-SME median (first 50% = Early, last 50% = Late). Distributions were then compared for gender, management level (MgtGroup; MgtCollapsedGroup), and age (AgeGroup;

AgeCollapsedGroup) across Early vs. Late respondents using chi-square tests with Cramér's V as the effect-size index. Note that categories had to be collapsed to achieve sufficient cell sizes in a multigroup analysis (Section 5.5), hence their inclusion here. Across all variables, the tests were non-significant, and effects ranged from negligible to small (see Table 5.6). These results indicate no meaningful shifts in the demographic composition between Early and Late respondents. By implication, there were no substantive demographic differences between respondents and nonrespondents. Consistent with best practice, the stability of the model relations was also evaluated via a multigroup analysis, which showed no differences at the model level between Early and Late respondents (see Section 5.5.9).

Table 5.6 Nonresponse bias statistics

Variable	Chi2	Degrees of freedom	p	Cramer's V
Gender	0.239	2	0.887	0.015
MgtGroup	2.027	4	0.731	0.044
MgtCollapsedGroup	1.325	2	0.516	0.036
AgeGroup	7.880	6	0.247	0.087
AgeCollapsedGroup	0.472	3	0.925	0.021

5.3 Core Architecture

5.3.1 Introduction

This section establishes the model's core architecture in two stages (Hair et al., 2022; Hair et al., 2018). First, measurement quality was assessed for reflective (PE, EE, ATT, CI, PIIT) (see Sections 5.3.2) and formative (IS, IF) (see Section 5.3.3) constructs using standard PLS-SEM criteria (reliability, convergent and discriminant validity, and colinearity). Second, the baseline structural model was estimated to identify the primary predictors of the endogenous constructs (Section 5.3.4). Thresholds and decision rules are summarised in Table 5.7 (Hair et al., 2022; Hair et al., 2018; Kock, 2015; Kock & Lynn, 2012; Sarstedt et al., 2023).

Table 5.7 PLS-SEM standards summary table

Construct Type	Reliability	Convergent Validity	Discriminant Validity	Colinearity
Reflective	CR $\geq$ 0.70, $\alpha \geq$ 0.70	Loadings $\geq$ 0.708, AVE $\geq$ 0.50	HTMT < 0.90	VIF < 5.0
Formative	N/A	Content validity; significant weights or substantial loadings	N/A	VIF < 3.3

5.3.2 Reflective Construct Evaluation

5.3.2.1 Factorability

As discussed in Chapter 3, three tests are completed prior to factoring: the Kaiser-Meyer-Olkin (KMO) criteria, the Bartlett's test of sphericity and Velicer's MAP to account for the large sample size (Hair et al., 2022) (see Appendix G for details). Sampling adequacy was excellent overall (KMO = .913). Taken individually, every item is suitable for factor analysis (all item KMOs $\geq$.788) (Tabachnick & Fidell, 2019). Bartlett's test also indicated factorability, supporting latent-variable modelling. Velicer's MAP achieves a minimum of 0.02 with 5 factors, but with the Bayesian Information Criteria (BIC) it finds 6 factors at a minimum BIC=-400.46, indicating viability for factor analysis (R psych package vss command was used).

5.3.2.2 Convergent Validity and Reliability

Following the protocol outlined in Chapter 3, the construct reliability was established because both the Cronbach's alpha and composite reliability values of the latent variables are all above 0.70 (Table 5.8). All factor loading values (reflective) are also above 0.70 (Hair et al., 2019). Furthermore, an Average Variance Extracted (AVE) of 0.50 or higher indicates that the latent construct is responsible for 50% or more of the variance in the observable variables. This was also fulfilled for all latent variables (Hair et al., 2019).

Table 5.8 Latent variables final data analysis

Latent variables	Items	Factor loading	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)

Attitude	ATT1	0.884	0.844	0.906	0.763
	ATT2	0.851			
	ATT3	0.885			
Continuance Intention	CI1	0.907	0.870	0.921	0.795
	CI2	0.931			
	CI3	0.834			
Effort Expectancy	EE1	0.836	0.847	0.895	0.681
	EE2	0.788			
	EE3	0.787			
	EE4	0.887			
IT-Enabled Innovative Behaviour	ITIB1	0.908	0.888	0.931	0.817
	ITIB2	0.888			
	ITIB3	0.916			
Performance Expectancy	PE1	0.901	0.927	0.948	0.820
	PE2	0.917			
	PE3	0.888			
	PE4	0.917			
Personal Innovativeness	PIIT1	0.859	0.861	0.905	0.704
	PIIT2	0.865			
	PIIT3	0.816			
	PIIT4	0.816			

5.3.2.3 Discriminant Validity

Discriminant validity ensures that each latent variable is unique and different from other latent variables. Discriminant validity was investigated by comparing the correlation coefficients (off-diagonal elements) of the constructs with the corresponding square root of AVE values (diagonal elements in *italic*). The square root of AVE was greater than the correlations and therefore adequate discriminant validity was achieved (see Table 5.9) (Fornell & Larcker, 1981; Tabachnick & Fidell, 2019).

Table 5.9 Discriminant validity final data analysis

	ATT	CI	EE	ITIB	PE	PIIT
ATT	<i>0.873</i>					
CI	0.686	<i>0.892</i>				
EE	0.499	0.381	<i>0.826</i>			
ITIB	0.442	0.604	0.269	<i>0.904</i>		
PE	0.703	0.619	0.459	0.499	<i>0.906</i>	
PIIT	-0.077	-0.068	-0.011	0.156	-0.051	<i>0.839</i>

Discriminant validity is also evaluated via Heterotrait-Monotrait Ratio (HTMT). HTMT measures the real correlations across components and a value of less than 0.90 is required (Hair et al., 2019). In this study, all values were below 0.90 and accordingly, discriminant validity is ensured (Hair et al., 2018) (Table 5.10).

Table 5.10 HTMT final data analysis

	ATT	CI	EE	ITIB	PE	PIIT
ATT						
CI	0.801					
EE	0.568	0.421				
ITIB	0.508	0.679	0.296			
PE	0.793	0.688	0.487	0.547		
PIIT	0.089	0.081	0.053	0.179	0.056	

5.3.3 Formative Construct Evaluation

5.3.3.1 Assess for Colinearity

For formative items, colinearity is not an issue: the highest VIF value is 2.124, well below even the more stringent 3.3 limit (see Table 9.21 in Appendix I1).

5.3.3.2 Evaluate Outer Weights

Evaluating the outer weights is based on bootstrapping the model, the usual 10000 sample size was applied (Table 5.11).

Table 5.11 Outer weights initial run

	Weight	Sample mean	Standard deviation	P value
IF1 -> IF	0.412	0.411	0.043	0.000
IF2 -> IF	0.523	0.522	0.043	0.000
IF3 -> IF	0.054	0.055	0.047	0.243
IF4 -> IF	0.240	0.240	0.046	0.000
IS1 -> IS	0.120	0.121	0.046	0.009
IS2 -> IS	0.066	0.066	0.049	0.179
IS3 -> IS	0.461	0.460	0.048	0.000
IS4 -> IS	0.277	0.276	0.050	0.000
IS5 -> IS	0.338	0.337	0.043	0.000

Two items are problematic: both of them are non-significant and represent a minimal contribution to Involvement Facilitation and Innovation Support (IF3 and IS2, respectively). In such a situation, outer loadings may be assessed as a secondary check for indicator validity, but the overall model may be considered as well. The outer loadings are above 0.5 for both variables, and thus they may be kept. However, a model test was conducted with and without these variables and they do not contribute to the model meaningfully. Consequently, they were removed from the model, supported by theoretical considerations (Table 5.12).

Table 5.12 Critical IS-IF items

IF3	<i>Our end users are consulted before the introduction of a new information technology.</i>	This statement has a strong overlap with IF4 (<i>Our end users are involved in information technology change and/or implementation</i>), having a correlation of 0.662. Thus it is not contributing to the formative construct.
IS2	<i>Employees and managers are supportive of each other.</i>	Possibly respondents felt this is a very critical item and provided less relevant answers: but it also presents a strong overlap with IS1 (<i>We have a very open communications environment</i> ; correlation 0.624). The more neutral IS1 was kept.

5.3.3.3 Content Validity

Reviewing the remaining items, the following sets of statements are used for identifying these factors and they are according to the definition of the constructs:

Involvement Facilitation

- *Employees are encouraged to try out new technologies.*
- *Employees are rewarded for using new technologies.*
- *Employees are involved in technology change and/or implementation.*

Innovation Support

- *We have a very open communications environment.*
- *Employees at all levels are rewarded for learning new skills.*
- *Experimental mind-sets and risk taking is encouraged.*
- *New ideas are easy to be implemented.*

As a final test, PCA was completed on the final set (Promax rotation), and the two-factor structure appeared properly (see Appendix I4).

5.3.4 Structural Model Analysis

5.3.4.1 Introduction

The structural model is assessed when the validity of the whole measurement model has been established (Hair et al., 2022; Hair et al., 2018). The structural model analysis is used to verify the hypotheses. The stated hypotheses that indicate the relevance of the relationships are accepted or rejected using structural model analysis (Byrne, 2013; Schumacker & Lomax, 2004). In this study, a bootstrapping approach with a subsample of 10000 was used to estimate the structural model (Hair et al., 2022; Henseler et al., 2016; Sarstedt et al., 2023). Path coefficients (beta), t statistics, and corresponding p-values are all displayed where required – detailed tables are available in the Appendix I5. As usual, the t-value is statistically significant in two-tailed testing when it is outside the range of -1.96 and +1.96, and the p-value is less than 0.05. Note: PLS-SEM is distribution-agnostic and does not assume multivariate normality (Hair et al., 2022), and the data is indeed not normally distributed. In addition, to ensure a conservative approach to the model, the Likert variables are set to ordinal in SMARTPLS4.

The estimation of the PLS-SEM model took place in two steps:

1. A theory-constrained baseline PLS-SEM model was estimated, only including confirmed pathways to preserve parsimony. This model was evaluated against the usual PLS-SEM criteria and is referred to as the baseline model (Henseler et al., 2016).
2. In a subsequent step, a fully augmented model is estimated and tested to evaluate mediation by including the requisite direct paths (e.g., PE→ITIB). Mediation in PLS-SEM is evaluated in the fully augmented model using bootstrapped direct, specific indirect, and total effects with 95% CIs. Based on the mediation analysis, comparing baseline and augmented models on explanatory (R^2 , f^2) and predictive (Q^2 , $PLSpredict$) criteria guides the development of the final model. Added paths are only retained in the final model when theoretically plausible, statistically significant, and predictively beneficial.

5.3.4.2 Baseline Model Analysis

Generally, model fit metrics like χ^2 , GFI, CFI, and RMSEA are not taken into account by PLS-SEM (Hair et al., 2018). Nevertheless, in terms of model fit SRMR should be less than 0.09. The model fit metrics show that the PLS analysis could yield SRMR 0.059. The results of the structural model analysis are shown on Figure 5.4 and the hypotheses are summarised in Table 5.13.

The assessment of prediction

The prediction ability of the exogenous constructs is determined by different measures such as the coefficient of determination (R^2), the effect size (f^2), cross-validated redundancy (Q^2), and the sizes and significance of the path coefficients (Hair, 2018). The path coefficients are also displayed in Table 5.13.

Figure 5.4 Baseline structural model (theory-constrained)

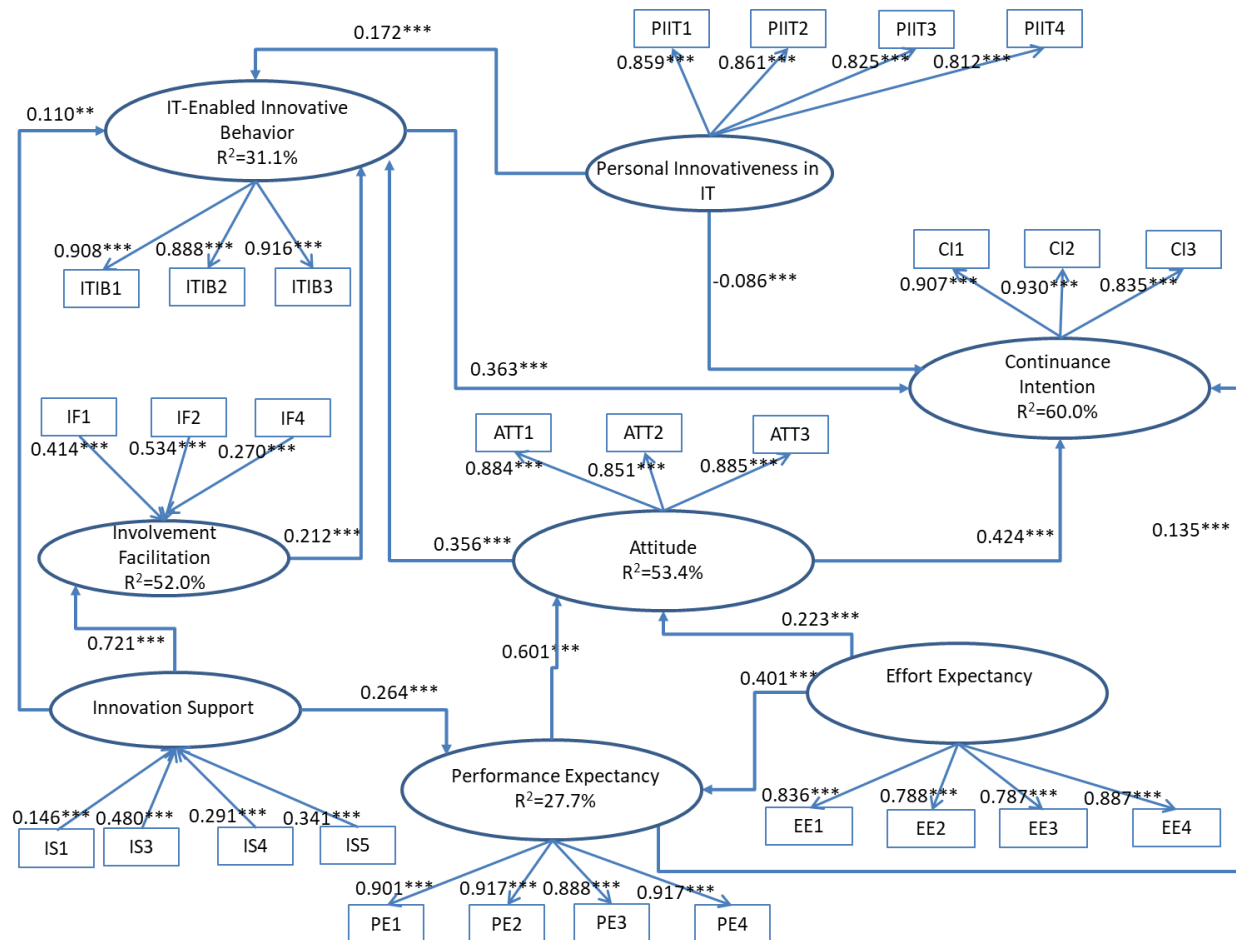


Table 5.13 Hypothesis summary baseline model

Hypothesis	Paths	Beta	T stat	P	95% Conflnt (LL-UL)		Result
H1	PE -> ATT	0.601	26.043	0.000	0.553	0.644	Sig
H2	PE -> CI	0.135	4.140	0.000	0.072	0.199	Sig
H3	EE -> ATT	0.223	8.818	0.000	0.173	0.271	Sig
H4	EE -> PE	0.401	14.351	0.000	0.345	0.455	Sig

Hypothesis	Paths	Beta	T stat	P	95% Conflnt (LL-UL)		Result
H5	ATT -> CI	0.424	13.630	0.000	0.364	0.487	Sig
H6	ATT -> ITIB	0.356	13.038	0.000	0.303	0.410	Sig
H7	ITIB -> CI	0.363	13.533	0.000	0.310	0.413	Sig
H8	PIIT -> ITIB	0.172	6.280	0.000	0.114	0.223	Sig
H9	IF -> ITIB	0.212	5.374	0.000	0.135	0.288	Sig
H10	IS -> ITIB	0.110	2.741	0.006	0.032	0.189	Sig
H11	PIIT -> CI	-0.086	3.809	0.000	-0.129	-0.042	Sig
H12	IS -> IF	0.721	39.830	0.000	0.682	0.755	Sig
H13	IS -> PE	0.264	9.244	0.000	0.206	0.317	Sig

Coefficient of determination (R^2)

The explanatory power of the structural model in PLS is determined by the coefficient of determination or R^2 (Hair, 2018). A higher value of R^2 indicates a better prediction of endogenous constructs: R^2 values of 0.75, 0.50, and 0.25 indicate substantial, moderate, and weak, respectively (Hair, 2018). Table 5.14 lists the values with classification: similar values are observed in meta-studies (Dwivedi et al., 2011; Taiwo & Downe, 2013a).

Table 5.14 R^2 of latent variables baseline model

Construct	R^2	Adjusted R^2	Comment
Attitude	0.534	0.533	Moderate
Continuance Intention	0.600	0.599	Moderate
Involvement Facilitation	0.520	0.520	Moderate
IT-enabled Innovative Behaviour	0.311	0.308	Moderate
Performance Expectancy	0.277	0.276	Moderate

Effect size (f^2)

The effect size, denoted as f^2 , is used to assess the impact on endogenous or outcome constructs due to removing the predictor construct (Hair, 2018). In other words, the f^2 value denotes what

changes may happen in the endogenous construct after removing any of the exogenous constructs. The f^2 values of 0.02, 0.15, and 0.35 indicate small, medium and large effects, respectively (Table 5.15).

Table 5.15 Effect size (f^2) baseline model

f-square for pathways	f2	T statistics	P values	2.50%	97.50%	Sig	Effect size
Attitude -> Continuance Intention	0.221	5.894	0.000	0.310	0.310	sig	medium
Attitude -> IT-enabled Innovative Behaviour	0.161	5.799	0.000	0.258	0.258	sig	medium
Effort Expectancy -> Attitude	0.084	4.149	0.000	0.127	0.127	sig	small
Effort Expectancy -> Performance Expectancy	0.212	6.026	0.000	0.302	0.302	sig	medium
Innovation Support -> Involvement Facilitation	1.085	9.407	0.000	0.662	0.662	sig	large
Innovation Support -> IT-enabled Innovative Behaviour	0.008	1.281	0.200	-0.034	-0.016	non-sig	none
Innovation Support -> Performance Expectancy	0.092	4.290	0.000	0.160	0.160	sig	small
Involvement Facilitation -> IT-enabled Innovative Behaviour	0.031	2.618	0.009	0.082	0.082	sig	small
IT-enabled Innovative Behaviour -> Continuance Intention	0.230	6.129	0.000	0.262	0.262	sig	medium
Performance Expectancy -> Attitude	0.611	8.435	0.000	0.575	0.667	sig	large
Performance Expectancy -> Continuance Intention	0.021	2.054	0.040	0.013	0.013	sig	small
Personal Innovativeness in IT -> Continuance Intention	0.017	1.842	0.066	-0.175	-0.175	non-sig	none
Personal Innovativeness in IT -> IT-enabled Innovative Behaviour	0.042	3.050	0.002	0.080	0.080	sig	small

Predictive relevance (Q^2)

If the value of Q^2 is more than 0.00, that means the predictive accuracy of the path model is acceptable (Hair, 2018) (Table 5.16).

Table 5.16 Construct cross-validated redundancy (Q^2 predict) baseline model

Construct	Q^2 predict	Comment
Attitude	0.284	Predictive relevance
Continuance Intention	0.183	Predictive relevance
Involvement Facilitation	0.515	Predictive relevance
IT-enabled Innovative Behaviour	0.192	Predictive relevance
Performance Expectancy	0.272	Predictive relevance

5.4 Under the Hood Analysis

5.4.1 Mediation Overview

Mediation analysis examines whether—and how much—the effect of an exogenous variable on an outcome is transmitted through one or more intervening variables (mediators) (Nitzl et al., 2016; Sarstedt et al., 2020). Rather than relying on the historical “causal steps” logic (Baron & Kenny, 1986), contemporary practice focuses on the statistical significance and magnitude of the indirect effect (Zhao et al., 2010). In technology-adoption and post-adoption settings, testing indirect effects directly is preferable, as it can reveal complementary or competitive mediation that a total-effect test might obscure (Nitzl et al., 2016; Zhao et al., 2010). In this context, multiple cognitive, affective, and behavioural mechanisms can operate simultaneously, and therefore simply requiring a significant total effect between predictor and outcome variables may not reveal the underlying mechanisms (Nitzl et al., 2016).

Consistent with current PLS-SEM guidance, this chapter evaluates mediation using the “core” bootstrapped results from the estimated structural model—i.e., bias-corrected bootstrap confidence intervals for each specific indirect path—rather than stepwise heuristics (Hair et al., 2022; Sarstedt et al., 2020). This approach

- a) aligns with PLS-SEM’s prediction-oriented estimation,
- b) provides higher power for indirect effects in complex serial chains, and
- c) yields a theoretically informative classification of mediation patterns (indirect-only, complementary, competitive, etc.) that can guide refinement of the model’s mechanisms (Sarstedt et al., 2020).

In this research, a complex mediation structure is proposed with multiple serial pathways. The bootstrap approach generates empirical sampling distributions of indirect effects by resampling the original dataset (with replacement) across 5,000-10,000 iterations, creating confidence intervals that accommodate the non-normal distribution (Sarstedt et al., 2020). This method is implemented within SmartPLS 4.0, which automatically calculates specific indirect effects for complex mediation models (Hair et al., 2022).

5.4.2 Mediation Typology and Serial Mediation

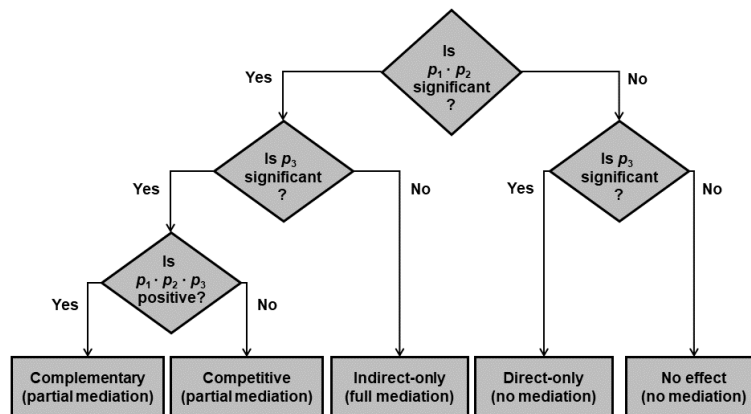
The study adopts Zhao et al.'s (2010) five-category mediation typology, which provides more nuanced theoretical insights than the traditional full/partial/no mediation classification (Nitzl et al., 2016). The framework distinguishes between (Zhao et al., 2010):

- 1) complementary mediation (indirect and direct effects in the same direction),
- 2) competitive mediation (opposite directions),
- 3) indirect-only mediation (significant indirect, non-significant direct),
- 4) direct-only non-mediation (significant direct, non-significant indirect), and
- 5) no-effect non-mediation (neither significant) (see Figure 5.5).

In the context of this study's focus on innovative technology behaviours in SMEs, competitive mediation patterns may reveal important boundary conditions where organisational enablers operate through different mechanisms than individual cognitive processes.

The study's theoretical model incorporates multiple serial mediation pathways (e.g., $IS \rightarrow PE \rightarrow ATT \rightarrow ITIB \rightarrow CI$), which reflect the complex cognitive-affective-behavioural sequences proposed in post-adoption technology use literature.

Figure 5.5 Mediation outcomes (adapted from Zhao et al. 2010)



5.4.3 Mediation Analysis

In this section, mediation is evaluated for every pathway, as outlined at the end of Chapter 2. For every mediation hypothesis, the hypothesis leads the paragraph in bold, followed by a one-sentence technical summary and the mediation table. An interpretation is provided after each mediation table.

M1: ATT mediates PE → ITIB (partial mediation expected). (H1, H6)

The result shows complementary partial mediation—direct PE→ITIB is significant ($\beta = .306$), and the indirect via ATT is significant ($\beta = .094$), so PE affects ITIB both directly and through ATT (Table 5.17).

Table 5.17 M1 mediation analysis

Effect type	Path	Beta	T stat	p	95% Conflnt (LL-UL)		Result
Direct effect	PE -> ITIB	0.306	7.629	0.000	0.224	0.380	sig
Indirect effect	PE -> ATT -> ITIB	0.093	4.061	0.000	0.049	0.139	sig
Total effect	PE -> ITIB	0.399	12.509	0.000	0.334	0.459	sig

PE influences ITIB both directly ($\beta=.306$, $p<.001$) and indirectly via ATT ($\beta=.093$, $p<.001$), indicating complementary partial mediation. This suggests that performance gains promote innovative use through two channels: cognitive (direct utility recognition) and affective (positive evaluations that lower barriers to experimentation). The total effect ($\beta=.399$) is substantially larger than either path alone, confirming ATT's meaningful role in the PE→ITIB relationship.

In practical terms, stronger beliefs that the system improves work directly boost innovative use, and also do so indirectly by improving attitudes. Both channels point in the same (positive) direction, so the total impact is larger than either route alone. This suggests that communicating concrete performance gains and fostering positive evaluations work together.

M2: ATT mediates EE → ITIB (full mediation expected). (H3, H6)

Indirect-only (full) mediation—EE→ITIB is non-significant ($\beta = -.002$), while the indirect via ATT is significant in the augmented model ($\beta = .035$, 95% CI [.018, .056]) (Table 5.18).

Table 5.18 M2 mediation analysis

Effect type	Path	Beta	T stat	p	95% Conflnt (LL-UL)		Result
Direct effect	EE -> ITIB	-0.002	0.057	0.957	-0.069	0.066	non-sig

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Indirect effect	EE -> ATT -> ITIB	0.035	3.639	0.000	0.018	0.056	sig
Total effect	EE -> ITIB	0.193	6.283	0.000	0.132	0.251	sig

Ease of use does not translate into innovative behaviour by itself; its influence works through attitudes. In short, making the system easier matters because it lifts how people feel about using it, and that attitude then unlocks innovative use.

M3: ITIB mediates PIIT → CI (partial mediation expected). (H8, H11, H7)

Bootstrapping showed a significant indirect effect of PIIT on CI, alongside a significant negative direct effect. The total effect was non-significant, indicating competitive mediation: PIIT simultaneously increases CI indirectly by enhancing innovative IT use, while directly decreasing CI, yielding a net null total effect (see Table 5.19).

Table 5.19 M3 mediation analysis

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Direct effect	PIIT -> CI	-0.085	3.748	0.000	-0.128	-0.040	sig
Indirect effect	PIIT -> ITIB -> CI	0.064	5.825	0.000	0.044	0.087	sig
Total effect	PIIT -> CI	-0.020	0.834	0.404	-0.067	0.028	non-sig

Two forces operate in opposite directions. More personally innovative staff tend to use IT more innovatively, which raises the intention to continue, but at the same time, they are more critical or restless, which reduces continuance directly. Because these push against each other, the total (net) effect looks small; the pattern is real, but competitive. This is why both the positive indirect and the negative direct need to be reported.

M4: ITIB mediates IF → CI (full mediation expected) (H9, H7)

Indirect-only (full) mediation—IF→CI is non-significant directly, but the indirect IF→ITIB→CI is significant ($\beta = .073$) (Table 5.20).

Table 5.20 M4 mediation analysis

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Direct effect	IF -> CI	0.021	0.710	0.477	-0.037	0.078	non-sig
Indirect effect	IF -> ITIB -> CI	0.073	4.965	0.000	0.045	0.103	sig

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Total effect	IF -> CI	0.094	2.789	0.005	0.026	0.159	sig

Day-to-day facilitation in the organisation helps by stimulating innovative behaviour, and that is what lifts continuance intentions. Facilitation does not move continuance on its own; its value is realised via ITIB.

M5: ITIB mediates IS → CI (full mediation expected) (H10, H7)

No simple mediation via ITIB—the single-mediator indirect is not significant ($\beta = .028$, $p = .057$), but see M8 for the serial route (Table 5.21).

Table 5.21 M5 mediation analysis

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Direct effect	IS -> CI	-0.054	1.752	0.080	-0.115	0.006	non-sig
Indirect effect	IS -> ITIB -> CI	0.028	1.905	0.057	-0.001	0.056	non-sig
Total effect	IS-> CI	0.184	6.302	0.000	0.124	0.238	sig

Broad innovation support alone does not deliver a simple “support → innovative use → continuance” chain. Its influence on continuance emerges through longer chains (see M9–M12), particularly when support first strengthens facilitation or performance beliefs.

M6: PE mediates IS → CI (full mediation expected) (H13, H2)

Table 5.22 M6 mediation analysis

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Direct effect	IS -> CI	-0.054	1.752	0.800	-0.115	0.006	non-sig
Indirect effect	IS -> PE -> CI	0.037	3.817	0.000	0.020	0.057	sig
Total effect	IS-> CI	0.184	6.302	0.110	0.124	0.238	sig

A supportive climate raises beliefs that the system improves performance, and those beliefs in turn raise continuance. The message is that “support” works when it shifts what people think the system can do for their job (Table 5.22).

M7: PE → ATT → ITIB → CI (positive serial mediation). (H1, H6, H7.)

Complementary partial serial mediation—PE→CI remains significant ($\beta = .139$) and the serial PE→ATT→ITIB→CI is significant ($\beta = .035$) (Table 5.23).

Table 5.23 M7 mediation analysis

Effect type	Path	Beta	T stat	p	95% Conflnt (LL-UL)		Result
Direct effect	PE -> CI	0.139	4.197	0.000	0.073	0.203	sig
Indirect effect	PE -> ATT -> ITIB -> CI	0.035	3.859	0.000	0.018	0.053	sig
Total effect	PE-> CI	0.539	19.604	0.000	0.485	0.594	sig

Performance beliefs have a direct link to continuance, and also a small but reliable chain: better performance beliefs → better attitudes → more innovative use → higher continuance. This shows a cognitive-to-affective-to-behavioural progression that adds to the direct effect.

M8: EE → ATT → ITIB → CI (positive serial mediation). (H3, H6, H7.)

Indirect-only serial mediation—EE→CI is non-significant ($\beta = .014$), but the serial EE→ATT→ITIB→CI is significant ($\beta = .013$) (Table 5.24).

Table 5.24 M8 mediation analysis

Effect type	Path	Beta	T stat	p	95% Conflnt (LL-UL)		Result
Direct effect	EE -> CI	0.015	0.568	0.570	-0.035	0.066	non-sig
Indirect effect	EE -> ATT -> ITIB -> CI	0.013	3.450	0.001	0.006	0.021	sig
Total effect	EE-> CI	0.337	11.646	0.000	0.278	0.392	sig

Ease of use increases continuance only when it first improves attitudes and then leads to innovative use. Usability is therefore a foundational enabler, not a stand-alone predictor of continuance.

M9 (serial): IS → IF → ITIB → CI (positive serial mediation). (H12, H9, H7.)

Indirect-only serial mediation—IS→CI is non-significant, while the serial IS→IF→ITIB→CI is significant ($\beta = .053$) (Table 5.25).

Table 5.25 M9 mediation analysis

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Direct effect	IS -> CI	-0.054	1.752	0.080	-0.115	0.006	non-sig
Indirect effect	IS -> IF -> ITIB -> CI	0.053	4.877	0.000	0.033	0.075	sig
Total effect	IS-> CI	0.184	6.302	0.000	0.124	0.238	sig

Organisational support strengthens involvement facilitation (tools, incentives, involvement), which then boosts innovative behaviour and ultimately continuance. This is the operational pathway through which culture translates into outcomes.

M10: EE → PE → ATT → ITIB → CI (positive serial mediation). (H1, H4, H6, H7.)

Indirect-only serial mediation—direct EE→CI is non-significant, but the full chain via PE and ATT is significant ($\beta = .337$) (Table 5.26).

Table 5.26 M10 mediation analysis

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Direct effect	EE -> CI	0.014	0.568	0.570	-0.035	0.066	non-sig
Indirect effect	EE -> PE -> ATT -> ITIB -> CI	0.014	3.734	0.000	0.007	0.022	sig
Total effect	EE -> CI	0.337	11.646	0.000	0.278	0.392	sig

When systems feel easy, users are more likely to see performance benefits; that improves attitudes, which encourages innovative use and, in turn, continuance. This stepwise chain explains how usability cascades into longer-term retention.

M11: IS → PE → ATT → ITIB → CI (positive serial mediation). (H13, H1, H6, H7.)

Indirect-only serial mediation—direct IS→CI is non-significant, but the full chain via PE and ATT is significant ($\beta = .009$) (Table 5.27).

Table 5.27 M11 mediation analysis

Effect type	Path	Beta	T stat	p	95% ConfInt (LL-UL)		Result
Direct effect	IS -> CI	-0.054	1.752	0.080	-0.115	0.006	non-sig
Indirect effect	IS -> PE -> ATT -> ITIB -> CI	0.009	3.508	0.000	0.005	0.015	sig

Effect type	Path	Beta	T stat	p	95% Conflnt (LL-UL)		Result
Total effect	IS-> CI	0.184	6.302	0.000	0.124	0.238	sig

A supportive climate helps users recognise performance value, which lifts attitudes and innovative use, and thereby continuance. The impact of “support” is thus channelled through beliefs and behaviour rather than a direct shove on continuance.

M12: IS → PE → ATT → CI (positive serial mediation). (H13, H1, H5.)

Indirect-only serial mediation—direct IS→CI is non-significant, but the full chain via PE and ATT is significant ($\beta = .067$) (Table 5.28).

Table 5.28 M12 mediation analysis

Effect type	Path	Beta	T stat	p	95% Conflnt (LL-UL)		Result
Direct effect	IS -> CI	-0.054	1.752	0.080	-0.115	0.006	non-sig
Indirect effect	IS -> PE -> ATT -> CI	0.067	7.026	0.000	0.049	0.087	sig
Total effect	IS-> CI	0.184	6.302	0.000	0.124	0.238	sig

Innovation support raises performance beliefs, which improves attitudes and is associated with higher continuance—even without invoking innovative use in the chain. This is the shortest route by which climate shifts can show up in retention intentions.

5.4.4 Final Model

Across mediators, the dominant pathway is PE/EE → ATT → ITIB → CI, with PE → ITIB adding meaningful direct explanatory power. Organisational levers (IS/IF) act indirectly, chiefly via IF → ITIB (serial).

PIIT exhibits competitive mediation (negative direct to CI, positive via ITIB), so both routes must be shown to avoid masking real but opposing effects.

Adding the PE → ITIB path results in a minor change: the ITIB R^2 / Adj. R^2 change from 0.311 / 0.308 to 0.354 / 0.351, and the SRMR decreases from 0.059 to 0.055. The PLSpredict Q^2 /RSME/MAE results don't change.

With IS → PE → ITIB path in place, the IS → ITIB direct path attenuated to non-significance ($\beta \approx .075$, $p \approx .056$), while IS → IF ($\beta \approx .721$, $p < .001$) and IS → PE ($\beta \approx .264$, $p < .001$) remained

strong; corresponding serial indirects $IS \rightarrow PE \rightarrow ITIB \rightarrow CI$ and $IS \rightarrow PE \rightarrow ATT \rightarrow (ITIB) \rightarrow CI$ were significant. With the $PE \rightarrow ITIB$ connection, the $IS \rightarrow ITIB$ direct path becomes non-significant ($\beta = .067$, $p=0.055$, $[-0.003;0.149]$) and this path is also dropped. For the PLS-SEM this has another important contribution: the f^2 was not significant for the $IS \rightarrow ITIB$ path (see Table 5.15). By removing the statistically non-significant direct connection, $IS \rightarrow IF$ and $IS \rightarrow PE$ gains in effect size. With this change, Hypothesis 10 is slightly modified: IS still impacts $ITIB$, but not directly, instead primarily through IF , but also via PE (for final model calculations, see Appendix I7).

In sum, the mediation analysis recommends retaining $PE \rightarrow ITIB$ and $PIIT \rightarrow CI$ in the final diagram. Non-significant direct $EE \rightarrow ITIB$, $IF \rightarrow CI$, $IS \rightarrow ITIB$ and $IS \rightarrow CI$ connections are dropped, and the model will rely on the mediated/serial channels for those pathways.

Considering the impact of the $IS \rightarrow PE$, the direct $IF \rightarrow PE$ link was explored as a robustness check. Although SRMR decreased slightly ($0.055 \rightarrow 0.052$), the path's effect size (f^2) was $< .02$, its coefficient was non-significant, and Q^2 / PLSpredict did not improve. Given the theory-measurement mismatch (IF generic; PE system-specific) and negligible predictive gains, $IF \rightarrow PE$ is excluded from the final model.

As noted, the model fit metrics show that the PLS analysis could yield SRMR 0.055 for the final model. A short comparison of the Baseline and Final models is included in Table 5.29. The results of the structural model analysis are shown on Figure 5.6 and the hypotheses are summarised in Table 5.30. The mediator chains are summarised in Table 5.31. The remaining relevant tables are included in the Appendix I8: for coefficient of determination (R^2) values see Table 9.31 ; effect sizes (f^2) are shown in Table 9.32; and predictive relevance (Q^2) in Table 9.33.

Comparison of Baseline and Final Model

Relative to the baseline, the final model improves fit (SRMR $0.059 \rightarrow 0.055$) and explanation of $ITIB$ (R^2 $0.311 \rightarrow 0.354$), while Q^2 /PLSpredict remain essentially unchanged—indicating the refinements primarily clarify mechanisms rather than prediction (see Table 5.29).

Table 5.29 Baseline and final model comparison

Metric	ITIB (Baseline)	ITIB (Final)	Δ	Notes	CI (Baseline)	CI (Final)	Δ	Notes
R^2	0.311	0.354	+0.043	↑ explanation	0.600	0.600	0.000	unchanged.
Adj. R^2	0.308	0.351	+0.043		0.599	0.599	0.000	.
Q^2 (blindfolding)	0.192	0.193	+0.001	tiny gain	0.183	0.183	0.000	.
PLSpredict RMSE	0.901	0.900	↓	lower = better	0.906	0.905	↓	lower = better.
PLSpredict MAE	0.729	0.729	—	unchanged	0.739	0.739	—	unchanged.
SRMR	0.059	0.055	↓	better fit	—	—	—	global model fit.
f^2 (PE→ITIB)	—	0.075	—	small, sig.	—	—	—	effect size.

Figure 5.6 Final structural model

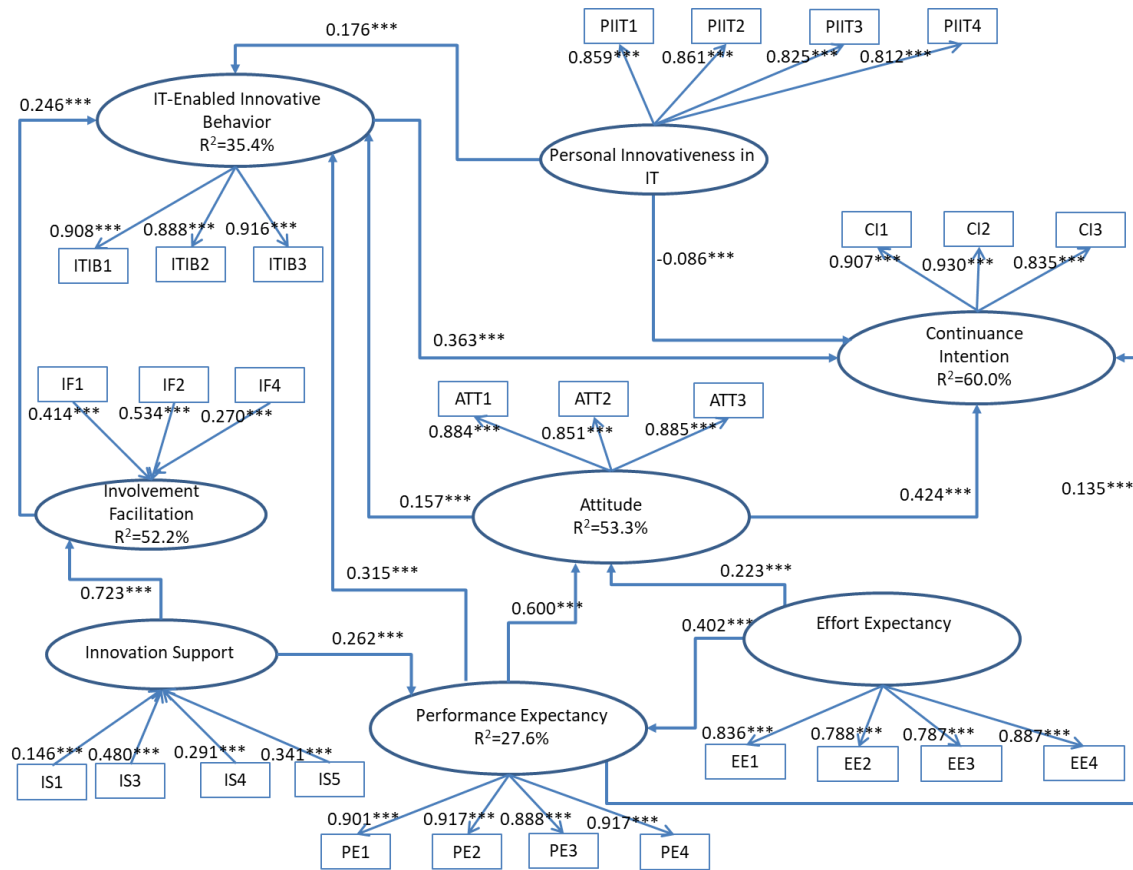


Table 5.30 Hypothesis summary

Hypothesis	Path	β	t	p	95% CI [LL, UL]	Result
H1	PE → ATT	0.600	25.993	0.000	[0.553, 0.644]	Supported
H2	PE → CI	0.135	4.138	0.000	[0.072, 0.199]	Supported
H3	EE → ATT	0.223	8.827	0.000	[0.173, 0.272]	Supported
H4	EE → PE	0.402	14.360	0.000	[0.345, 0.455]	Supported
H5	ATT → CI	0.424	13.633	0.000	[0.363, 0.486]	Supported
H6	ATT → ITIB	0.157	4.252	0.000	[0.086, 0.231]	Supported
H7	ITIB → CI	0.363	13.553	0.000	[0.310, 0.414]	Supported

Hypothesis	Path	β	t	p	95% CI [LL, UL]	Result
H8	PIIT $\rightarrow$ ITIB	0.176	6.732	0.000	[0.124, 0.227]	Supported
H9	IF $\rightarrow$ ITIB	0.246	8.425	0.000	[0.185, 0.301]	Supported
H10 (reform.)	IS raises ITIB indirectly via IS $\rightarrow$ IF $\rightarrow$ ITIB and IS $\rightarrow$ PE $\rightarrow$ (ATT) $\rightarrow$ ITIB: supported indirect-only.					Supported
H11	PIIT $\rightarrow$ CI	-0.086	3.810	0.000	[-0.129, -0.042]	Supported (negative, competitive mediation)
H12	IS $\rightarrow$ IF	0.723	40.189	0.000	[0.683, 0.755]	Supported
H13	IS $\rightarrow$ PE	0.262	9.154	0.000	[0.203, 0.315]	Supported

To summarize, the strongest mediated channels remain PE/EE $\rightarrow$ ATT $\rightarrow$ ITIB $\rightarrow$ CI; organisational levers (IS, IF) act indirectly (not directly to CI), and PIIT shows competitive mediation (negative direct to CI, positive via ITIB).

Table 5.31 Mediator chains final model

From	To	Mediator chain	β	t	p	95% CI [LL, UL]
PE	CI	ITIB	0.114	6.888	0.000	[0.082, 0.148]
PE	CI	ATT $\rightarrow$ ITIB	0.034	3.967	0.000	[0.018, 0.053]
PIIT	CI	ITIB	0.064	5.827	0.000	[0.044, 0.087]
IS	CI	IF $\rightarrow$ ITIB	0.065	7.039	0.000	[0.047, 0.083]
IS	CI	PE $\rightarrow$ ATT $\rightarrow$ ITIB	0.009	3.507	0.000	[0.005, 0.015]
EE	CI	ATT $\rightarrow$ ITIB	0.013	3.505	0.000	[0.006, 0.021]
EE	CI	PE $\rightarrow$ ATT $\rightarrow$ ITIB	0.014	3.883	0.000	[0.007, 0.022]
EE	CI	PE $\rightarrow$ ITIB	0.046	6.075	0.000	[0.032, 0.062]
IF	CI	ITIB	0.089	7.346	0.000	[0.066, 0.115]

From	To	Mediator chain	β	t	p	95% CI [LL, UL]
IS	CI	PE → ATT	0.067	7.032	0.000	[0.049, 0.086]
IS	CI	PE	0.035	3.819	0.000	[0.019, 0.055]
PE	ITIB	ATT	0.094	4.242	0.000	[0.052, 0.140]
EE	ITIB	ATT	0.035	3.744	0.000	[0.018, 0.056]
EE	ITIB	PE	0.127	6.675	0.000	[0.089, 0.164]
IS	ITIB	IF	0.178	7.998	0.000	[0.132, 0.220]
IS	ITIB	PE → ATT	0.025	3.723	0.000	[0.013, 0.040]
IS	ITIB	PE	0.083	6.212	0.000	[0.060, 0.112]
PE	ATT	(via none listed in final)				
EE	ATT	PE	0.241	12.312	0.000	[0.203, 0.280]
EE	CI	ATT	0.095	7.317	0.000	[0.071, 0.122]
EE	CI	PE → ATT	0.102	9.447	0.000	[0.083, 0.124]
ATT	CI	ITIB	0.057	3.955	0.000	[0.030, 0.087]

5.4.5 Leave-One-Firm-Out Sensitivity

Sensitivity checks (re-estimating models with and without borderline cases) did not change substantive inferences. Given clustering within firms and two large sites, a leave-one-firm-out (LOFO) sensitivity test was conducted to ensure conclusions are not unduly dependent on any single organisation.

The final model was re-estimated 21 times, omitting all observations from one firm at a time (ns per run: 824–1,029; SRMR = .055 in every run). Across paths, coefficients were stable:

- the largest absolute shift was $|\Delta\beta|_{\max} = .010$ for EE→PE (from .417 to .407);
- other non-trivial movements were $\leq .008$ (e.g., PE→CI .143→.135, PE→ITIB .320→.315);
- no sign-change was observed for paths;
- endogenous variance explained moved only marginally ($\max |\Delta R^2| = .009$ for CI, .008 for PE, .006 for ITIB, .002 for ATT, .002 increase for IF);

- effect sizes were likewise steady: the largest change was $|\Delta f^2| = .014$ on EE→PE (remaining well above Cohen's "small" threshold), with all other $\Delta f^2 \leq .003$ –.007.

Taken together, these results show that no single firm materially alters the pattern or strength of the structural relations or the explanatory power of the model; conclusions do not hinge on any one organisation. In sum, LOFO re-estimates (dropping SME01...SME21 in turn) produced only small, directionally consistent shifts in coefficients and R^2 , with no sign or confidence-interval flips, indicating that no single firm unduly dominates the findings.

5.5 Boundary Analysis

5.5.1 Introduction

Having established the final model and confirmed its robustness, this section tests the boundaries of the theory by examining whether these core relationships remain stable across key demographic and organisational subgroups using multigroup analysis (Cheah et al., 2020). This section also deals with the moderation effects of gender and age of the UTAUT model, looking at the overall effects of these demographic variables on the model (Hair et al., 2022).

MGA compares structural paths across groups formed by the categories, which is the recommended strategy for non-continuous moderators (Hair et al., 2022; Sarstedt et al., 2011). This method avoids imposing linear interaction forms and yields easily interpretable, group-specific effects across the entire model (Hair et al., 2022).

Consistent with best practice, measurement invariance will be assessed via the Measurement Invariance of Composite Model, or MICOM procedure to ensure comparability of composites across groups (Henseler et al., 2015). Micom includes the following steps (Cheah et al., 2023; Henseler et al., 2016) (Table 5.32):

Table 5.32 MICOM steps with description

MICOM Steps	Description
Step-1 – Configural invariance	Same indicators, data treatment, and algorithm settings across groups; model is specified and estimated identically. Passing Step 1 is a prerequisite for all later steps.
Step-2 – Compositional invariance	Using a permutation test, correlate each group's composite with the pooled (or reference) composite. If the empirical correlation c is not significantly below 1 (i.e., $H_0: c = 1$ not rejected), the construct's

MICOM Steps	Description
	weights are invariant (compositional invariance holds). Achieving Steps 1 + 2 yields partial measurement invariance, which is sufficient to compare structural relations (e.g., path coefficients, R^2) across groups.
Step-3: Step-3a – Equality of composite means and Step-3b – Equality of composite variances	Also via permutation; if the 95% confidence intervals for the mean difference (3a) and variance ratio (3b) include 0 and 1, respectively (i.e., not significant), full measurement invariance is established. Full invariance allows valid comparisons of latent means and variances in addition to structural parameters.

Following recommendations, as much as possible, groups were collapsed using the following logic (Cheah et al., 2023; Cheah et al., 2020):

- Best: ~150–200 per group → robust MICOM and MGA.
- Acceptable: ≥ 100 per group → typically fine.
- Workable but fragile: 50–99 per group: proceed, but expect lower power and wider CIs.
- Avoid: < 50 per group (and especially < 30): permutation tests may get noisy and Type II errors are likely.

Between-group path comparisons are only meaningful if (at least) partial invariance is supported (Step-1 and Step-2) (Henseler et al., 2015) and therefore this was the first step for each group variable. In addition, Step-3 was completed to establish limitations. All significant mean and variance limitations are listed in the Appendix J, but in the chapter text, only those are added which may be relevant for the path changes. Group differences were then tested using established PLS-MGA frameworks (permutation and bootstrap-based tests) (Cheah et al., 2023; Hair et al., 2022). These approaches make minimal distributional assumptions and are well-suited to unequal sample sizes (Sarstedt et al., 2011). Between-group differences in path coefficients ($\Delta\beta$) are reported alongside 95% permutation intervals and permutation p-values, with changes in explained variance (ΔR^2) and effect sizes (Δf^2) (see Appendix J).

As group comparisons test many paths in parallel (e.g., in this study, each pairwise comparison tests $m=13$ paths; $m = 5 R^2$ values; $m = 13 f^2$ values), the study has to control for inflated Type I errors (false positives). In this study, false discovery rate (FDR) was controlled using Benjamini–

Hochberg (BH) ($q = .05$) within each pairwise comparison and within each family. As a robustness check, BH/FDR will also be applied pooled across the pairs for multi-level moderators (for 3 levels paths $m = 39$, $R^2 m = 15$, $f^2 m = 39$) (Sarstedt et al., 2011). Controlling the FDR with BH keeps the expected proportion of false rejections among all rejections at a chosen level (e.g., $q = .05$), offering a better power–error trade-off than conservative family-wise controls (e.g., Bonferroni), which can be overly harsh in SEM contexts with correlated tests and bootstrap variability (Hair et al., 2022; Sarstedt et al., 2011). Final results are reported after FDR. However, for exploratory reasons, statistically significant differences *before* the FDR control are also noted in *italic*.

5.5.2 Management Level

MGA comparing employees ($n=717$) and managers ($n=274$) (missing $n=49$) established configural equivalence (identical indicators / specifications) for MICOM Step-1. However, during MICOM Step-2, the Innovation Support (IS) composite showed a lack of compositional invariance driven by indicator IS1 (*We have a very open communications environment*). Given the conceptual plausibility of level-specific interpretation (employees vs managers) and to ensure invariant measurement across groups, IS1 was removed. The model was re-estimated using IS3–IS5: reliability and validity did not change (MGA model data is displayed in Table 9.36 and Table 9.37, SRMR=.055).

MICOM was repeated with the revised specification, and compositional invariance held for all constructs; thus, group comparisons via MGA were warranted. MICOM Step-3a indicated no mean differences across groups for any construct. Variance equality held except for Effort Expectancy (EE) ($p = .049$), suggesting heterogeneous dispersion for EE between employees and managers. These results permit valid MGA; interpretations for paths involving EE are reported with this variance caveat in mind.

None of the path changes, R^2 , or effect-size differences reached significance after the pairwise FDR correction.

From the exploratory point of view, the path from Attitude (ATT) to Innovative IT Behaviour (ITIB) was stronger in managers ($\beta=0.276$) than in employees ($\beta=0.084$). This difference was significant in both Permutation MGA ($p=.025$) and PLS-MGA (bootstrap) (two-tailed $p=.019$), and was corroborated by a significant f^2 difference ($p=.030$). This finding may suggest that positive attitudes translate more readily into innovative IT behaviours among managers than among employees. However, none of these items survives FDR.

5.5.3 Gender

MICOM Step-1 and Step-2 satisfied partial measurement invariance for gender-based MGA (Female n=323; Male n=700, missing n=17). Step-3 indicated mean differences for ATT, EE, PE, and PIIT, and variance differences for CI, IF, and IS. These Step-3 findings do not preclude MGA, but they are reported as distributional caveats.

None of the path changes, R^2 , or effect-size differences reached significance after the pairwise FDR correction.

From the exploratory point of view, the effect of Innovation Support (IS) on Involvement Facilitation (IF) was stronger for males ($\beta_M=0.749$ vs $\beta_F=0.658$), significant in both bootstrap PLS-MGA ($p=.024$) and permutation MGA ($p=.015$). This was mirrored in a significant f^2 difference for $IS \rightarrow IF$ ($p=.025$) and a higher R^2 for IF among males ($\Delta R^2=.129$, $p=.023$). However, after controlling for FDR, all these items became non-significant.

5.5.4 Age

Across the three collapsed age groups (18-30 n=379; 31-40 n=415; 41-80 n=215; missing n=31) MICOM Step-1 and Step-2 established partial measurement invariance. Distributional caveats apply due to differences in means and variance across the three groups (see Appendix J4). Specifically for the 18-30 vs 31-40 group, IF, IS, ITIB, and PIIT means are different.

None of the path changes, R^2 , or effect-size differences reached significance after the pairwise FDR correction.

From the exploratory point of view, for the 18-30 vs 31-40 pair $PE \rightarrow CI$ was different ($\beta_{18-30}=0.209$ vs $\beta_{31-40}=0.042$), significant in both bootstrap PLS-MGA ($p=.022$) and permutation MGA ($p=.024$), implying a stronger Performance Expectancy – Continuance Intention link for younger participants. There was also a significant f^2 difference for $ATT \rightarrow ITIB$ ($p=.048$) and for $PIIT \rightarrow CI$ ($p=.031$). None of these items survives FDR.

5.5.5 Location

MICOM was completed to compare Capital (n=680), City (n=261) and Rural locations (n=99). MICOM Step-1 and Step-2 established partial measurement invariance. Distributional caveats apply due to differences in means (PIIT and CI for Capital vs City) and variances (see Table 9.64, Table 9.68 and Table 9.72). For the Capital vs City group, CI and PIIT means differ. For the Capital vs Rural group, PIIT means, and variances both differ.

A significant difference is noted between Capital and City: PIIT → CI was less negative in Capital ($\beta_{\text{Capital}}=-.028$ vs $\beta_{\text{City}}=-.211$), significant in both bootstrap PLS-MGA and permutation MGA ($p<=.001$). There was also a significant f^2 difference for PIIT→CI ($p=.001$).

From the exploratory point of view, PIIT → CI was also less negative in Capital ($\beta=-0.028$) than Rural ($\beta=-0.197$), $\Delta\beta=.169$; PLS-MGA ($p=.023$) and Permutation ($p=.041$) converged.

The other difference concerned Innovation Support → Perceived Ease (IS→PE). The path much stronger in Capital ($\beta=0.264$) than Rural ($\beta=0.025$), significant in PLS-MGA ($p=.019$) and Permutation ($p=.018$), with a corresponding f^2 difference ($p=.015$). The same effect was in place in City vs Rural relation. Possible interpretation that, in general, Innovation Support is more effective in the Capital, in contrast to City or Rural locations. However, none of these differences survives FDR.

5.5.6 Sector

MICOM Step-1 and Step-2 satisfied partial measurement invariance for sector-based MGA (ICT $n=624$; Manufacturing $n=144$, Services $n=272$). Distributional caveats apply due to differences in means and variances (see Appendix J6).

After controlling the false discovery rate within each pair and family, ICT vs Services showed the only robust differences: the path PIIT → CI (less negative in ICT; $\Delta\beta=.183$, $q=.039$) and the corresponding f^2 difference ($q=.039$).

From the exploratory point of view, for ICT vs Manufacturing, a single R^2 difference emerged: CI was better explained in ICT than Manufacturing ($\Delta R^2=.137$, $p=.019$).

For ICT vs Services, MGA showed another path difference: IS→IF is stronger in ICT ($\beta_{\text{ICT}}=0.741$ vs $\beta_{\text{Services}}=0.622$; $p=.008$ perm=.005). R^2 for IF is also higher in ICT ($\Delta R^2=.162$, $p=.008$).

For Manufacturing vs Services, MGA shows one path difference: IS→IF is stronger in Manufacturing ($\beta_{\text{Manufacturing}}=0.759$ vs $\beta_{\text{Services}}=0.622$; $p=.029$ perm=.043). R^2 for IF is higher in Manufacturing ($\Delta R^2=.189$, $p=.031$), while CI is lower ($\Delta R^2=-.138$, $p=.026$). For f^2 the PIIT→CI path is different in Services ($\Delta\beta=-.110$; $p=.027$).

However, none of these differences survives FDR.

5.5.7 Sample Concentration

This sample-concentration analysis examines whether the two most numerically dominant firms in the sample - SME16 ($n=216$) and SME19 ($n=189$) - produce structural results that differ from

the remaining 19 firms (SMEREST, n=635). This is a sample concentration check rather than a firm-size comparison: all participating organisations fall within the medium or small SME bands, and the grouping tests whether high respondent counts from two sites introduce systematic bias into the model. As a theory-driven exploration, this heterogeneity test (MGA) was completed to evaluate whether structural relations differ across theoretically defined groups. In contrast, the role of the influence check (LOFO) was to assess whether results hinge on any single firm (and the answer was a resounding no, see 5.4.5).

MICOM Step-1 and Step-2 satisfied partial measurement invariance for sample-concentration comparison. Distributional caveats apply due to differences in means and variances (see Appendix J7).

None of the path changes, R^2 , or effect-size differences reached significance after the pairwise FDR correction.

From the exploratory point of view, for SME16 vs SME19, two path differences appeared: EE→ATT was stronger in SME16 ($\beta_{\text{SME16}}=.318$ vs $\beta_{\text{SME19}}=.065$; $p=.005$ perm=.002). PE→ATT had the opposite effect SME16 ($\beta_{\text{SME16}}=.475$ vs $\beta_{\text{SME19}}=.666$; $p=.020$ perm=.020). f^2 also shows stronger prediction for EE→ATT in SME16 ($\Delta f^2=.146$, $p=0.007$).

For SME16 vs SMEREST, also two path differences were shown: PIIT→ITIB was stronger in SMEREST ($\beta_{\text{SME16}}=.045$ vs $\beta_{\text{SMEREST}}=.213$; $p=.018$ perm=.008). PE→ATT had a similar effect ($\beta_{\text{SME16}}=.475$ vs $\beta_{\text{SMEREST}}=.617$; $p=.026$ perm=.017). f^2 also showed stronger prediction for these routes: PE→ATT ($\Delta f^2=-.361$, $p=0.026$); PIIT→ITIB ($\Delta f^2=-.067$, $p=0.018$).

For SME19 vs SMEREST, one difference appeared: EE→ATT was stronger in SMEREST ($\beta_{\text{SME19}}=.065$ vs $\beta_{\text{SMEREST}}=.235$; $p=.030$ perm=.014). f^2 also showed stronger prediction for this route: EE→ATT ($\Delta f^2=-.096$, $p=0.016$).

As none of these differences survives FDR, group differences (where present) are interpreted as population heterogeneity, not artefacts of one influential site.

5.5.8 Outlier Analysis

Following the protocol outlined in Chapter 3, multigroup analysis was completed for the entire set and with the 14 outliers removed (Full=1040; Outlier=1026). There were no significant differences in Step-1, Step-2, 3a and 3b MICOM tables or in the paths, R^2 or f^2 values (see Appendix J8).

None of the path changes, R^2 , or effect-size differences reached significance.

5.5.9 Nonresponse Bias Analysis

Following the protocol outlined in Chapter 3, multigroup analysis was completed for the early and late respondents (Early: $n=513$; Late: $n=527$). There were no differences in MICOM Step-1, Step-2 and 3a MICOM tables (see Appendix J9). MICOM Step-3b showed a single significant difference in IF variances. There were no differences in paths, R^2 or f^2 values, confirming that there were no model differences between early and late respondents.

None of the path changes, R^2 , or effect-size differences reached significance.

5.5.10 Multigroup Analysis Summary

The primary finding from the multigroup analysis is the broad stability of the structural model. After applying rigorous measurement invariance checks and controlling for the false discovery rate, the analysis revealed remarkably limited heterogeneity, indicating that the core pathways are largely consistent across management levels, genders, age groups, and even firm sizes within this sample.

The significant differences (surviving FDR) were:

- I. Location effects: for Capital vs City, PIIT→CI differed (both path and f^2).
- II. Sector effects: in ICT vs Services, the PIIT→CI path was less negative in ICT (both path and f^2).

Taken together, the core model generalises well, with boundary conditions appearing mainly where individual dispositions (PIIT) drive continued use. This is an important element for qualitative interviews, as the competitive mediation already flagged this pathway. A complementary “big-SME impact” heterogeneity showed no sign, or CI flips and only trivial shifts in β , R^2 , and f^2 , indicating that observed differences reflect population heterogeneity rather than influence from any single firm.

5.6 Translating Theory Into Action

IPMA was run in SmartPLS 4 using total effects (incl. indirect paths) as importance and rescaled latent-variable scores (0–100) as performance. Options: Calculations → Importance–Performance Map Analysis → Performance scale: 0–100; Use unstandardized LV scores: ON; Include indirect effects: ON. Targets were Continuance Intention (CI) and IT-enabled Innovative Behaviour (ITIB); predictors included PE, EE, ATT, IS, IF, PIIT (and ITIB when CI was the target). The structural model was estimated with the path weighting scheme and bootstrapping (e.g., 5,000 subsamples) as reported earlier.

5.6.1 IPMA: Continuance Intention target

For CI, the most important predictors are PE ($\beta=.539$) and ATT ($\beta=.482$), both already performing well (64–63%) (Figure 5.7). The largest actionable gain is raising ITIB ($\beta=.363$), given its mid-level performance (51.9%). IS and IF underperform ($\approx 48\%$) but contribute little to moderate importance to CI; they are better framed as supporting levers rather than first-order CI priorities (Table 5.33).

Figure 5.7 IPMA Continuance Intention

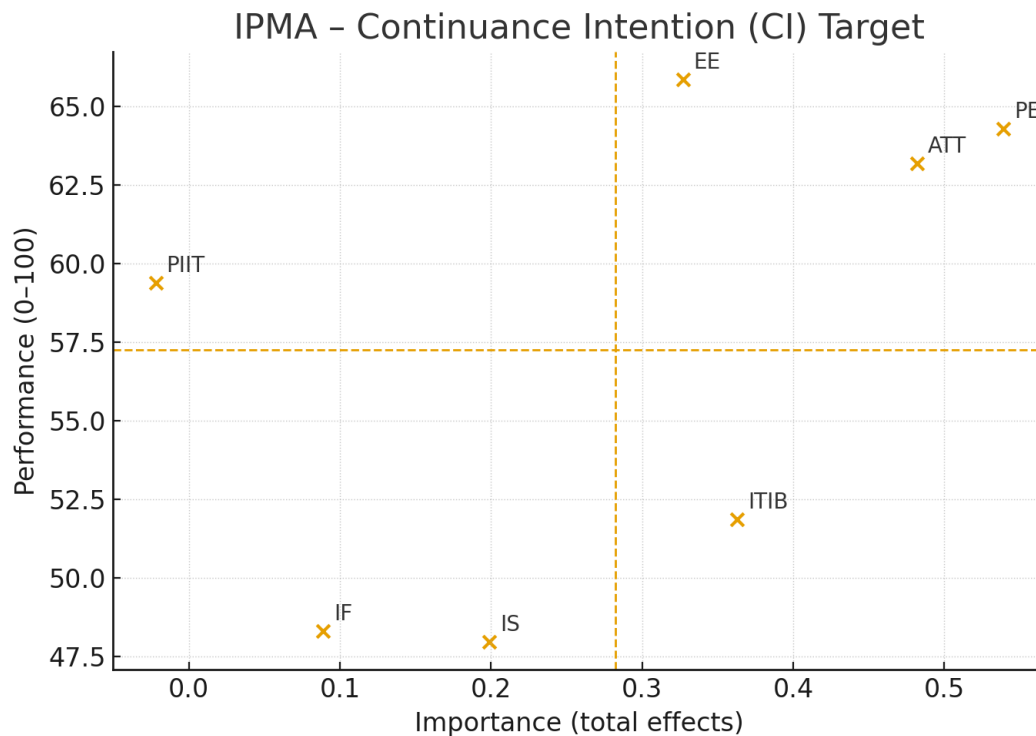


Table 5.33 Importance–Performance Map for Continuance Intention (CI)

Predictor	Importance to CI (β_{total})	Performance (0–100)	Priority note
PE	0.539	64.282	Maintain/optimize
ATT	0.482	63.173	Maintain/optimize
ITIB	0.363	51.869	Priority (improve)
EE	0.327	65.847	Maintain/optimize

Predictor	Importance to CI (β_{total})	Performance (0–100)	Priority note
IS	0.199	47.985	Secondary/monitor (low perf, borderline importance)
IF	0.089	48.320	Secondary/monitor (low perf, low importance)
PIIT	–0.022	59.397	Monitor (negligible/negative)

5.6.2 IPMA: IT-enabled Innovative Behaviour Target

For ITIB, PE is most important ($\beta=.410$) with strong performance, but the clearest priorities are IS ($\beta=.279$; perf 48.0%) and IF ($\beta=.245$; perf 48.3%)—both influential and underdeveloped—indicating that strengthening support and day-to-day facilitation offers the biggest practical lift in innovative use (Figure 5.8 and Table 5.34).

Figure 5.8 IPMA IT-enabled Innovative Behaviour

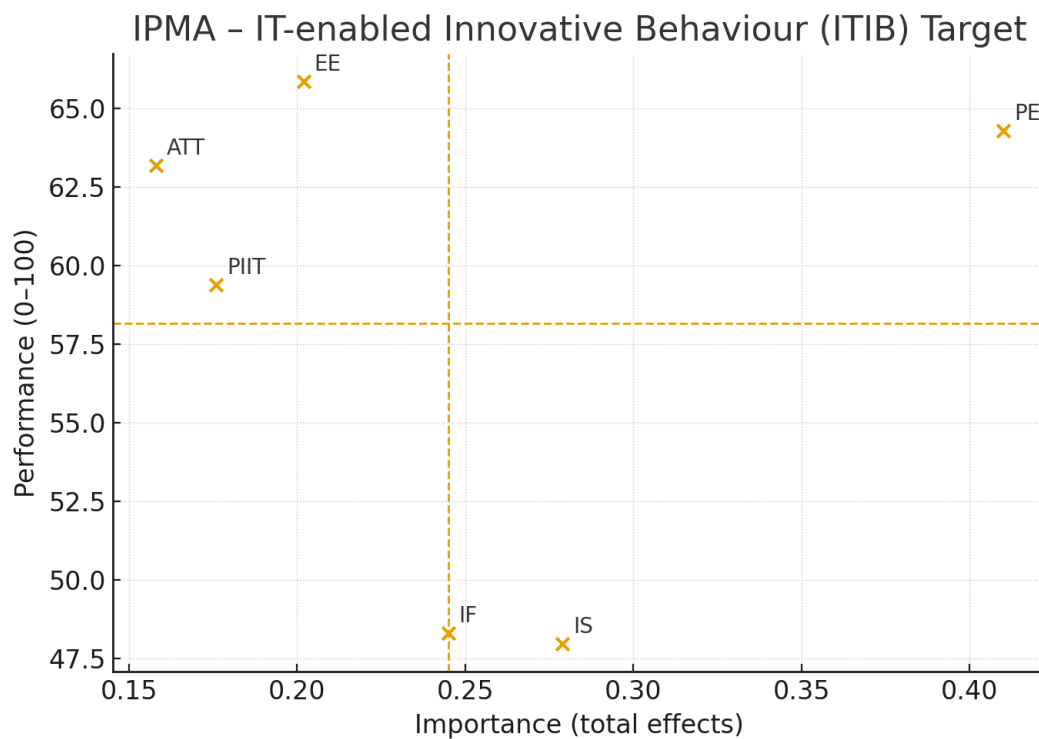


Table 5.34 Importance–Performance Map for IT-enabled Innovative Behaviour (ITIB)

Predictor	Importance to ITIB (β_{total})	Performance (0–100)	Priority note
PE	0.410	64.282	Maintain/optimize
IS	0.279	47.985	Priority (improve)
IF	0.245	48.320	Priority (improve)
EE	0.202	65.847	Maintain/optimize
PIIT	0.176	59.397	Monitor/secondary
ATT	0.158	63.173	Monitor

IPMA used total effects as importance and rescaled latent-variable scores (0–100) as performance. For CI, expectancy/attitude predictors (PE, ATT) are both highly important and already strong performers; improving ITIB offers the largest marginal gain. For ITIB, the organisational levers—Innovation Support (IS) and Involvement Facilitation (IF)—combine meaningful importance with low performance, marking them as top priorities for managerial action. PE/EE remain ‘maintain/optimize’ areas given high importance, but already have solid performance. Negative/near-zero effects (e.g., PIIT→CI) are not practical improvement levers for the given target.

5.7 Chapter Summary

5.7.1 Overview

This chapter presented the quantitative findings from a survey of 1,040 employees across 21 Hungarian SMEs to test a comprehensive model of post-adoption tablet use. The analysis proceeded through five stages:

1. establishing data quality and sample characteristics;
2. validating the reflective and formative measurement models;
3. developing and testing the structural model through a three-stage process;
4. examining model stability through multigroup and sensitivity analyses;
5. and identifying practical priorities via an importance-performance map analysis.

The findings provide robust support for the proposed theoretical framework. In addition, they uncover several nuanced mechanisms that are associated with continuance intention and innovative technology use in an organisational context.

Following rigorous data screening, the measurement models for all constructs were confirmed to be reliable and valid. The development of the structural model resulted in a final, parsimonious model with strong explanatory power (e.g., $R^2 = 0.600$ for Continuance Intention; $R^2 = 0.354$ for IT-enabled Innovative Behaviour) and good overall fit (SRMR = 0.055).

The analysis confirmed all 13 of the study's core hypotheses (summarised in Table 5.35). The study confirmed the foundational roles of Performance Expectancy (PE) and Effort Expectancy (EE) in shaping user attitudes and subsequent behaviours. Organisational factors, namely Innovation Support (IS) and Involvement Facilitation (IF), were found to be powerful antecedents to these core user perceptions and innovative behaviours. A key finding from the heterogeneity analysis is the broad stability of the structural model. PLS-SEM indicates that the core mechanisms underlying innovative behaviour and continuance intention are largely consistent across key demographic and organisational contexts.

The analysis of the structural model moved beyond direct effects to reveal the critical mechanisms through which influence operates. Attitude (ATT) and IT-enabled Innovative Behaviour (ITIB) emerged as crucial mediators. These constructs channel the effects of initial perceptions and organisational support through to Continuance Intention (CI).

A key theoretical contribution emerged in the discovery of a competitive mediation pattern for Personal Innovativeness in IT (PIIT). While an individual's innovativeness was positively associated with continuance intention indirectly, via fostering more innovative use of the technology, it simultaneously exerted a small but statistically significant negative direct association with continuance. This finding reveals a fundamental tension for management: the very employees most likely to generate value through innovative use are also inherently less likely to remain committed to a given technology. In this sense, personal innovativeness represents a "double-edged sword" in a mandated-use context. Although the direct PIIT → CI effect is modest in size ($f^2 \approx 0.02$), its theoretical importance lies in establishing this competitive dynamic when contrasted with the positive indirect influence via ITIB.

The robustness of these findings was confirmed through multiple rigorous tests. A leave-one-firm-out sensitivity analysis demonstrated that the results were not dependent on any single organisation in the sample. The key pathways held true across management levels, genders, sectors, and locations, with only a few theoretically coherent boundary conditions identified (for example, a stronger attitude-to-behaviour link for managers and a less negative PIIT → CI path in certain sectors and locations).

From a practical standpoint, the importance-performance map analysis identified a clear strategic path for intervention. To foster long-term continuance, the key lever is enhancing innovative behaviour (ITIB). Managers should prioritise investments in the currently underperforming but highly important organisational levers of Innovation Support (IS) and Involvement Facilitation (IF). Finally, while these quantitative results identify which factors predict continuance and innovative behaviour, they cannot by themselves explain how these relationships unfold in the daily reality of these SMEs. The subsequent qualitative inquiry in Chapter 6 explores the “why” behind the “what”, focusing on three key puzzles that emerged from the model:

- unpacking the 'double-edged sword' of personal innovativeness by exploring the lived experience behind the competitive mediation effect;
- investigating how employees perceive and experience 'innovation support' in their daily work; and
- providing rich, narrative evidence of the process through which positive attitudes translate into innovative behaviours.

To unlock the “black box” of these statistical relationships and to understand the trajectories of these users over the subsequent seven years, Chapter 6 presents the qualitative findings from the Phase 2 retrospective analysis.

5.7.2 Key Statistical Results

For readers interested in the technical detail, the tables below (Table 5.35, Table 5.36, Table 5.37 and Table 5.38) summarise the final model’s hypothesis tests, indirect effects and importance–performance profiles. Full bootstrapping outputs, multigroup analysis statistics and diagnostic indicators are reported in Appendix I and Appendix J (Tables 9.15-9.103).

Table 5.35 Hypothesis summary (final model)

H#	Hypothesised effect (short form)	Path(s) tested	β	t	p	95% CI [LL, UL]	Outcome
H1	Performance Expectancy → Attitude (positive)	PE → ATT	0.600	25.993	.000	[0.553, 0.644]	Supported, +
H2	Performance Expectancy → Continuance Intention (positive)	PE → CI	0.135	4.138	.000	[0.072, 0.199]	Supported, +

H#	Hypothesised effect (short form)	Path(s) tested	β	t	p	95% CI [LL, UL]	Outcome
H3	Effort Expectancy → Attitude (positive)	EE → ATT	0.223	8.827	.000	[0.173, 0.272]	Supported, +
H4	Effort Expectancy → Performance Expectancy (positive)	EE → PE	0.402	14.360	.000	[0.345, 0.455]	Supported, +
H5	Attitude → Continuance Intention (positive)	ATT → CI	0.424	13.633	.000	[0.363, 0.486]	Supported, +
H6	Attitude → IT-enabled Innovative Behaviour (positive)	ATT → ITIB	0.157	4.252	.000	[0.086, 0.231]	Supported, +
H7	IT-enabled Innovative Behaviour → Continuance Intention (positive)	ITIB → CI	0.363	13.553	.000	[0.310, 0.414]	Supported, +
H8	Personal Innovativeness in IT → ITIB (positive)	PIIT → ITIB	0.176	6.732	.000	[0.124, 0.227]	Supported, +
H9	Involvement Facilitation → ITIB (positive)	IF → ITIB	0.246	8.425	.000	[0.185, 0.301]	Supported, +
H10 (reform.)	Innovation Support increases ITIB indirectly (via IF and via PE→ATT)	IS→IF→ITIB; IS→PE→(ATT)→ITIB					Supported (indirect-only)
H11	Personal Innovativeness in IT → CI (direct effect; competitive)	PIIT → CI	-0.086	3.810	.000	[-0.129, -0.042]	Supported (negative), Competitive mediation
H12	Innovation Support → Involvement Facilitation (positive)	IS → IF	0.723	40.189	.000	[0.683, 0.755]	Supported, +

H#	Hypothesised effect (short form)	Path(s) tested	β	t	p	95% CI [LL, UL]	Outcome
H13	Innovation Support → Performance Expectancy (positive)	IS → PE	0.262	9.154	.000	[0.203, 0.315]	Supported, +

Table 5.36 Significant indirect effects on CI (final model)

From	To	Mediator chain	β	t	p	95% CI [LL, UL]
PE	CI	ITIB	0.114	6.888	.000	[0.082, 0.148]
PE	CI	ATT	0.255	12.352	.000	[0.216, 0.298]
PIIT	CI	ITIB	0.064	5.825	.000	[0.044, 0.087]
IF	CI	ITIB	0.073	4.965	.000	[0.045, 0.103]
IS	CI	PE → CI	0.037	3.817	.000	[0.020, 0.057]
PE	CI	ATT → ITIB	0.035	3.859	.000	[0.018, 0.053]
EE	CI	ATT → ITIB	0.013	3.450	.001	[0.006, 0.021]
IS	CI	IF → ITIB	0.053	4.877	.000	[0.033, 0.075]
EE	CI	PE → ATT → ITIB	0.014	3.734	.000	[0.007, 0.022]
IS	CI	PE → ATT → ITIB	0.009	3.508	.000	[0.005, 0.015]
IS	CI	PE → ATT	0.067	7.026	.000	[0.049, 0.087]
EE	CI	PE	0.054	3.816	.000	[0.028, 0.084]
EE	CI	ATT	0.095	7.317	.000	[0.071, 0.122]
ATT	CI	ITIB	0.057	3.955	.000	[0.030, 0.087]

Table 5.37 Significant indirect effects on ITIB (final model)

From	To	Mediator chain	β	t	p	95% CI [LL, UL]
PE	ITIB	ATT	0.094	4.061	.000	[0.049, 0.139]
EE	ITIB	ATT	0.035	3.639	.000	[0.018, 0.056]
IS	ITIB	IF	0.178	7.998	.000	[0.132, 0.220]
IS	ITIB	PE → ATT	0.025	3.723	.000	[0.013, 0.040]
IS	ITIB	PE	0.083	6.212	.000	[0.060, 0.112]

From	To	Mediator chain	β	t	p	95% CI [LL, UL]
EE	ITIB	PE	0.127	6.675	.000	[0.089, 0.164]

Table 5.38 Total effects (final model)

Total effects	β	t	p	95% CI [LL, UL]
ATT -> CI	0.482		0.000	[0.415,0.547]
ATT -> ITIB	0.157		0.000	[0.086,0.231]
EE -> ATT	0.465		0.000	[0.412,0.511]
EE -> CI	0.324		0.000	[0.285,0.360]
EE -> ITIB	0.200		0.000	[0.166,0.235]
EE -> PE	0.402		0.000	[0.345,0.455]
IF -> CI	0.089		0.000	[0.066,0.115]
IF -> ITIB	0.246		0.000	[0.185,0.301]
IS -> ATT	0.157		0.000	[0.120,0.194]
IS -> CI	0.206		0.000	[0.169,0.240]
IS -> IF	0.723		0.000	[0.683,0.755]
IS -> ITIB	0.285		0.000	[0.238,0.329]
IS -> PE	0.262		0.000	[0.203,0.315]
ITIB -> CI	0.363		0.000	[0.310,0.414]
PE -> ATT	0.600		0.000	[0.553,0.644]
PE -> CI	0.538		0.000	[0.491,0.585]
PE -> ITIB	0.409		0.000	[0.352,0.464]
PIIT -> CI	-0.022		0.364	[-0.068,0.026]
PIIT -> ITIB	0.176		0.000	[0.124,0.227]

6 QUALITATIVE ANALYSIS AND FINDINGS

6.1 Introduction

This section documents the implementation of the qualitative phase of the mixed methods research design outlined in Chapter 3. Following the explanatory sequential design (Creswell & Plano Clark, 2018), this phase builds upon the quantitative findings presented in Chapter 5. This chapter focuses on exploring the underlying processes, mechanisms, and contextual factors that shape tablet continuance and innovative use in Hungarian SMEs.

As detailed in Chapter 3, the study employs the Gioia methodology (Gioia et al., 2013; Magnani & Gioia, 2023) to inductively develop a theory from interview accounts. However, the process maintains connections to the UTAUT-based conceptual framework established in Chapter 2. Consequently, there will be references to the relevant UTAUT constructs and therefore a short overview of the UTAUT constructs is presented below.

The qualitative sampling strategy, introduced in Chapter 3, employed quantitatively-guided purposive selection to identify theoretically informative cases from the Phase 1 survey respondents (21 SMEs, 1,040 employees, 2014–2015) (Palinkas et al., 2015; Patton, 2015).

This chapter documents how the interview design was operationalised: which SMEs were selected and how recruitment proceeded through gatekeeper-mediated access (Sections 6.2.2 and 6.2.3), the interview protocol and data collection procedures (Sections 6.2.5 and 6.2.6), and evidence of thematic saturation (Section 6.2.7). Subsequent sections present the emergent data structure (Section 6.3) and a detailed overview organised by aggregate dimensions (Sections 6.4–6.7).

6.2 Qualitative Method Data Collection

6.2.1 Research Question for the Qualitative Phase

Research Question 2 (SRQ2), specifically targeting the qualitative phase, asks: “What organisational, contextual, and task-related mechanisms shaped post-adoption outcomes (continuance, discontinuance, routine use, innovative use) during 2014-2021, and how do these mechanisms relate to the structural relationships identified in the 2014-15 quantitative phase?”.

For ease of reading, the construct names and the initial conceptual model are reproduced in Table 6.1 and Figure 6.1, respectively.

The quantitative analysis (Chapter 5) identified significant predictors of Continuance Intention: Attitude (ATT→CI), Performance Expectancy (PE→CI) or IT-enabled Innovative Behaviour (ITIB→CI). However, the model did not reveal how these factors operate in everyday work contexts or why some employees continue using tablets while others discontinue.

The quantitative model also demonstrated that Personal Innovativeness (PIIT → ITIB), Innovation Support (IS → ITIB), Involvement Facilitation (IF → ITIB) and Attitude (ATT → ITIB) significantly predict innovative behaviour. Again, the nature of these behaviours—what employees actually do when they experiment, repurpose, or creatively appropriate tablets—and the organisational and social processes through which innovations emerge, diffuse, and become routinised remain unspecified.

While the multigroup analysis established the broad stability of the structural model, the quantitative findings revealed significant but moderate path coefficients (e.g., Involvement Facilitation (IF→CI) and Innovation Support (IS→CI)). The analysis suggested that the strength of these relationships may vary across contexts. This question investigates the boundary conditions and moderating factors—organisational infrastructure, management practices, IT governance policies, workflow design, and temporal contexts (2014–2015 vs. 2021) that amplify, attenuate, or fundamentally alter the dynamics captured in the quantitative model. The Gioia methodology's inductive-abductive logic (Gioia et al., 2013; Magnani & Gioia, 2023) provides the analytical framework to move systematically from participants' accounts to theoretical insights that inform, extend, and contextualise the quantitative findings.

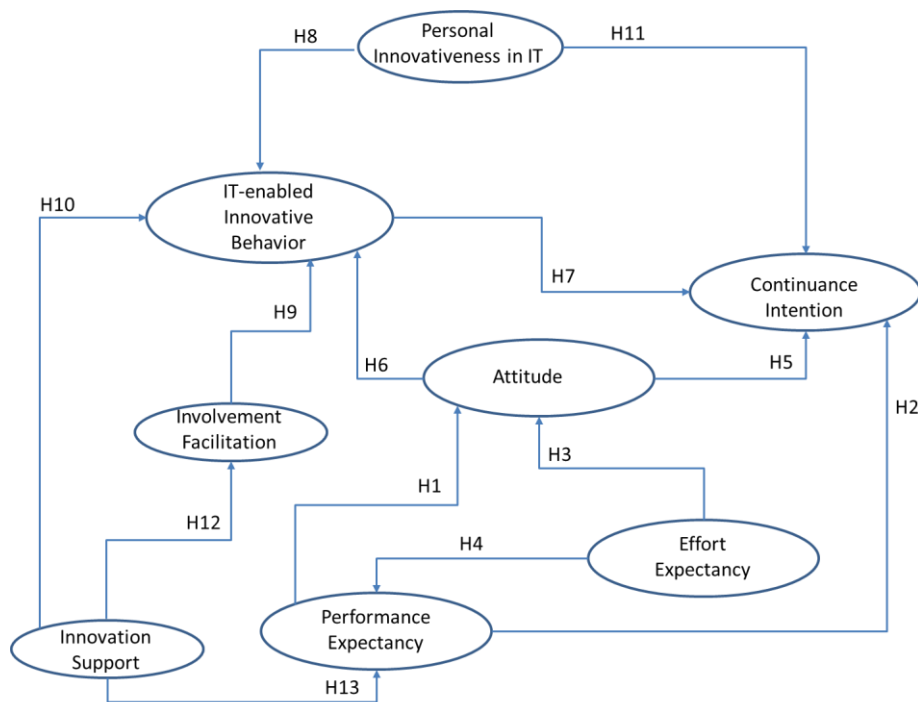
This section documents which SMEs were selected and why, how gatekeeper-mediated recruitment proceeded, the temporal context of data collection, and recruitment outcomes and limitations.

Table 6.1 Construct names and abbreviations

Abbrev.	Construct name
PE	Performance Expectancy
EE	Effort Expectancy
ATT	Attitude
ITIB	IT-enabled Innovative Behaviour
CI	Continuance Intention

Abbrev.	Construct name
PIIT	Personal Innovativeness in IT
IF	Involvement Facilitation
IS	Innovation Support
FC	Facilitating Conditions

Figure 6.1 Conceptual model for continuance and IT-enabled innovative behaviour in SMEs



6.2.2 From 21 Candidate Firms to 9 Interview Sites

To identify theoretically informative cases, firm-level profiles were constructed for each of the 21 participating SMEs by aggregating employee responses on key constructs (ATT, PE, EE, IS, IF, ITIB, CI) and computing z-scores relative to the distribution of firm means. As detailed in Chapter 3, the selection strategy employed four complementary lenses to ensure both extreme cases and systematic variation were captured:

1. Extreme profiles (highest outlier scores) to illuminate mechanisms obscured in typical cases (Flyvbjerg, 2006; Patton, 2015);

2. Contradictory configurations (e.g., High IS–Low ITIB, High ATT–Low CI) to probe disjunctions between expected relationships (Miles et al., 2014; Seawright & Gerring, 2008);
3. Climate fragmentation (within-firm dispersion of ITIB and CI) to contrast homogeneous versus contested climates (Miles et al., 2014; Patton, 2015); and
4. Maximum variation across sector (Manufacturing, Services, ICT) and location (Capital, City, Rural) (Palinkas et al., 2015; Patton, 2015).

The selection process prioritised SMEs satisfying multiple lenses simultaneously. For example, SME16 (ICT, Capital, n=216) exhibited both extreme positive innovation support ($zIS = +1.8$) and contradictory low innovative behaviour ($zITIB = -1.2$), whilst also providing a large-sample representation of the ICT sector. Similarly, SME08 (Services, Capital, n=17) represented an extreme negative profile (all construct z-scores ≤ 0), offering insight into systemic adoption failure. Full selection criteria, firm-level z-scores, and rationales are provided in Appendix K1 (see Table 9.104 and Table 9.105).

From this analysis, 10 SMEs were shortlisted for interview recruitment, deliberately spanning:

- Extreme positive cases (SME14: all z-scores $> +1$, OutlierScore = 6.45)
- Extreme negative cases (SME08: all z-scores ≤ 0 , OutlierScore = 3.32)
- Contradictory configurations (SME16: High IS–Low ITIB; SME20: High ATT–Low CI; SME03: High ATT–Low IS/IF)
- Sector coverage (4 ICT, 3 Manufacturing, 3 Services)
- Geographic coverage (6 Capital, 2 City, 2 Rural)

6.2.3 Recruitment

Following the gatekeeper-mediated recruitment strategy outlined in Chapter 3, organisational contacts (who facilitated the 2014–2015 survey) were recontacted via email (see Appendix K3 for email template). Gatekeepers were asked to:

- Identify employees who participated in the original survey and remain with the firm,
- Forward the interview invitation to those employees (emphasising voluntary participation),
- Nominate diverse cases, explicitly including "employees who stopped using tablets or expressed dissatisfaction."

All 10 shortlisted SMEs were recontacted. Eight SMEs agreed to participate (SME01, SME03, SME04, SME07, SME08, SME14, SME16, SME19). Two SMEs (SME18, SME20) did not

respond to repeated contact attempts despite both firms remaining operational. To maintain theoretical coverage, SME12 was recruited from the follow-up candidate list (Services, Capital, n=29, typical profile with moderate IS and low CI), bringing the final recruited sample to 9 participating SMEs.

Gatekeepers forwarded invitations to an estimated 36 potential participants (precise counts were not reported). 18 employees agreed to participate, yielding an approximate employee-level response rate of 50%—substantially higher than expected for cold-contact approaches and supporting the theoretical prediction (Chapter 3) that gatekeeper endorsement enhances legitimacy in Hungarian SME contexts.

Critically, all 18 participants were employees who had participated in the original 2014–2015 survey and remained at their respective SMEs, ensuring continuity and enabling longitudinal process tracing. Table 6.2 presents the final participant sample, showing coverage across sectors (3 ICT, 2 Manufacturing, 4 Services), gender (12 male, 6 female), age bands (21–30 to 50–60), and firm contexts.

Table 6.2 SME interviewee list

SME_ID	I_ID	Sector	Location	Size	Gender	Age
SME01	D01	Manufacturing	Rural	50-250	Male	41-50
	F01				Female	31-40
SME03	C01	Services	Capital	50-250	Female	31-40
	E01				Male	31-40
SME04	M01	Services	City	50-250	Male	41-50
	N01				Female	21-30
SME07	A01	Manufacturing	City	50-250	Male	41-50
	J01				Female	31-40
SME08	G01	Services	Capital	10-50	Male	41-50
	H01				Male	31-40
SME12	R01	Services	Capital	50-250	Male	50-60
	S01				Female	40-50
SME14	B01	ICT	Capital	50-250	Male	31-40
	I01				Male	21-30
SME16	K01	ICT	Capital	50-250	Male	31-40
	L01				Male	31-40
SME19	Q01	ICT	Capital	50-250	Male	21-30
	P01				Male	41-50

6.2.4 Temporal Context and Recruitment Limitations

Interviews were conducted between June and October 2021—approximately six to seven years after the Phase 1 survey (2014–2015). This solution enabled longitudinal process tracing. The temporal gap created a retrospective-prospective lens: participants reflected on their adoption experiences during the 2014–2015 period, but also discussed 2021 use patterns. The interviews revealed post-adoption trajectories, discontinuance, routinisation, and innovation evolution.

To mitigate recall bias, interview prompts anchored discussions in concrete artefacts, tasks, and incidents—specific apps, workflows, connectivity events, project contexts—rather than abstract recollections of survey responses. As Miles et al. (2014) note, memory lapses in process-tracing studies are themselves informative: what participants remember signals what they consider important. Forgotten details often indicate routinisation or abandonment. Nevertheless, the recall bias (participants may misremember 2014–2015 attitudes or experiences) is acknowledged.

Although initially viewed as a potential limitation, the six-year temporal gap provided unexpected analytical leverage:

- Process tracing: Participants could narrate how adoption dynamics evolved longitudinally;
- Stabilisation versus discontinuance: The span revealed post-adoption trajectories absent from cross-sectional designs: continued use, discontinued use, or routinisation;
- Contextual change: Participants situated tablet use within broader organisational transformations (restructuring, COVID-19 remote work shifts, technology upgrades, cloud migration), surfacing moderators unobservable in 2014–2015.

Consistent with the bias mitigation strategies outlined in Chapter 3, two specific limitations were actively addressed during recruitment and analysis:

Limitation 1: Gatekeeper filtering (success-story bias)

Gatekeepers may preferentially nominate successful adopters, creating positive case bias. To counter this, the recruitment email explicitly requested diverse cases (see Appendix K3). This strategy succeeded: analysis includes multiple divergent cases—for example, Participant M01 (SME04) stated, *"So, they [tablets] just disappeared from the office."*—and findings explicitly surface failed rollout patterns, infrastructure constraints, and innovation problems.

Limitation 2: Survivorship bias

Two SMEs from the shortlist did not respond (SME18, SME20), and within participating SMEs, employees who left due to turnover are unobservable. Findings are therefore bounded to

employees who remained at adopting SMEs for six-plus years, limiting transferability to contexts characterised by high employee turnover or organisational instability.

6.2.5 Interview Protocol

Semi-structured interviews were conducted to enable both standardisation across participants and flexibility to pursue emerging insights (Ruslin et al., 2022). A detailed interview protocol (see Appendix K2) was developed, pilot-tested with two university colleagues, and refined prior to field implementation. The protocol consisted of seven thematic modules, each with specific probes aligned to research questions and UTAUT constructs, whilst remaining open to participant-initiated directions and concrete examples.

The interview structure proceeded through key phases to facilitate narrative flow and contextual grounding:

- Opening and Consent (2–3 minutes): Ethical framing, confidentiality assurance, permission for audio recording, and the invitation to skip questions or pause at any time
- Warm-up and Role Context (2–3 minutes): Current role, key responsibilities, tenure, and typical daily tasks (field vs. office-based) to establish context and enable concrete anchoring
- Tablet Usage Profile (4–5 minutes): Access, frequency, device type, key applications, and duration of use to establish baseline device familiarity
- Critical Incidents and Task Episodes (5–6 minutes): Two concrete narratives—one where tablets clearly helped; one where they created friction—to shift from abstract attitudes to situated practices (Symon & Cassell, 1998)
- Attitudes, Continuance, and Future Intentions (3–4 minutes): Overall affect, plans to continue, and task-device fit comparisons to surface continuance mechanisms
- Innovative Behaviour and Support (4–6 minutes): Examples of new uses, peer diffusion, barriers to experimentation, and organisational support received (training, resources, governance)
- Organisational Support and Infrastructure (4–6 minutes): Reliability of connectivity, device management policies, IT support responsiveness, and governance constraints

The protocol was designed to encourage concrete examples rather than abstract opinions. Rather than asking, "What is your attitude toward tablets?", participants were asked, "Think of the last time the tablet clearly helped with your work. What happened?" This critical incident technique

anchors responses in specific tasks, applications, and outcomes, reducing recall bias and enabling process tracing (Miles et al., 2014; Ruslin et al., 2022; Symon & Cassell, 1998).

6.2.6 Interview Administration

Interviews were conducted between June and October 2021, primarily via video conferencing (Zoom, Microsoft Teams) and telephone, depending on participant preference and due to ongoing COVID-19 restrictions in Hungary. The medium was left to participants to choose.

All interviews were conducted in Hungarian, the participants' native language, to enable nuanced discussion of workplace experiences and avoid abstraction through translation. This decision reflected the importance of capturing local idiom, workplace humour, and implicit meaning that often dissolves in translation (Birbili, 2000). Immediately following each interview, the researcher completed a post-interview memo documenting non-verbal cues (e.g., hesitations, enthusiasm, engagement) and contextual observations (e.g., interruptions) relevant to interpretation.

Session duration ranged from 12 to 35 minutes (median: 24 minutes). Some participants had to conclude early due to work commitments, consistent with SME time pressures.

Audio recording and transcription proceeded as follows:

- 18 interviews were audio-recorded with explicit participant consent obtained at the start of each session.
- Recordings were uploaded to secure institutional storage (GDPR-compliant, encrypted).
- Verbatim transcription was completed by the researcher within 48–72 hours of each interview while details and context remained fresh, yielding approximately 26,000 words of interview transcript (average 1,400 words per interview).

Following best practices for cross-language qualitative research (Croot et al., 2011; Squires, 2009; Temple & Young, 2004), analysis was conducted in Hungarian to preserve semantic richness, cultural context, and participants' own meaning-making processes during the critical open-coding stage.

Working in the source language enabled the researcher to:

- Preserve workplace idioms, technical jargon, and culturally-specific expressions;
- Maintain verb aspects signalling habituality, experimentation, intention, and obligation—distinctions that are theoretically important for understanding continuance and innovation but often collapse in English translation;

- Avoid premature interpretive closure by deferring translation decisions until analytical patterns have stabilised.

Translation of First-Order Concepts and Quotes

Once the data structure stabilised (226 first-order concepts, 24 second-order themes, 4 aggregate dimensions), first-order concept labels were systematically translated into English to enable international academic readability. This translation process followed rigorous procedures:

- Initial translation of each first-order concept label from Hungarian to English, preserving closeness to participants' language
- Verification against source transcripts: Each English concept label was checked against the 3–8 Hungarian quotes it represented to ensure fidelity
- Colleague review: A bilingual colleague with qualitative research expertise reviewed a random sample of 30% of concept labels (n=68), flagging ambiguities or alternative renderings
- Backtranslation verification: Critical concepts where translation involved interpretive decisions (e.g., *magára hagyatva* = "abandoned" vs. "left autonomous") were backtranslated to confirm semantic equivalence

Similarly, illustrative quotes selected for inclusion in the findings (Sections 6.4–6.7) were translated using the same four-step process.

This approach—coding in the source language, translating analytical products—aligns with established practice in cross-language Gioia methodology research (e.g., (Mohamad Nasri et al., 2020)) and ensures both interpretive fidelity and academic accessibility.

6.2.7 Saturation Assessment: Data and Theoretical Saturation

6.2.7.1 Overview

Interviews were sequenced strategically—proceeding SME-by-SME rather than random order—to enable within-SME comparison. Two participants from each SME were interviewed consecutively (or within the same week when scheduling allowed) to maintain contextual coherence. The interview sequence followed the SME order: SME19 → SME07 → SME04 → SME12 → SME14 → SME08 → SME03 → SME01 → SME16. This ordering prioritised large-sample SMEs early (e.g., SME19, n=189; SME14, n=11) to establish baseline themes before moving to smaller or more complex cases.

Between interviews, the researcher reviewed recordings and preliminary transcripts, refining probes for subsequent interviews. For example, after SME07 participants mentioned spontaneous discovery of workaround solutions ("tricks"), subsequent interviews explicitly asked participants to describe how they shared these discoveries with colleagues, leading to the emergence of Theme 4.1 Peer Diffusion. This iterative refinement—data collection informing analytical categories which then refine subsequent data collection—is core to the Gioia methodology's inductive-abductive logic (Gioia et al., 2013; Magnani & Gioia, 2023).

For the Gioia methodology, the structured progression from first-order concepts through second-order themes to aggregate dimensions requires precise saturation assessment (Gioia et al., 2013). Following the interview sequence, a saturation curve tracked the accumulation of first-order concepts and the emergence of second-order themes across interviews. The curve reveals three distinct phases:

- Phase 1 (Interviews 1–8: SME19 → SME12): Rapid accrual of first-order concepts, reflecting diverse participant experiences and initial theme emergence.
- Phase 2 (Interviews 9–15: SME14 → SME01): Continued concept accumulation and theme refinement. By interview 15 (SME01, participant D01), approximately 90% of first-order concepts (203/226) had been identified, and no major new second-order themes emerged. This plateau indicates thematic saturation at the theme level.
- Phase 3 (Interview 16–18: SME01, SME16): The final interview yielded only narrow, firm-specific refinements to existing themes. No new second-order themes emerged, providing confirmatory evidence that the thematic structure had achieved both coding saturation (new concepts rare) and thematic sufficiency (conceptual completeness across the four aggregate dimensions).

This progression demonstrates that Gioia saturation was achieved by the sixteenth interview, with the final interview serving confirmatory rather than exploratory purposes (Guest et al., 2006). This provides methodological rigour for stopping at 18 participants: a decision grounded in evidence rather than convenience or resource constraints (Hennink et al., 2017; Malterud et al., 2016; Saunders et al., 2018).

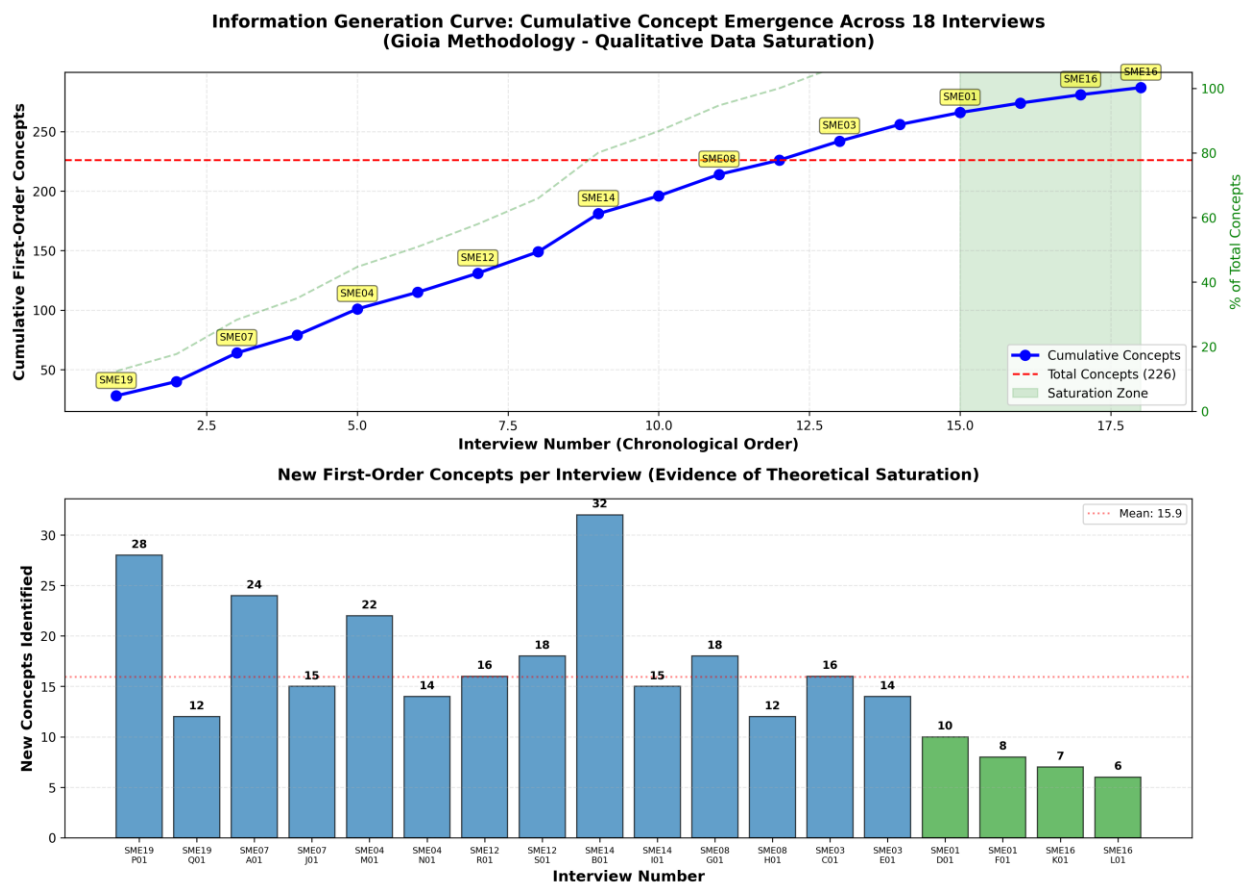
6.2.7.2 Data and Theoretical Saturation

In line with Hennink et al.'s (2017) distinction between code and meaning saturation, the pattern in Figure 6.2 indicates that data saturation was reached at the level of participants by approximately the sixteenth interview. By that point, new participants contributed additional

illustrations and firm-specific nuances, but did not yield substantively new first-order concepts or second-order themes. Interviews 17–18, therefore, functioned primarily as confirmatory cases rather than expanding the analytic space.

At the same time, the four aggregate dimensions developed through the Gioia analysis (Task–Technology Fit and Use Contexts; Technology Maturation and Adoption Trajectories; Organisational Context and Support; Constraints on Innovation) were each grounded in multiple second-order themes and supported by participants across different SMEs, roles, and usage histories. No aggregate dimension depended on a single participant or idiosyncratic firm, and additional interviews did not challenge the structure or relationships among these dimensions. On this basis, the qualitative strand is judged to have achieved theoretical saturation.

Figure 6.2 Gioia information saturation curve



6.2.7.3 Implications for Sample Size

The saturation evidence supports the theoretical prediction outlined in Chapter 3 that sample sizes of 12–20 interviews would achieve analytical sufficiency for Gioia methodology applied to

this context. The actual $n=18$ aligns with this prediction and reflects the convergence of three factors:

- Theoretically-guided sampling: Selecting extreme cases, contradictions, and maximum variation (Section 6.2.3) accelerated theme emergence compared to random sampling;
- Concurrent data collection and analysis: Iterative refinement during fieldwork enabled recognition of saturation in real time;
- Interview quality: Semi-structured interviews with concrete critical incident prompts generated rich, theoretically-relevant narratives rather than superficial responses.

6.2.8 Ethical and Governance Procedures

Consistent with the ethical framework outlined in Chapter 3, the following procedures were implemented:

- Informed Consent: Formal written consent was obtained from all participants prior to interviews, with explicit mention of voluntary participation, right to withdraw, and audio recording permissions. Consent forms were provided in Hungarian and signed before each session commenced.
- Anonymisation and Pseudonyms: All identifying information (names, email addresses) was immediately removed upon receipt of consent. Participants were assigned pseudonyms following a coding scheme (SME##_LETTER#, e.g., SME01_D01), ensuring that neither SME names nor individual identities are disclosed in reporting, tables, quotes, or appendices.
- Data Security and Retention: Audio recordings, Hungarian transcripts, and analytical files were stored in an encrypted institutional repository. Access was restricted to the researcher and, when necessary, the supervisory team. Recordings will be deleted upon thesis submission; transcripts anonymised and retained for a limited time per institutional data governance policy.
- Ethical Approval and Compliance: The study received formal ethical approval from the University Research Ethics Committee (reference: UH ECDA BUS/PGT/UH/04934, valid: 09/06/2021-01/10/2021). All procedures—recruitment, consent, data handling—conform to GDPR, and the university's research integrity guidelines.

6.3 Data Analysis Process: Applying the Gioia Methodology

6.3.1 Stage 1: Open Coding and First-Order Concepts

The analysis began with open coding of the 18 interview transcripts in MS Excel. All interviews were imported into a single worksheet, with numbered paragraphs and columns identifying the SME, interviewee and paragraph (e.g., SME08_G01_45). This produced 853 rows, which were reduced to 564 after removing interviewer prompts and metadata. Working in Hungarian, each paragraph was read line by line and assigned one or more descriptive first-order codes capturing participants' own expressions (e.g., "on and off use", "company should pay for apps", "drawing live, make tweaks"). Coding was supported by simple Excel VBA scripts to speed up sorting and filtering, but all interpretive decisions were made manually. Iterative comparison across transcripts led to consolidation of overlapping labels, resulting in 287 preliminary first-order codes that were further collapsed to 226 final first-order concepts. These concepts formed the empirically grounded base of the data structure and were later translated into English using a separate, documented translation procedure.

6.3.2 Stage 2: Axial Coding and Second-Order Themes

In the second stage, first-order concepts were grouped into higher-level, researcher-centric categories. Concepts were compared and clustered to address the question, "What broader mechanisms do these statements collectively represent in the context of tablet use in SMEs?" The UTAUT-based framework from Chapter 2 and the quantitative findings from Chapter 5 served as sensitising devices, but themes were allowed to emerge inductively from the data. Through several rounds of comparison and refinement (including checking for negative or contradictory cases), the 226 first-order concepts were first organised into 24 provisional themes and then consolidated into 14 second-order themes. Examples include Technology Evolution and Maturity (e.g., "five years ago hype only", "now can load useful apps"), Failed Organisational Rollouts ("project funded no support", "batteries dead, outdated") and COVID-Accelerated Cloud Transformation ("COVID forced acceleration", "tablet beautiful terminal"). These themes provided the main interpretive bridge between raw interview material and the aggregate dimensions.

6.3.3 Stage 3: Selective Coding and Aggregate Dimensions

The final stage involved selective coding to organise the second-order themes into a smaller set of aggregate dimensions that speak directly to the research questions. Related themes were examined together and grouped under overarching theoretical categories that captured the key socio-technical processes shaping tablet continuance and innovation. This iterative process,

conducted in dialogue with the supervisory team, resulted in four aggregate dimensions: (1) Task–Technology Fit and Use Contexts (how tablets support or constrain specific work activities), (2) Technology Maturation and Adoption Trajectories (changes in devices, applications and usage patterns over time), (3) Organisational Context and Support (company-level enablers and barriers to tablet use) and (4) Innovation-Oriented Behaviours and Emergent Use (experimentation, peer diffusion and constraints on innovation). Together, these dimensions structure the findings reported in Sections 6.4–6.7. A more detailed, step-by-step account of the Gioia coding procedures, including additional examples and tables, is provided in Appendix L. The next section introduces a worked example of the process described.

6.3.4 Worked Example of Gioia Coding

To illustrate the coding process described in Sections 6.3.1–6.3.3, this section traces a single thematic thread—ecosystem and platform maturation—from raw interview data through to its placement in the aggregate data structure. The example draws on participants’ accounts of how tablet capabilities changed between 2014–15 and 2021, which later informed Theme 2.1 Ecosystem and Platform Maturation within Aggregate Dimension 2: Technology Maturation and Adoption Trajectories.

First, three illustrative excerpts are presented (describing the evolution of tablet and ecosystem capabilities over time):

“[in 2015] even multitasking was a problem, but this one I bought last year has a better OS, much better, can multitask [...] five years ago it was a lot of hype and very little action [...] Now you can actually load up useful stuff, project management apps.” [SME04_N01_13] [SME04_N01_15] [SME04_N01_16]

“At that time it was quite basic. You just had the same applications like you have on your mobile phone. The only difference was that you would have a bigger screen... Now iPad Pro can use everywhere, take notes easily like notebook.” [SME03_E01_12] [SME03_E01_13]

“Five years ago, the dream was bigger than the reality. The ecosystem was still limited. The software often felt like just a blown-up phone app, not a dedicated tablet experience. [...] The gap is closing now. The hardware has become incredibly powerful” [SME16_K01_27] [SME16_K01_28]

In **Stage 1 (open coding)**, these excerpts were coded as separate first-order concepts capturing participants’ own language (e.g. “basic apps only, like a phone”, “multitasking was a problem”, “dream bigger than reality; now powerful hardware”). In **Stage 2 (axial coding)**, these concept

labels were compared across interviews and clustered into the second-order theme Ecosystem and Platform Maturation, which synthesised how improvements in hardware, platform capabilities, applications and the wider tablet ecosystem over time transformed perceived usefulness and task–technology fit. In **Stage 3 (selective coding)**, this theme was then grouped with other temporally focused themes under Aggregate Dimension 2: Technology Maturation and Adoption Trajectories, which captures broader patterns in how tablet-related technologies matured and diffused over time.

Table 6.3 summarises this worked example, showing the full Gioia ladder from raw quotes through to the aggregate dimension.

Table 6.3 Gioia ladder worked example

Illustrative quote (translated)	First-order concept (English label)	Second-order theme	Aggregate dimension
"[in 2015] even multitasking was a problem, but this one I bought last year has a better OS, much better, can multitask [...] five years ago it was a lot of hype and very little action [...] Now you can actually load up useful stuff, project management apps." [SME04_N01_13] [SME04_N01_15] [SME04_N01_16]	Early limitations vs later full-task capability	Ecosystem and Platform Maturation (Theme 2.1)	Technology Maturation and Adoption Trajectories (Dim. 2)
"At that time it was quite basic. You just had the same applications like you have on your mobile phone. The only difference was that you would have a bigger screen... Now iPad Pro can use everywhere, take notes easily like notebook." [SME03_E01_12] [SME03_E01_13]	Early basic phone-like apps; poor fit for professional note taking. Over time improved notetaking.	Ecosystem and Platform Maturation (Theme 2.1)	Technology Maturation and Adoption Trajectories (Dim. 2)
"Five years ago, the dream was bigger than the reality. The ecosystem was still limited. The software often felt like just a blown-up phone app, not a dedicated tablet experience. [...] The gap is closing now. The hardware has become incredibly powerful" [SME16_K01_27] [SME16_K01_28]	Dream–reality gap; subsequent hardware and performance maturity	Ecosystem and Platform Maturation (Theme 2.1)	Technology Maturation and Adoption Trajectories (Dim. 2)

6.3.5 Gioia Aggregate Dimensions and Themes

Table 6.4 presents the complete data structure, organised left-to-right from first-order concepts (raw participant observations and experiences) through second-order themes (interpretive

patterns identified by the researcher) to aggregate dimensions (theoretical categories). Reading across the table traces how raw data progressively aggregates into increasingly abstract analytical levels. For each second-order theme, 2 quotes are given – additional quotes for each theme are provided in Appendix M.

Table 6.4 Gioia data structure from first-order concepts to aggregate dimensions

First-Order Concepts (samples)	Second-Order Theme	Aggregate Dimension
Reading, Watching video, Note taking	1.1 Reading & Light Documentation	1. Task-Technology Fit and Use Contexts
Sharing during meeting, No wall during meeting	1.2 Meetings & Collaborative Work	
Salesreps client visit, Warehouse checking	1.3 Role-specific Workflows	
Need laptop for serious work, Cant divide screen	1.4 Boundaries for Complex Work	
Years ago hype, Now more useful	2.1 Technology and Device Maturation	2. Technology Maturation and Adoption Trajectories
COVID forced cloud, Tablet terminal to cloud	2.2 COVID-Accelerated Cloud Transformation	
On and off use, Periodical use	2.3 Discontinuous Usage Patterns	
Management support, Peer learning, Training	3.1 Organisational Support Mechanisms	3. Organisational Context and Support
Connectivity (WI-FI), Device management	3.2 Infrastructure Constraints	
Funded no support, Outdated device	3.3 Failed Organisational Rollouts	
Standardised for tasks, Long term use	3.4 Successful Organisational Rollouts	
Show apps to each other, Share apps	4.1 Peer-Driven Innovation Diffusion	4. Innovation-Oriented Behaviours and Emergent Use
Implement new apps, Play and find solution	4.2 Emergent Innovation Processes	
Restrictive enviroment, Cant install anything	4.3 Constraints on Innovation	

6.4 Aggregate Dimension 1: Task-Technology Fit and Use Contexts

6.4.1 Introduction

Analysis of the interviews began with the missing piece from the quantitative phase: the concrete work tasks for which employees actually used tablets. The survey captured attitudes,

expectations, and continuance intentions, but not the situated activities in which tablets were applied. During the interviews, it became immediately clear that “tablet use” was not a single phenomenon; participants described very different task profiles depending on role, setting, and workflow.

To make sense of these patterns, the Aggregate Dimension 1 is supported by the Task-Technology Fit (TTF) theory (Goodhue & Thompson, 1995; Marikyan & Papagiannidis, 2023). The TTF theory considers that the impact of a technology arises not from its features alone, but from how well it aligns with users' specific tasks and work contexts (Goodhue & Thompson, 1995).

The themes in this dimension, therefore, trace how tablets are woven into everyday work: from reading and light documentation, through meetings and collaborative work, to role-specific field and service workflows, and finally to the point where complex tasks still require traditional PCs. This task-level perspective provides the empirical foundation for understanding why continuance and innovation are concentrated in certain work slices rather than being evenly distributed across employees and activities.

The very first theme emerged as a core use of tablets: media consumption was mentioned by most participants.

6.4.2 Theme 1.1 Reading & Light Documentation

The predominant use for tablets in the workplace was content consumption and simple documentation. Tablets were routinely employed for reading reports, technical documentation, training videos, answering emails, and annotating PDFs with a stylus:

“[...] mostly just used it for watching training videos or something of that sort or reading.”
[SME01_D01_25]

“Its part of my daily routine, I check news, do some basic stuff, communicate, email on it.”
[SME01_F01_23]

These foundational activities build initial positive attitudes and confidence, aligning with prior research documenting the gateway role of reading and information consumption in tablet adoption across user groups (Henderson & Yeow, 2012; Magsamen-Conrad et al., 2015). Even users sceptical of complex tablet deployment recognised the device's superior reading and annotation capabilities:

“[...] I like tablets. They’re excellent for media consumption and light productivity.[...] But if I’m honest, the impact on our company was limited.[...] Comfortable reading—reports, specs, annotated PDFs.” [SME07_A01_25] [SME07_A01_30]

Consumption tasks set a stable core for continuance: their high frequency and low friction ensure the tablet remains a convenient option, even among ambivalent users. Leisure uses such as crosswords and news checking were also noted, but these sustained the core value proposition through ease-of-use rather than expanding tablet deployment.

However, media consumption tasks represent only the individual, largely one-way use of tablets. Once the conversation moved to shared work, participants shifted from convenience and readability to the social dynamics of device use. The next theme, therefore, moves from solitary reading to meetings and collaborative work.

6.4.3 Theme 1.2 Meetings & Collaborative Work

Participants recounted the unique role of tablets in meetings. Unlike laptops, which introduce physical and psychological barriers ("building a wall"), tablets facilitate open, collaborative environments:

“In a meeting, we can pull up a Miro board or a Figma design, and everyone can interact, sketch, and leave notes on their own device. It breaks down the barrier of one person presenting from a laptop.” [SME19_P01_43] [SME19_P01_44]

“And you can’t go into a meeting with a computer or notebook, it is not possible. It separates you from the others, so its not a good impression. Tablet is good in that sense.” [SME03_E01_24]

The tablet’s flat form factor, shared viewing angles, and portability encourage social transparency and direct interaction. Prior research has found that tablets and smartphones engender more positive social perception in group contexts than laptops (Oulasvirta et al., 2012). This collaborative affordance extends TTF beyond individual performance to encompass what might be termed social task-technology fit (Lu & Yang, 2014): contexts where group outcomes and interpersonal dynamics, not solely individual productivity, drive technology value.

From a practical perspective, organisations should leverage tablets’ collaborative affordances—pairing them with large displays for projection, training in shared annotation tools, and positioning tablets as meeting devices distinct from productivity laptops.

While meetings revealed tablets’ value in general organisational settings, subsequent findings revealed that the greatest performance gains and continuance intention emerged not in broad

deployment contexts but in highly specialised, role-specific workflows where tablets' unique characteristics aligned precisely with task requirements.

6.4.4 Theme 1.3 Role-specific Workflows

In role-specific situations, tablets were not just generic devices, but workflow appliances integrated with systems such as ERP, CRM, and inventory management. The participants described situations where task requirements encompassed more than information processing: portability, instant availability, and environmental ruggedness—all dimensions where tablets outperform laptops:

“Retail POS audits: Pull daily sales, reconcile cash vs card, attach evidence photos.[...] Document capture and OCR: Invoices, delivery notes, receipts—auto-crop and send to our accounting pipeline.” [SME14_B01_57] [SME14_B01_58]

“Niche excellence: rugged tablets for warehouses, retail POS, and field service—those will keep growing.” [SME07_A01_54]

Outside traditional office contexts—especially in field operations and design work—tablets replaced clipboards and cumbersome laptops. The mechanism through which field contexts amplify CI is twofold: substitution (e.g., tablets replace clipboards, eliminating paper-digital transcription steps) and enablement (e.g., tablets enable workflows infeasible with laptops, such as real-time inventory updates). Similar patterns have been documented in organisational mobile technology adoption, showing that functional capabilities interact with organisational characteristics (work location, time criticality) to determine performance impacts (Liang et al., 2007; Yuan et al., 2006). Substitution delivers incremental productivity gains; enablement delivers workflow transformation. Lee et al. (2017) documented sector-specific tablet adoption patterns showing that verticals with highly standardised, repetitive workflows (retail point-of-sale, healthcare patient intake, hospitality ordering) achieved higher adoption rates and productivity gains than knowledge-work sectors.

Tailored apps enabled improved processes and creative workflows, often producing transformative performance gains:

“The unit’s sales representatives have notebook computers, but we rarely bring them on sales calls because the devices are too bulky [...] When our salespeople walk into shops, the people managing the counter are dealing with customers. [...] We’re fighting for their attention. [...] iPads make it easy.” [SME07_J01_9]

Stylus input in design workflows approximates traditional artistic tools (drawing, erasing, pressure sensitivity) while adding digital affordances (undo, layers, infinite canvases). Hinckley et al. (2009) documented in their Codex dual-screen tablet research how stylus-enabled tablets unlock creative workflows through direct manipulation and haptic feedback that keyboard-mouse interfaces cannot replicate, creating what designers describe as “*best of both worlds*” [SME19_Q01_16].

Organisations should prioritise tablet deployment in domains where mobility, creative workflows, or standardised niche apps deliver the greatest return. App ecosystem maturity in relevant verticals should guide deployment decisions.

This specialisation principle extends in one critical direction: the same characteristics that make tablets ideal for field and creative work simultaneously disqualify them for others. Participants drew sharp, consistent boundaries around complex analytical, programming, and intensive production work—contexts where laptops and desktops remained indispensable.

6.4.5 Theme 1.4: Boundaries for Complex Work

Participants described clear limitations in using tablets for complex, input-heavy tasks:

“It’s a tool for a very specific job. My phone is for communication. My laptop is the factory floor—that’s where the actual work gets done. The tablet is caught in the middle. [...] and for any serious work—I mean juggling twenty browser tabs, complex spreadsheets, or writing a proper report—the tablet is simply inefficient. You need a real keyboard and a trackpad for that kind of speed.” [SME12_R01_13]

“For serious programming, you need a proper keyboard, multiple large screens, and the processing power and flexibility of a desktop OS.” [SME16_K01_35]

Complex analytical, multi-window, and programming work consistently pushed users back to laptops and desktops. These realities define a natural boundary condition for the Continuance Intention construct: for many, the device “fits” only a certain slice of their working life.

Lin and Wang (2012a) documented similar task complexity ceilings in e-learning contexts, showing that simple content delivery tasks exhibited high TTF for tablets, but complex analytical tasks (e.g., multi-source integration) required desktop environments. Zhou et al. (2010) integrated TTF with UTAUT to explain mobile banking adoption, finding that task complexity acted as a moderator—simple transactions (balance checks) showed positive fit, but complex operations

(loan applications requiring document uploads and multi-page forms) triggered device abandonment and laptop reversion.

These boundaries reflect not only the practical limits of device capabilities—screen size, input modality, processing power—but also a distinctly human dimension: professional identity and occupational self-image.

“But if you are in software development or have deeper interaction with software, then you just cannot use [the tablet].” [SME19_Q01_19]

This highlights that perceived device misfit is as much an identity and culture issue as it is about utility. Symbolic appropriation—where adoption reflects alignment with occupational identity and professional community norms—explains this resistance (Boudreau & Robey, 2005). Carter et al. (2020) demonstrated empirically that individuals' technology-related self-concepts moderate relationships between system characteristics and usage intentions; those identifying as 'power users' or 'tech experts' evaluate technologies through identity-congruence lenses, accepting or rejecting based on symbolic fit with professional self-image. Symbolic appropriation and social categorisation thus create a dual-fit requirement: technologies must align with both task requirements and users' professional group norms.

Realistically, the tablet fits a specific slice of working life. In essence, the boundaries outlined here reflect not only task complexity but fundamental modality misalignment between how accountants, programmers, and knowledge workers need to interact with information and how tablets facilitate that interaction.

6.4.6 Aggregate Dimension 1 Synthesis

Across these four contexts—consumption, collaboration, specialised workflows, and boundaries—task-technology fit emerges not as a fixed property of tablets but as a dynamic interplay between device affordances, task characteristics, user identity, and organisational context. These themes demonstrate that PE is not device-global but task-segmented. Employees do not form undifferentiated judgments about whether “tablets are useful”; instead, they assess tablet performance relative to specific work activities.

Reading and light documentation tasks (Theme 1.1) show consistently high fit across roles. Meeting contexts (Theme 1.2) reveal modality-specific advantages: the tablet enables note-taking, client presentations, and collaborative visibility. Role-specific workflows (Theme 1.3) demonstrate how tablets are embedded in particular professional contexts. At the same time, Theme 1.4 shows that there are complexity boundaries.

When asked about continued tablet use during the 2021 interviews, respondents frequently referenced their primary or most frequent use case rather than averaging across all work activities. Sales representatives pointed to client meetings; operations staff highlighted field inspections; administrative roles mentioned documentation review. This suggests that global continuance decisions may be anchored to specific high-frequency task contexts rather than reflecting uniform assessments. At the same time, these considerations raise a measurement question central to interpreting the 2015 quantitative model: Does the survey's global PE measure reflect task-specific assessments weighted by importance, or continuance decisions anchored to dominant work activities?

Theoretical foundations support the plausibility of task-segmented PE: task-technology fit theory (Goodhue & Thompson, 1995) proposes that employees assess tools relative to specific task requirements rather than abstractly. However, the interview findings that respondents are anchored to particular high-frequency tasks have important implications for how survey responses should be interpreted. If employees' continuance decisions reflect their experience with dominant work activities primarily, then understanding the PE→CI pathway requires distinguishing between dominant-task anchoring and portfolio-wide averaging—a measurement interpretation question Chapter 7 addresses.

From a practical perspective, organisations should explicitly avoid positioning tablets as universal laptop replacements. Instead, adoption should be framed around specific use cases—meetings, travel, creative workflows, and field operations—where evidence demonstrates high fit. This targeted positioning manages user expectations, prevents disappointment when devices encounter “complexity ceilings”, and sustains positive attitudes towards tablets within their intended niches.

Participants consistently contrasted their 2015 experiences with their 2021 realities, suggesting that the fit between tablets and work tasks is not static but evolves as both technology and organisational practices mature. The following dimension traces how the technology and its perceived value changed over this period.

6.5 Aggregate Dimension 2: Technology Maturation and Adoption Trajectories

6.5.1 Introduction

These trajectories over time—from early hype in 2014–2015 to a more mature technology by 2021—sit at the centre of the second Aggregate Dimension. The task–technology fit patterns

documented in Dimension 1 are not static properties of tablets; they are dynamic outcomes shaped by temporal evolution. Participants described their experiences in 2015 ("a lot of hype, very little action") very differently from their assessment in 2021 ("now you can actually load useful stuff").

The first strand of this temporal story concerns the maturation of tablet technology and ecosystems over time, to which the next section now turns.

6.5.2 Theme 2.1: Ecosystem and Platform Maturation

A stark contrast emerged between participants' assessments of tablets in 2015 versus 2021. Multiple respondents described the 2014-2015 period as characterised by "hype" that failed to match reality, whereas contemporary devices were viewed as having matured sufficiently to enable genuinely productive work. Three layers are distinguished: software applications refer to individual applications used for work, such as note-taking or collaboration tools; platform refers to the operating-system and system environment, such as iOS/iPadOS or Android; and ecosystem refers to the broader interdependent environment of hardware, platform capabilities, software applications, accessories, cloud infrastructure and complementary services.

"[in 2015] even multitasking was a problem, but this one I bought last year has a better OS, much better, can multitask [...] five years ago it was a lot of hype and very little action [...] Now you can actually load up useful stuff, project management apps." [SME04_N01_13] [SME04_N01_15] [SME04_N01_16]

These accounts reveal that PE is temporally contingent. In 2015, tablets may have lacked the broader ecosystem support necessary to fulfil (over)promised productivity gains. This possibly dampened PE regardless of organisational support or individual attitudes. By 2021, the overall technology changes transformed the value proposition.

The ecosystem evolution was particularly evident in business-critical applications:

"As of 2021, the tablet itself wasn't 'innovative' anymore—it was mature. The innovation was in workflows: better note-taking with cloud sync, e-signature, live collaboration in docs." [SME07_A01_48]

This finding extends the TTF theory by demonstrating that "fit" is not solely determined by alignment between task requirements and device affordances at a single point in time, but evolves as ecosystems mature (Gebauer & Ginsburg, 2009). Early adopters in 2014-2015 encountered more negative TTF not because their tasks were inherently unsuitable for tablets, but because

ecosystem immaturity created capability gaps. The same tasks exhibited better fit assessments six years later as platform capabilities, business applications and the overall tablet ecosystem matured.

The mechanism underlying this transformation is ecosystem interdependence: tablets' productivity value depends not just on hardware specifications or individual software applications, but on the maturity of the surrounding ecosystem: the availability of complementary enterprise apps, cloud infrastructure, synchronisation services, and accessories such as styluses, keyboards, and mounting solutions working in concert. In 2015, this ecosystem was incomplete; by 2021, maturation across all components enabled better role-specific workflows documented in Dimension 1, Theme 1.3.

As for the future of tablets, participants emphasised the convergence of devices:

"I don't see them replacing laptops in a business context. I see them being absorbed. Look at new laptops—many have touch screens and support styluses. The devices are converging. The future for the pure tablet is in those niche, vertical B2B deployments I mentioned, and as a media consumption device at home." [SME12_R01_34]

Ecosystem maturation followed a gradual trajectory from 2015 through 2019, but the COVID-19 pandemic triggered a discontinuous acceleration. The next section examines how forced remote work, rapid cloud migration, and reconfigured workflows fundamentally transformed what tablets could accomplish in everyday tasks.

6.5.3 Theme 2.2: COVID-Accelerated Cloud Transformation

The advent of cloud services, accelerated by COVID-19, fundamentally shifted the meaning of "task fit". With computation and storage offloaded, the tablet was reconfigured from a standalone device into a portal into cloud-based systems.

For participants working from home (and in cloud-ready SMEs), the pandemic was described as a tipping point:

"[...] COVID forced acceleration to cloud, game-changer [...]" [SME19_P01_26]

"Covid helped. Lots of red tapes were quickly cut and suddenly I could connect from home freely." [SME14_I01_32]

In these firms, enforced remote work prompted rapid migration to cloud services and remote desktop environments, effectively dissolving some of the earlier boundaries between "tablet tasks"

and “PC tasks”. However, where cloud infrastructure remained underdeveloped, the pandemic had little impact on tablet work:

“Well, actually, Covid didn’t change things either. Of course, we worked from home a lot, but everyone worked from home and from the computer. Sometimes I used it [the tablet].”
[SME08_G01_33]

Cloud enablement thus broke through former task–device limitations and extended tablets’ reach into domains (database access, coding, server maintenance) that previously required desktops. This points to infrastructure as a moderator of task–technology fit: the same device–task pairing, assessed in pre-cloud versus post-cloud contexts, yields fundamentally different fit judgements. Marston et al. (2011) theorized this shift as moving from “fat client” to “thin client” computing paradigms, where processing and storage migrate from local devices to remote servers, decoupling performance from endpoint hardware specifications. Sultan (2011) documented similar cloud-enabled transformations in SMEs, where constrained capital budgets for desktop workstations were partially offset by cloud subscriptions providing enterprise-grade computing accessible through inexpensive endpoints.

The mechanism through which cloud infrastructure transforms TTF is computational offloading. Tasks that previously required substantial local storage and processing (e.g. video editing, database queries, server management) become feasible on tablets once computation occurs server-side and the device functions primarily as a high-resolution terminal for input and display. As a result, the TTF bottleneck shifts from device capability to network reliability. In pre-cloud SMEs, PE is limited by device specifications; in cloud-enabled SMEs, PE is increasingly contingent on network bandwidth and latency.

Together, these accounts show how pandemic-driven cloud adoption did not simply increase tablet usage volume, but qualitatively redefined what “fits” on a tablet, setting the stage for the more cyclical and discontinuous usage patterns explored in the next theme.

6.5.4 Theme 2.3: Discontinuous Usage Patterns

6.5.4.1 Theme Introduction

Rather than following the stage-based progression assumed by classic adoption models, many participants described “on–off” usage patterns in which tablets cycled between intensive use and extended dormancy. Post-adoption did not mean steady routinisation; instead, use spiked around particular tasks or periods and then dropped back again:

"Sometimes I don't use it for a week, then charge it and use it for a week, on and off really."
[SME01_D01_52]

"[using the tablet] on and off for a decade. Daily during travel or when I'm moving between the factory and the office. If I'm desk-bound, it's less central." [SME07_A01_19]

These accounts already complicate simple categories of "adopter" versus "non-adopter": the same device moves in and out of the foreground as work contexts change.

6.5.4.2 Mechanisms driving discontinuous use

Two key mechanisms underpinned these cyclical patterns.

A. Role transitions and task shifts

When employees moved into roles with different task profiles, tablet utility changed accordingly. The same device that offered little value in spreadsheet-intensive office work became central in client-facing, mobile, or meeting-heavy roles:

"I use it every day, but in bursts. I'll have it with me in all my meetings, which can be two to three hours a day. I'll use it for maybe 30 minutes to review documents or test a build. Then it might sit on my desk for hours while I'm coding on my main computer. So, it's not continuous use"
[SME16_K01_31]

Warehouse workers also described how their daily duty cycle shaped discontinuous tablet use. Similarly, in project-based environments, tablets were drawn into particular phases (e.g. design, client interaction) and receded during back-office work.

B. Infrastructure and access fluctuations.

Connectivity gaps or temporary loss of app access created enforced dormant periods. Once technical issues were resolved, use often resumed:

"On tablets, preloaded templates are good. Ticking a webpage questionnaire, selecting dropdown boxes for some manufacturing stuff is good. [...] Wi-Fi sometimes drops, floors are tricky. [...] Also it has to match the local infrastructure." [SME01_D01_42] [SME01_D01_43]
[SME01_D01_57]

These limitations are enforced by the enterprise infrastructure, unlike the role transitions or task shifts. Infrastructure constraints will be further discussed in Theme 3.2.

6.5.4.3 Discontinuity as rational adaptation

Crucially, participants did not frame these on–off patterns as failure or rejection. One trajectory illustrates temporary dormancy followed by renewed, role-driven uptake:

"I got bored after a couple of months, I did not use it extensively [...] Then I got into the design/drawing team and it really got a lot more useful. [...] And now, I am using it again for a lot of note taking as well." [SME03_C01_29] [SME03_C01_32] [SME03_C01_37]

In such cases, the tablet remained available in the background, ready to be pulled back into active use when task–technology fit improved. Discontinuous usage, therefore, appears as rational task-matching over time, rather than inconsistent commitment. It suggests that continuance in this context is better understood as readiness to re-engage when fit is high than as a commitment to steady daily use. These examples point to tablet use as an adaptive, context-sensitive process in which engagement rises and falls with changing roles and infrastructures. The implications of this more flexible notion of continuance are developed further in the Dimension 2 synthesis and in Chapter 7.

6.5.5 Aggregate Dimension 2 Synthesis

Across the interviews, time emerged as a critical dimension of tablet adoption and continuance. Participants contrasted early experiences of “hype with little action” around 2014–2015 with more selective, purposeful use by 2021. These interviews suggest that task–technology fit is not a static property of tablets but an evolving relationship shaped by device capabilities, cloud infrastructure, and shifting work practices. What counted as a “good fit” in 2015 was often re-evaluated in light of later hardware generations, richer app ecosystems, and the rapid normalisation of remote work.

Taken together, the themes in this dimension point to two interconnected temporal phenomena:

A. Temporal Contingency of Performance Expectancy

Improvements over time in hardware, operating systems, and specialised apps gradually expanded the range of tasks that could be credibly performed on tablets. COVID-accelerated cloud migration represented an inflexion point in this trajectory. Once core business systems and remote desktop solutions moved to the cloud, tablets were reconfigured from limited, standalone devices into high-resolution portals into powerful remote servers. This transformation dissolved earlier task boundaries (e.g. database access, server administration, complex document handling), shifting the bottleneck from local device specifications to

infrastructure quality (bandwidth, latency, security policies). Performance Expectancy changed over time, based on overall technology maturation and capabilities.

B. Discontinuous, context-triggered usage patterns

Instead of progressing neatly from adoption to routinisation and stable infusion (Cooper & Zmud, 1990; Rogers, 2003), tablet use followed cyclical “on–off” patterns. The same device moved into the foreground during particular roles (field work, client-facing activities), projects (design phases, workshops), and receded during desk-bound, input-heavy tasks. Tablet use in these interviews exhibited adaptive structuration (DeSanctis & Poole, 1994; Schmitz et al., 2016; Shao & Li, 2022): employees iteratively appropriate technology based on shifting task demands, organisational contexts, and personal circumstances rather than following predetermined stages. Periods of dormancy did not necessarily indicate rejection; tablets often remained ready to be reactivated when task–technology fit improved, or when connectivity and organisational policies caught up.

These temporal dynamics identify important boundary conditions relevant to interpreting the quantitative results. The PE → CI relation was formed during a specific technology and usage cycle (2014-15 early adoption, immature ecosystem). Six years later, the same task-device pairings showed improved PE, suggesting that temporal context (ecosystem maturity) may be a moderating factor. Whether this ecosystem evolution actually altered the PE→CI pathway strength would require longitudinal measurement.

The interviews reveal that UTAUT-style constructs (that are treated as static in the survey model) are, in practice, temporally contingent judgements. Theoretically, this dimension therefore reframes tablet continuance in SMEs as a temporal, episodic process rather than a one-off post-adoption decision.

These temporal dynamics complicate direct integration between 2015 quantitative findings and 2021 qualitative insights. The ecosystem maturation documented here means that contemporary tablet capabilities, task-technology fit assessments, and organisational infrastructures differ substantially from early-adoption contexts. Chapter 7 addresses this challenge further.

Practically, these findings suggest that organisations should not interpret dips in daily usage as a failure. These are simply signals of shifting fit that can be addressed through targeted interventions (if necessary): aligning tablets with emerging roles and projects, timing training to coincide with hardware and cloud upgrades, and designing policies that make it easy for employees to “pick tablets back up” when circumstances change.

These temporal patterns do not unfold in a vacuum. They are enabled or constrained by organisational choices. The next dimension turns to this organisational context, examining how management practices and digital maturity shape whether evolving technologies and episodic usage patterns translate into sustained, value-adding tablet use.

6.6 Aggregate Dimension 3: Organisational Context and Support

6.6.1 Introduction

The situations documented in Aggregate Dimensions 1 and 2 unfold within organisational contexts that either enable or constrain sustained use. This dimension progresses through three interconnected themes: organisational support mechanisms (training and management resources), infrastructure and governance constraints (technical systems, infrastructure policies, device lifecycle), and integration outcomes (success or failure). This progression mirrors organisational decision-making: a) what support do organisations provide? b) what barriers exist? and c) what does success (or failure) look like?

6.6.2 Theme 3.1: Organisational Support Mechanisms

In terms of support, two elements stood out in participants' accounts: (i) how people learned to use tablets (training and peer learning), and (ii) how management backed that use with resources and policies.

6.6.2.1 Training and Peer Learning

Training provision ranged from formal programmes to informal, peer-based knowledge sharing. Crucially, participants distinguished between training as a one-off event and as an ongoing capability:

"Sure, there was training at the beginning and then we were showing each other tricks."
[SME01_D01_37]

While formal sessions helped initial uptake, peer support transmitted situated practices—"here's how we use this for our warehouse workflow"—which proved immediately applicable and task-relevant:

"And I could always ask my colleagues, so they would show if there were some new tricks and those became used by everybody." [SME01_F01_22]

Successful organisations institutionalised peer learning into regular team meetings, creating deliberate "show-and-tell" moments where employees demonstrated workarounds and

techniques. These accounts imply that training should extend beyond rollout to sustain continuance. Consistent with Schepers and Wetzels (2007), social influence mechanisms—including peer support—can materially shape technology acceptance and ongoing use.

6.6.2.2 Management Support

Management support operated inconsistently across SMEs, revealing a critical distinction between symbolic endorsement (managers stating support for tablet use) and material provisioning (e.g., budgets for apps).

"[...] management supports it that we use it." [SME01_F01_13]

Where endorsement was not matched by resources or clear responsibility, progress stalled.

"Well, officially there is no tablet support, [...] I can go to the IT department and ask, but officially there's no support for the tablet." [SME08_H01_12]

Taken together, training/peer learning and managerial resourcing act as proactive organisational enablers: this is what organisations do to facilitate adoption and continuance. In the quantitative model, these elements map onto the innovation-support constructs (IS, IF) and are revisited in Theme 4.3. At the same time, even strong enablement can be blunted by structural barriers—notably infrastructure limitations and non-existent lifecycle management—which the next theme examines.

6.6.3 Theme 3.2: Infrastructure Constraints

Technical infrastructure and IT governance policies created persistent friction that undermined both Performance Expectancy and Effort Expectancy, often overwhelming positive attitudes or innovation intentions.

6.6.3.1 Technical Infrastructure: Connectivity

Wi-Fi reliability emerged as daily frustration that overshadowed tablets' inherent affordances:

"Mind you, Wi-Fi is a key for using these devices." [SME03_C01_64]

Participants were explicit about the mechanism: tablets' value is infrastructure-dependent. Unlike laptops with robust local processing and offline capability, tablets optimised for connected workflows depend critically on reliable networks. When Wi-Fi failed, apps stalled and synchronisation broke; users reverted to alternatives.

6.6.3.2 Device Lifecycle Management

Constraints extended beyond networks to fleet management. Practices varied widely across organisations. Positive experiences were tied to planned refresh cycles:

"My iPad was replaced a couple of times, getting better, faster, easier to use." [SME03_C01_33]

Device lifecycle management functions as an organisational infrastructure equivalent to network connectivity. Organisations institutionalising systematic 3-4 year hardware refresh cycles maintained possibly high PE and CI over time as employees experienced continuous performance improvements. Where no lifecycle was managed, predictable decay set in:

"It slowly faded away. The iPads got older, the batteries started to fail, and the operating systems became outdated." [SME04_M01_33]

Mechanistically, compound capability erosion drives PE and CI decline over time: hardware degradation (battery life, processor speed) combines with ecosystem advancement (new app versions requiring newer OS; discontinued support for older devices) to widen performance gaps. In UTAUT terms, this is a temporal decay within Facilitating Conditions (FC): what begins as high FC (functional, current devices) deteriorates predictably without active organisational management. The next themes emerged as partly a consequence of Theme 3.1 and 3.2, describing a coherent story of how tablets succeeded (or failed) in organisations.

6.6.4 Theme 3.3: Failed Organisational Rollouts

Several SMEs described a common failure mode: large, hardware-centric procurements that were not matched with software, training, or support. Initial enthusiasm gave way to rapid decay, with devices drifting into personal or entertainment use and the initiative acquiring the label of "another failed IT project". Across cases, the sequence played out in a similar way:

- Bulk hardware purchase (either external or internal funding)
- Initial employee enthusiasm
- Hardware-only provision (no apps, training, support budgets)
- Capability stagnation and decay (2-3 years): batteries degrade, no replacements
- Appropriated for home use (entertainment / family devices)
- Organisational abandonment and reputational damage

One participant described these events with their own words:

"[...] it was a big project and in this big project we practically got a lot of hardware, there were computers, several computers and tablets, so this is how it came together. [...] The project

practically only brought in the hardware so we got everything but there wasn't much software [...] there was no official support for this [the tablet] [...] In the end, [results are] nothing really. I mean, I always use my tablet for watching movies." [SME08_G01_9] [SME08_G01_10]

Participants shared their negative experiences after the 2014-15 rollout:

"There was a lot of excitement; it was the "cool" new thing to have. But there was no real strategy behind it. The IT support was basic, and there was no business case for integrating them into our core processes." [SME12_R01_17]

Mechanistically, failure stemmed from resource misalignment: capital expenditure on hardware without operational budgets for apps, integration, training, support, ownership, and timely replacement. In UTAUT terms, Facilitating Conditions (FC) briefly spiked at rollout (new devices) but collapsed quickly as enabling resources were absent; PE and EE degraded accordingly. The reputational hangover was tangible: by 2021, several participants reported scepticism towards new initiatives:

"Most people, I am sure, just took them home. They probably ended up with their family or kids for playing games and watching videos. [...] The money for a tablet could be better used for a more powerful laptop for an engineer, for example." [SME04_M01_35] [SME04_M01_43]

A markedly different opinion emerged in successful rollouts, as the next theme shows.

6.6.5 Theme 3.4: Successful Organisational Rollouts

Contrasting sharply with failed implementations, several organisations achieved deep, productive tablet integration by redesigning workflows around tablet affordances and sustaining support over time. One case illustrates the approach succinctly:

"At work we standardised on iPads for field staff and a mix of rugged Android tablets for warehouse and shop-floor tasks.[...] Inventory counts & cycle counting: Scan barcodes/QRs, adjust counts, capture shelf photos. " [SME14_B01_7] [SME14_B01_56]

Tangible gains followed from these tailored workflows:

"Our cycle counts used to take a full day with paper forms, [...]. With tablets + barcode sleds, the same count is done in half a day, and the system is updated immediately. The interface shows product photo, last count, expected quantity, and variance thresholds—if someone scans the wrong item, they see it instantly. Training new hires dropped from days to hours." [SME14_B01_72]

Successful integration required sociotechnical co-design—simultaneous attention to technical systems (infrastructure, governance), organisational processes (workflow redesign, resource allocation), and human capabilities (training, support structures). This aligns with sociotechnical systems theory (Orlikowski, 1992) and validates the DASAT framework's emphasis on implementation adaptations as a prerequisite for technology infusion (Kahveci, 2025).

Organisations that treated tablet deployment as purely technical (provision of devices + generic training) failed; those treating it as sociotechnical transformation succeeded. As Greenhalgh et al. (2017) documented in their review of healthcare IT adoption, implementation effectiveness depends on alignment between technology properties, organisational structures, and work practices—no single factor suffices.

6.6.6 Aggregate Dimension 3 Synthesis

Across the four themes, organisational context acts as a multi-level system of enablers and constraints that determines whether individual motivation and task–technology fit translate into sustained adoption.

In a broader organisational context, training and peer learning (IF) reduce effort and build competence; app budgets, time, and permission to experiment (IS) fuel enthusiasm and ongoing use. Connectivity quality and device lifecycle management set the floor for daily viability; without refresh cycles, capability erosion (battery/OS/app drift) depresses PE and CI over time. Wi-Fi is important for tablets: without Wi-Fi, PE decreases considerably.

Contrasting Themes 3.3 (Failed Rollouts) and 3.4 (Successful Rollouts) reveals that adoption outcomes depend on organisational capability to sustain sociotechnical systems, not merely device provision:

Failed rollouts:

- One-time hardware procurement (often grant-funded)
- No operational budgets for apps, support, replacements
- Devices appropriated for personal use within 2-3 years
- Organisational memory dampened future technology enthusiasm

Successful rollouts:

- Process redesign aligned with tablet affordances
- Continuous support infrastructure (IF + IS sustained)
- Systematic device lifecycle management (3-year refresh)

- Innovation-friendly governance (sandbox testing environments)
- Role-specific deployment matching task-technology fit

From the practical point of view, institutionalising peer learning beyond rollout helps sustained use. SMEs should budget device refresh as core infrastructure, balance governance with safe sandboxes, and redesign workflows to match tablet affordances. In short, SMEs should provide both IF and IS reliably over time.

Organisational support structures establish the conditions enabling adoption, but they do not fully determine outcomes. Even within similar organisational contexts, employees exhibited marked variation in how they appropriated tablets—some discovering novel uses, sharing innovations with peers, and creatively solving problems, while others remained locked into routine or minimal use. The following dimension examines the micro-level processes through which individual agency, social diffusion, and organisational constraints interact to generate emergent innovations.

6.7 Aggregate Dimension 4: Innovation-Oriented Behaviours and Emergent Use

6.7.1 Introduction

Listening to the interviews, it became clear that participants described three interconnected mechanisms when they were asked about innovating with tablets: peer-driven diffusion networks through which innovation-oriented early adopters spearhead innovation spread; emergent innovation processes encompassing both pragmatic problem-solving and exploratory play; and structural constraints (time scarcity, governance rigidity, resource limits) that suppress innovation despite enabling conditions. These mechanisms are described below.

6.7.2 Theme 4.1: Peer-Driven Innovation Diffusion

Reading the accounts of participants, it was interesting that a few of them identified themselves as early adopters. They emphasised that they had acquired tablets before the organisational rollouts and were actively supporting their colleagues or organisations.

One participant explicitly identified as an experimenter or pioneer:

"I was really an early adopter or an innovator in this technology because I started to use an older solution in the beginning. This was a PDA solution. It was 15 years ago when I bought my first tool like this. [...] [at the rollout] there was training at the beginning and then we were showing each other tricks. I was happy to show others how to use the tablets. [SME01_D01_11] [SME01_D01_12] [SME01_D01_37]"

These innovation-oriented early adopters acted as opinion leaders and source nodes in social networks. Intrinsically motivated and comfortable with risk, they explored new use cases ahead of the mainstream and then functioned as knowledge brokers via informal channels:

"I have several [tablets] actually. Nowadays I have one ipad and an android I use frequently. We have a WhatsApp group where people share things they've discovered... someone finds a shortcut or a useful app feature, they post it, everyone learns." [SME14_I01_7]

This peer-driven transmission differed from formal training (Theme 3.1). Rather than generic feature walkthroughs, peers shared situated practices ("here's how I do this task"), enabling immediate, task-relevant appropriation. The mechanism is classic diffusion: individual discovery → peer visibility → local trial → wider adoption. Opinion leaders had credibility (visible personal success), accessibility (co-location or chat groups), and relevance (they solved recognised problems), aligning with Rogers' (2003) account of innovators/early adopters occupying central network positions. The present findings validate this: early adopters (in terms of tablets) described being curious and sharing their findings with colleagues. This amplification mechanism works as individual discovery → peer visibility → collective adoption. The next theme examines how these ideas may appear and how they may be turned into workable solutions.

6.7.3 Theme 4.2: Emergent Innovation Processes

6.7.3.1 Theme Introduction

Innovation did not occur solely through deliberate, rational problem-solving. Instead, two qualitatively distinct innovation pathways emerged: pragmatic problem-solving (task-driven, instrumental) and ludic exploration (curiosity-driven, intrinsic). Importantly, these were not separate tracks but a ludic-to-pragmatic pipeline in which playful discovery often seeded later, practical innovations.

6.7.3.2 Pragmatic Pathway: Opportunistic Problem-Solving

Participants shared snippets of stories during the interviews, which became very important upon re-reading the content:

"By the way, this started from compliance inspections: lots of manual paperwork, data entry errors. Someone realised we could do it all on the tablet with a custom form, photos, real-time database sync. Changed everything." [SME14_B01_53]

This story shows that employees encountered workplace friction—tasks that current tools handled poorly—and opportunistically discovered tablet-based solutions. This reflected what Senyard et

al. (2014) term *bricolage*: recombining available resources to solve immediate problems through improvisation.

These pragmatic innovations emerged contextually: problems visible to one user (compliance inefficiency, sales issues) triggered experimentation with tablet affordances; when solutions worked, they were demonstrated and (possibly) formalised into standard workflows. This trajectory helps explain ITIB → CI: visible, work-improving innovations strengthen continuance as they embed in everyday routines.

6.7.3.3 *Ludic Pathway: Peripheral Exploration and Playful Discovery*

Alongside pragmatic fixes, innovation also emerged from playful tinkering—intrinsic, low-stakes exploration that later found work value. One participant vividly recalled such a situation:

“Though sometimes we show fun new apps to each others in the office. Even useful ones, I saw some useful tools my colleague was showing me. True, we started from some filtered generated photo laughing, but we ended up discussing scanning and OCR and the scanned image can be translated into text that we could paste into the online timesheet.” [SME01_D01_35]

This aligns with playful work design (Scharp et al., 2022) and broader accounts of play as an incubator for innovation (Bateson & Martin, 2011): play creates cognitive slack for lateral combinations; in technology contexts, “poking around” surfaces features that later become instrumental.

6.7.3.4 *Overview of Emergent Innovation Processes*

The pragmatic pathway is more predictable (organisations can target known pain points); the ludic pathway is serendipitous, but may supply the raw ideas that pragmatic actors later refine. Successful innovations tended to pass through stages: ideation (pragmatic or ludic) → demonstration (peer/manager validation) → trial (small-scale testing) → adoption (SOP/formalisation) → routinisation (habituated practice).

Progress can stall at any stage: ideas that never get shown; demos that fail to convince; trials blocked by constraints; adoptions left optional and never routinised. The next theme examines where and why these pipelines may break in SMEs, identifying the organisational frictions that interrupt this process.

6.7.4 Theme 4.3: Constraints on Innovation

6.7.4.1 Theme Introduction

Even where enabling conditions were present (IS, peer networks, organisational permission), innovation was often suppressed by two classes of constraints: temporal (workload pressure, routine lock-in) and structural (governance rigidity, resource scarcity, cultural risk-aversion). Participants provided examples of both classes.

6.7.4.2 Temporal Constraints

Many participants, even innovation-oriented individuals in supportive organisations, reported that workload pressure curtailed experimentation:

"Maybe if I had time, I could experiment and scan it on the tablet and then now I'll fire it up and experiment with it to see what works and how. But I usually don't have the time." [SME08_H01_20]

Time scarcity acts as a suppressor: motivation remains, but translation into behaviour stalls. Under pressure, employees satisfice—using tools “well enough” and avoiding the overhead of exploration. This aligns with technostress accounts (Tarafdar et al., 2007): when cognitive slack is consumed by workload, technology shifts to stressor, and exploratory learning collapses.

6.7.4.3 Structural Constraints

Participants identified two major structural barriers in organisational structures actively suppressing innovation:

A. IT Governance and Mobile Device Management (MDM) Policies

Governance policies designed for security and compliance inadvertently dampened innovation by creating bureaucratic friction:

"We did some... let's call it "creative enablement" early on—jailbreaking and sideloading—so we could run the apps we needed. Later Android and iOS got stricter, and we moved to proper mobile device management with signed builds. Less fun, more secure." [SME14_B01_11]

But IT governance was only part of the picture: organisational culture also played a role.

B. Organisational Culture and Risk Aversion

Organisations where failures were reframed as learning opportunities experienced higher ITIB; those treating failures punitively suppressed risk-taking. One participant specifically commented on this:

"Failed experiments are seen as mistakes, not learning. So people don't take risks. Everyone plays it safe." [SME04_M01_36]

Culture moderates whether perceived organisational support for innovation translates into actual experimentation.

6.7.4.4 Overview of Constraints on Innovation

Temporal and structural limitations suggest that constraint variables (time, governance, budgets) may be necessary conditions for innovation, whereas support variables (IS, PIIT) are sufficient conditions. In other words, high IS without time and budget is unproductive; protected time and permissive governance without PIIT generates little innovation. Both must be present.

6.7.5 Aggregate Dimension 4 Synthesis

Across this dimension, innovation appears as a local, social, and episodic process rather than a top-down programme. Three elements interact:

- A. **Peer diffusion:** Innovation-oriented early adopters act as opinion leaders and knowledge brokers, turning resources and permission (IS) into visible prototypes and quick wins that peers can imitate. Diffusion travels through everyday channels (meetings, chats, WhatsApp groups), not formal rollouts.
- B. **How ideas arise (dual pathways):** Innovation is seeded along two intertwined pathways:
 - the pragmatic route (pain-point → bricolage → working fix → routine), and
 - the ludic route (playful tinkering → discovery → later instrumentalisation).
- C. **Where momentum stalls (constraints):** Even with IS and active peer networks, time scarcity and structural frictions (MDM approvals, budgets, risk-averse culture) frequently close behavioural pathways from ideation to trial to routinisation. Support variables (IS, PIIT) are insufficient without slack time, streamlined governance, and minimal viable budgets.

These mechanisms suggest how Innovation Support and Personal Innovativeness might combine to enable IT-Enabled Innovative Behaviour. The peer diffusion process (Theme 4.1) implies that innovation-oriented individuals serve as innovation catalysts, but their impact depends on organisational context (IS provision, constraint mitigation). The constraint findings (Theme 4.3) suggest the IS→ITIB pathway may be moderated by time availability and governance flexibility.

While these mechanisms were identified in 2021, organisational innovation literature (Rogers, 2003; DeSanctis & Poole, 1994) suggests peer diffusion and resource dependence represent

general processes. However, ecosystem immaturity during 2014-15 (Theme 2.1) likely constrained the scope of innovations employees could attempt—fewer mature apps and limited cloud infrastructure reduced prototyping opportunities compared to 2021 contexts. Chapter 7 examines these mechanisms further.

Nevertheless, based on the interviews, organisations that want more innovation should design for diffusion and velocity. Part of this journey includes identifying and supporting opinion leaders. For innovation to happen, management should legitimise playful exploration alongside targeted problem-solving. Protecting small pockets of time and light, predictable governance allows the innovation process to happen. Innovation, in this view, is not a one-off initiative but a repeatable pipeline—from discovery to working prototype to routinised practice—kept alive by peer energy and protected by organisational scaffolding.

6.8 Chapter summary

The four dimensions operating together explain how tablet continuance and innovation unfold in Hungarian SMEs:

- Dimension 1 (Task-Technology Fit and Use Contexts) specifies for what purposes tablets deliver value—consumption, collaboration, field work, creativity—and where they fundamentally fail (complex analysis, heavy content creation).
- Dimension 2 (Technology Maturation and Adoption Trajectories) shows not only how technology matured over the 2014-2021 time frame, but also how individuals adopted the tablets in a non-continuous manner.
- Dimension 3 (Organisational Context and Support) reveals what enables or inhibits adoption: training institutions, management resources, infrastructure reliability. This dimension also summarises successful and less successful cases.
- Dimension 4 (Innovation-Oriented Behaviours and Emergent Use) illuminates how novel applications emerge—through peer diffusion, pragmatic problem-solving, playful exploration—and what constrains their realisation (time scarcity, governance rigidity).

Together, these dimensions present lived organisational experiences, detailing nuances of the theoretical model. Across cases, continuance was not driven by general positivity towards tablets but by task–device fit that could be routinised into everyday work (signatures, photos, quick demoing). Input-heavy or multi-window tasks remained laptop-centric. Organisational support mattered when it was tangible (time to tinker, peer micro-learning, managerial shielding). Purely symbolic or policy-only support produced limited experimentation.

These findings also connect to the "double-edged sword" finding in the previous chapter. Chapter 5 identified competitive mediation for Personal Innovativeness in IT (PIIT): highly innovative individuals drove continuance indirectly through IT-enabled innovative behaviours (ITIB), but simultaneously reduced continuance directly. The qualitative findings illuminate plausible mechanisms underlying both edges of this sword.

The positive edge (Theme 4.1): Innovation-oriented early adopters act as opinion leaders who spearhead peer-driven innovation diffusion. They experiment with novel uses, share discoveries informally, and demonstrate viable innovations that colleagues imitate. This process converts individual innovativeness into collective ITIB, strengthening continuance indirectly through visible, work-improving innovations that become routinised.

The negative edge (Theme 4.3): These same innovative individuals encounter organisational constraints—time scarcity, approval bottlenecks, restrictive MDM policies, device maturity and risk-averse cultures—that interrupt the ludic-to-pragmatic pipeline. When experimentation is blocked or delegitimised, innovation-oriented individuals become frustrated. Their innovativeness, rather than driving commitment, fuels restlessness and critique: "Why continue with a device the organisation won't let me use creatively?" or "Why continue with a device that limits my creativity?" This mechanism may explain the negative direct PIIT→CI pathway.

The competitive mediation thus reflects a structural tension: innovative employees generate value (positive indirect via ITIB) when organisational conditions permit, but withdraw commitment (negative direct to CI) when constraints or technology maturation neutralise their creative potential. While the 2021 interviews cannot directly explain the 2015 competitive mediation pattern, they reveal a theoretically plausible and conceptually stable mechanism—peer diffusion versus constraint-driven frustration—that likely operated across both temporal contexts, though ecosystem immaturity during 2014-15 (Theme 2.1) may have amplified constraint effects by limiting the scope of viable innovations. Chapter 7 will examine this mechanism in detail further.

Taken together, the qualitative evidence illuminates plausible mechanisms and contextual factors that may shape how technology adoption patterns emerge in SMEs. While these mechanisms were identified retrospectively in 2021, they reveal general processes—task-technology fit dynamics, temporal ecosystem evolution, organisational support structures, and peer-driven innovation—that theoretically connect to the structural relationships observed in the 2015 quantitative model. Chapter 7 systematically examines these connections, acknowledging the temporal and methodological boundaries of cross-phase integration.

7 DISCUSSION

7.1 Introduction

In mixed-methods research, the results of the quantitative and qualitative analyses are often integrated into joint displays that bring strands together in overarching themes or topics (Venkatesh et al., 2013). The joint-display focused approach aims to present a unified framework that maintains analytical coherence while addressing all required components (Fetters & Tajima, 2022). In this thesis, joint displays provide the main integrative device for connecting structural relationships from the quantitative model with socio-technical mechanisms identified in the qualitative phase.

Consequently, this chapter starts with three joint displays that synthesise the quantitative and qualitative strands in relation to key topics: task-anchored performance expectancy, the double-edged role of Personal Innovativeness in IT, and the organisational support pathway from Innovation Support to Involvement Facilitation and IT-enabled innovative behaviour. Each joint display is evaluated and discussed within this chapter, with local synthesis subsections drawing out the main integrated insights. Chapter 8 then builds on these integrated findings to restate the research questions, articulate overarching conclusions, and develop the theoretical and practical contributions, limitations and directions for future research.

The three key joint displays are summarised in Table 7.1.

Table 7.1 Joint display overview

Joint Display	Topic	Core Contribution	Connects to
JD1: Performance Expectancy	Second-level divide (usage access), task-technology fit	PE is task-anchored, not device-global; continuance is cyclical, not linear	DASAT: DAI→DTCI
JD2: Personal Innovativeness (PIIT)	Individual trait effects, innovation constraints	PIIT is a double-edged sword: it predicts ITIB but suppresses CI when constrained	DASAT: DSR governance
JD3: IS→IF→ITIB	Organisational support, mediation mechanisms	IS requires IF operationalisation; support alone is insufficient	DASAT: DSR→DAI→DTCI loop

Each joint display in this chapter operates through a consistent two-stage integration logic. First, the quantitative path coefficients identify whether a statistically supported association is present and estimate its direction and magnitude. However, these coefficients cannot, by themselves, explain why the association occurs, what socio-technical mechanism may underpin it, or under what conditions it may weaken or break down. Second, the qualitative themes provide an explanatory layer by identifying the processes through which the statistical associations may be enacted in practice.

In each joint display, the starting point is a specific quantitative pattern, such as a strong total effect, an indirect-only mediation, or a competitive mediation. The qualitative analysis is then used abductively to identify mechanisms that are recurrent across cases, consistent with the constructs involved, and temporally and contextually plausible given the Hungarian SME setting. The accompanying synthesis sections link particular structural paths to relevant second-order themes and aggregate dimensions and explain why these provide the most plausible interpretation of the quantitative relationship when both strands of evidence are considered.

This approach follows mixed-methods integration guidance, where joint displays are used to link numeric trends and narrative mechanisms into coherent meta-inferences (Creswell & Plano Clark, 2018; Fetters et al., 2013). The three joint displays that follow apply this logic to three patterns in the quantitative model.

The overall research question in Chapter 1 was formulated as follows: “How do individual-level factors (cognitive, affective, and trait-based) and organisational-level support mechanisms interact to shape the post-adoption continuance and IT-enabled innovative behaviour of employees using tablet devices within the socio-technical context of Hungarian SMEs?”

As recommended for mixed methods research, a sub-question was specifically targeting the integration phase (SRQ3): “How do the qualitative findings (mechanisms, processes) explain, expand, and contextualize the quantitative results (predictive paths) to produce an integrated, actionable framework for fostering employee-driven digital innovation in resource-constrained environments?”

This chapter, therefore, focuses on integration quality, synthesising the strand-specific findings into meta-inferences that address SRQ3 and then answer the overall research question.

Throughout the chapter, three core elements are referenced: the quantitative results, the qualitative results and the DASAT model. For ease of reading, the key terms and results are presented below (Table 7.2, Table 7.3, Figure 7.1 and Figure 7.2).

Table 7.2 Gioia data structure from first-order concepts to aggregate dimensions

First-Order Concepts (samples)	Second-Order Theme	Aggregate Dimension
Reading, Watching video, Note taking	1.1 Reading & Light Documentation	1. Task-Technology Fit and Use Contexts
Sharing during meeting, No wall during meeting	1.2 Meetings & Collaborative Work	
Salesreps client visit, Warehouse checking	1.3 Role-specific Workflows	
Need laptop for serious work, Cant divide screen	1.4 Boundaries for Complex Work	
Years ago hype, Now more useful	2.1 Technology and Device Maturation	2. Technology Maturation and Adoption Trajectories
COVID forced cloud, Tablet terminal to cloud	2.2 COVID-Accelerated Cloud Transformation	
On and off use, Periodical use	2.3 Discontinuous Usage Patterns	
Management support, Peer learning, Training	3.1 Organisational Support Mechanisms	3. Organisational Context and Support
Connectivity (WI-FI), Device management	3.2 Infrastructure Constraints	
Funded no support, Outdated device	3.3 Failed Organisational Rollouts	
Standardised for tasks, Long term use	3.4 Successful Organisational Rollouts	
Show apps to each other, Share apps	4.1 Peer-Driven Innovation Diffusion	4. Innovation-Oriented Behaviours and Emergent Use
Implement new apps, Play and find solution	4.2 Emergent Innovation Processes	
Restrictive enviroment, Cant install anything	4.3 Constraints on Innovation	

Table 7.3 Construct names and abbreviations

Abbrev.	Construct name
PE	Performance Expectancy
EE	Effort Expectancy
ATT	Attitude
ITIB	IT-enabled Innovative Behaviour

Abbrev.	Construct name
CI	Continuance Intention
PIIT	Personal Innovativeness in IT
IF	Involvement Facilitation
IS	Innovation Support

Figure 7.1. Digital Transformation Framework (DASAT) (Kahveci, 2025)

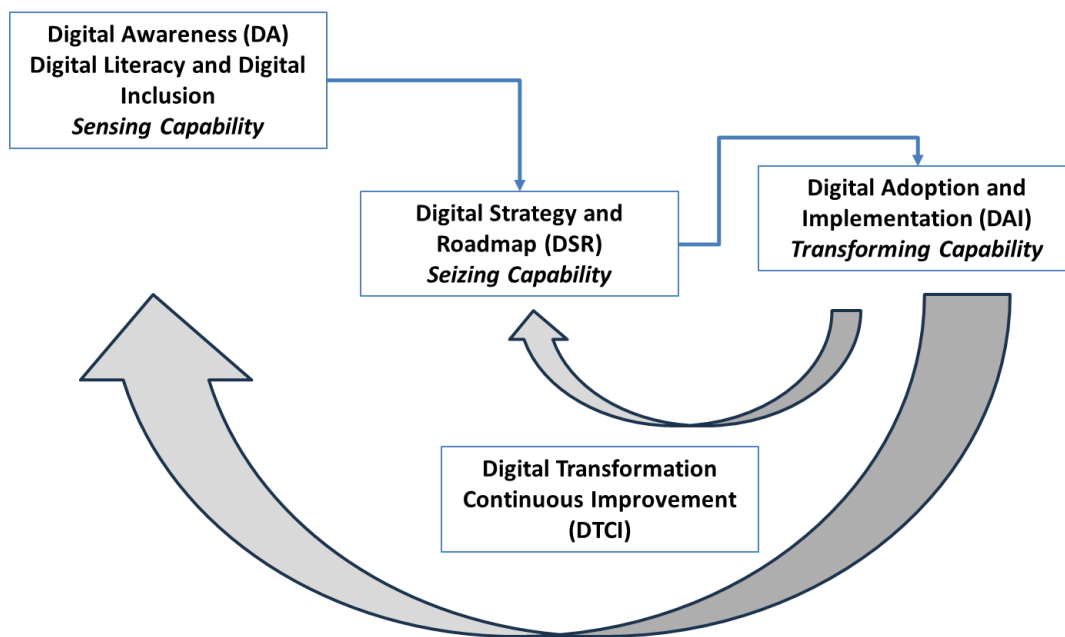
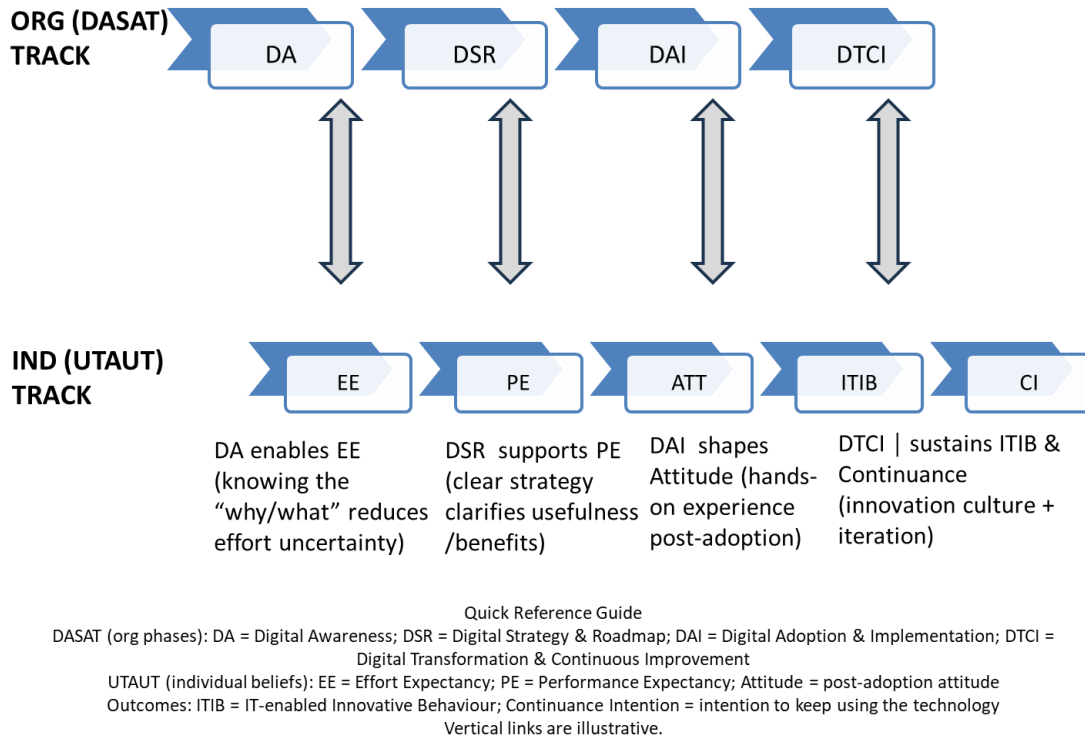


Figure 7.2 Dual-track mapping: DASAT and UTAUT



7.2 Joint Display 1: Performance Expectancy

7.2.1 Introduction

Performance Expectancy (PE) is a natural candidate for a joint display. PE is one of the strongest predictors overall, and it has the strongest effect on Continuance Intention (CI) (total effect: $\beta=0.539$). Throughout this integration, 'Continuance Intention' (Phase 1) is conceptualised as the quantitative proxy for Routine Appropriation, while 'IT-enabled Innovative Behaviour' (Phase 1) represents Innovative Appropriation. By mapping the qualitative themes from Phase 2 onto these constructs, this chapter reveals the socio-technical mechanisms that determine which appropriation pathway an employee follows (Table 7.4).

However, before progressing to the joint display, an important question is how respondents interpreted the PE statements. The 2014-15 quantitative model measured PE using global survey

items like “Using this tablet device enhances my performance in my work”. These items invite respondents to form overall assessments across all their work activities. The qualitative evidence (Aggregate Dimension 1: Task-Technology Fit and Use Contexts) implies that PE is not experienced uniformly but varies systematically by task context—high for consumption/meetings, lower for complex analytical work. This raises a critical measurement interpretation question: When respondents provided global PE ratings in 2015, what did they mean?

This question is of particular importance because research on Task-Technology Fit emphasises that technology utility perceptions are inherently task-specific (Goodhue and Thompson 1995). Studies integrating TTF with UTAUT have shown that task characteristics moderate the relationship between performance expectancy and behavioural intention, suggesting that global PE measures may mask important heterogeneity (Huang and Chuang 2021; Chavarnakul, Lin, Khan and Chen 2024). Consequently, the next section will look at this question in light of the qualitative and quantitative data of this study.

7.2.2 The PE Measurement

How respondents reply in such situations to overall assessment questions is a much-debated topic (e.g., Doi et al., 2022). There are two competing hypotheses in the literature:

A. Portfolio-wide (weighted) averaging

Under this hypothesis, a respondent mentally surveys their task portfolio and weights each context by frequency or importance before arriving at a global score. Schematically: meetings (high utility) + email (medium) + spreadsheets (low) → weighted average = moderate overall PE rating.

B. Dominant-task anchoring

This approach assumes that respondents base their global assessment primarily on the task contexts where they use tablets most frequently or where tablets have the strongest (positive or negative) impact. In this case, the internal thought process would be: ‘My main work is client meetings, and tablets excel there → high utility’ OR ‘My main work is complex analysis, and tablets fail there → low utility.’

Both approaches are summarised in the heuristic-systematic model: portfolio-wide averaging represents systematic processing, while dominant-task represents heuristic processing (Chaiken, 1980).

Various research streams are concerned with this problem, ranging from recollections to retrospective emotional self-reports (Ganzach & Yaor, 2019; Kahneman et al., 1993; Robinson & Clore, 2002). In terms of emotional experiences over a longer timeframe, respondents shift from episodic recall (retrieving specific instances) to semantic knowledge (beliefs about oneself and attitude formation) (Glasman & Albarracin, 2006; Robinson & Clore, 2002), supporting the weighted average hypothesis.

However, tablet use is not just an emotional experience; it is a more complex situation. Kahneman et al. (1993) showed that people judge (more complex) experiences largely based on the peak impressions. Similarly, retrospective evaluations in more complex situations favour the dominant-task anchoring (Ganzach & Yaor, 2019; Tversky & Kahneman, 1974).

The answer is further complicated by the required cognitive effort of completing the survey. Survey response literature demonstrates that respondents often minimise cognitive effort in surveys (Tourangeau et al., 2000) and this would favour the dominant-task anchoring approach as cognitively less demanding. Recency effects (e.g., the last time I used the tablet, it was effective/useless) may also shift the answer (Luebbers et al., 2024).

The literature review shows that how participants cognitively aggregate task-specific experiences into global survey responses remains theoretically ambiguous (Doi et al., 2022; Glasman & Albarracin, 2006). Consequently, the next section looks at what can be interpreted from the qualitative and quantitative data in this study.

7.2.3 The PE Measurement Evidence From Data

The quantitative and qualitative evidence provide four supporting considerations for anchoring over averaging:

A. Spontaneous References to Specific Contexts

When asked about continued tablet use during the 2021 interviews, respondents frequently referenced their primary or most frequent use case rather than averaging across all work activities (e.g., sales representatives pointed to client meetings, design staff anchored to creative work).

Notably, respondents did not spontaneously describe trade-offs or averaging logic. Instead, their continuance judgments were categorically tied to specific, salient task contexts. Language was anchored: "tablets are good for meetings" (categorical) rather than "tablets are somewhat useful depending on the task" (averaging/hedged).

B. Cognitive Psychology Alignment

Kahneman & Tversky (1974) emphasised that the most frequent or memorable instances disproportionately shape global judgments, rather than systematic averaging. Indeed, when asked about tablet utility, participants recalled a vivid, frequent use case (a client meeting, a field inspection, a design project) and used that exemplar to anchor their global judgment.

C. Role-Transition Narratives and Dynamic Anchoring

Theme 2.3 (Discontinuous Usage Patterns) provides the strongest evidence for anchoring rather than averaging: global PE changed when the dominant task changed, even though the device remained the same (e.g. "I got bored after a couple of months... Then I got into the design/drawing team, and it really got a lot more useful." [SME03-C01]).

The qualitative data show that PE and continuance intentions shift dynamically as the dominant task shifts. When a role transition moves someone from analytical work (low-fit) to meeting-heavy work (high-fit), their global assessment of tablet utility jumps. This dynamic pattern is consistent with anchoring to the current dominant task—each role shift brings a new anchor point. It contradicts portfolio-averaging, which would predict smoother, more stable assessments.

D. Statistical Distribution Evidence Supporting Anchoring

Finally, hypothetically, if portfolio-wide averaging were the cognitive process, individuals mentally averaging high-fit and low-fit task utilities would produce a distribution clustered around the scale midpoint. Instead, a between-person clustering is observed at task-specific anchor points (high-fit roles → PE $\approx$ 4-5; low-fit roles → PE $\approx$ 2-3), consistent with dominant-task anchoring. The 2014-15 data show:

- Full scale range utilised (1–5, no ceiling/floor effects)
- Mean above midpoint (PE items: $M = 3.53\text{--}3.61$)
- Moderate standard deviation ($SD \approx 0.90\text{--}1.10$)

If averaging were operating, the distribution would likely change (central limit theorem (Wasserman 2004)):

- Compressed distributions ($SD < 0.70$)
- Central tendency toward midpoint ($M \approx 3.0$)
- Fewer extreme scores (limited 1s and 5s)

The observed statistical pattern, combined with qualitative evidence of spontaneous task-specific references and cognitive psychology's availability heuristic, supports dominant-task anchoring as the more plausible mechanism.

It has to be emphasised that without a proper experiment, this is plausibility and not proof for either hypothesis. Participants may have reacted with a mix of approaches to these questions – some of them averaging, some of them focusing on the dominant task.

7.2.4 The CI Measurement

Reflecting on the qualitative results (Aggregate Dimension 1: Task-Technology Fit and Use Contexts and 2.3 Discontinuous Usage Patterns), a similar question may be raised in terms of the CI statements. Similar to the PE statements, these are overall statements (e.g. I intend to continue using this tablet device in my work). However, the task-technology fit focus raises a measurement interpretation question: When respondents provided global CI ratings in 2015, what did they actually mean?

When a respondent in 2014-15 indicated a high CI rating, did this reflect:

- A. Commitment to daily, routine use across all tasks?
- B. Readiness to use tablets in specific, high-fit contexts (meetings, travel, field work) whenever those contexts arise?
- C. Anticipated use in their current dominant task context?

Naturally, only a carefully designed experiment could distinguish decisively among A, B, and C. However, the qualitative results suggest that (B) and (C) are more plausible than (A). Respondents' CI ratings likely reflected:

- High CI for employees in stable high-fit roles (field staff, sales reps) → anticipation of continued use because dominant tasks match tablet affordances.
- Moderate CI for employees in multi-task roles → anticipation of context-dependent use (high during meetings/travel, low during desk work).
- Low CI for employees in stable low-fit roles (analysts, programmers) → realistic assessment that dominant tasks don't match tablet capabilities.

This also clarifies that while the SMEs were provisioning the tablet, mandatory use was not enforced through drastic policy measures – none of the interviewees mentioned any concerns like this. While this was not asked specifically during the 2014-15 questionnaire, all interview respondents implied that they had the possibility to fall back to standard desktop computer usage,

if required. Consequently, the CI was likely interpreted by survey respondents as a latent readiness state to use tablets in specific scenarios, rather than a blanket 'mandated use' answer.

7.2.5 Discontinuous Usage Dynamics

The dominant-task anchoring mechanism also generates a distinctive pattern observed throughout the qualitative interviews: discontinuous usage, characterised by cyclical "on-off" engagement rather than stable, continuous adoption. This pattern challenges traditional technology acceptance models, which typically assume continuance is binary (adopt or abandon) or linear (gradual intensity decline). The integrated evidence reveals that tablet usage in organisational contexts operates through context-dependent cycles driven by two primary mechanisms: task-anchoring shifts and infrastructure disruptions.

The dominant-task anchoring mechanism predicts that when employees' primary work activities shift, their PE assessments—and consequently their usage patterns—shift correspondingly. The qualitative evidence (Theme 2.3: Discontinuous Usage Patterns) documents this repeatedly.

This pattern demonstrates that the employee did not "fail to adopt"—the device remained available, and the employee retained competence. Rather, the initial role provided low task-technology fit (PE anchored to low-utility contexts), creating rational dormancy. When role responsibilities shifted to design-intensive work, the dominant-task anchor moved to a high-fit context (stylus-based creative work), triggering renewed engagement.

Similarly, employees in roles with fluctuating task portfolios exhibited accordion-like usage patterns. These patterns are not an adoption failure. The employee maintains device access, preserves operational familiarity, and can rapidly re-engage when dominant tasks shift back to high-fit contexts. Traditional continuance models would misclassify these employees as "low continuance intention" or "declining engagement," missing the underlying mechanism: PE reassessment triggered by task-context changes.

Beyond task-anchoring shifts, discontinuous usage patterns also emerged from infrastructure-level disruptions independent of employee preferences. These disruptions create forced dormancy—periods when tablets become temporarily unavailable or unusable due to technical constraints rather than task-fit considerations. Connectivity failures were frequently cited as creating temporary usage gaps. Employees working in buildings with unreliable Wi-Fi, travelling to client sites with poor mobile coverage, or operating in field environments with intermittent connectivity experienced enforced dormancy.

Finally, the interaction between task-anchoring dynamics and ecosystem maturation (Theme 2.1: Technology and Device Maturation) further complicates discontinuous usage patterns. In contrast to 2014-15, by 2021, ecosystem maturation (robust app ecosystems, cloud integration, stylus support, multitasking improvements, pandemic-driven cloud migration) dramatically expanded the range of viable high-fit tasks. This temporal shift created a distinctive pattern: employees who had experienced dormancy in 2014-15 re-engaged in 2021 because their previously low-fit dominant tasks had become high-fit through ecosystem evolution. This temporal re-engagement pattern reveals that discontinuous usage can span years, with dormancy triggered by ecosystem limitations rather than task changes or infrastructure failures. Employees who maintained device access but experienced multi-year dormancy due to ecosystem immaturity represent a latent adoption pool—ready to re-engage when technological constraints lift.

Recent research in consumer health technology has begun documenting non-linear post-adoption trajectories that challenge linear stage assumptions. Gorm and Shklovski (2019) introduce the concept of "episodic use" in self-tracking devices, observing that use is "episodic in nature, as priorities in life change over time" (p. 2515). Their qualitative study of 22 users found that "leaving activity-tracking devices behind for a while is a way for users to deal with complex social situations and life changes" (p. 2516), positioning temporary abandonment as a productive coping strategy rather than adoption failure.

Similarly, research on wearable health technologies has documented "intermittent discontinuance"—defined by Shen et al. (2018) as "a state where people neither continuously use the focal information technology nor entirely abandon it" where "a cycle of 'discontinuance-readoption' will be observed" (p. 46). This framework has been extended by Dhir et al. (2024), emphasising the cyclical rather than terminal nature of technology disengagement.

Attig and Franke's (2020) comprehensive review of personal wearable abandonment reinforces this temporal complexity, finding that "the choice to abandon tracking is typically not a permanent one for most ex-users" (p. 233). Their survey of 159 former activity tracker users revealed that abandonment decisions were driven primarily by interruptions and priority shifts rather than fundamental technology rejection. More recently, Platzer et al. (2025) have formalised this as "IS use resumption", documenting that "users may be detained in a cycle of discontinuance and IS use resumption, meaning that they might iterate between discontinuance and IS use resumption" (p. 2). While this emerging literature provides valuable insights into non-linear technology use patterns, it focuses predominantly on voluntary adoption of personal consumer technologies. Nevertheless, the pattern described among the interview respondents shows a similar cyclic use,

primarily depending on task fit. Before progressing to the synthesis, the last item that should be recognised is how participants described the improvement in tablet usage over the years.

7.2.6 Device and Ecosystem Maturity

The quantitative model in 2014-15 captured PE at a single moment in time, when tablets and their ecosystems were still developing. Early adopters formed their expectations amid genuine capability gaps: limited multitasking, constrained app choices, immature cloud services, and basic hardware often restricted what tablets could do. PE ratings represented a judgment about ecosystem readiness. The “hype without action” reported by participants meant even positive perceptions of tablets were dampened by incomplete solutions.

By 2021, interviewees described a transformed landscape. Platform maturation fundamentally expanded the value proposition: richer app libraries, stylus and keyboard integration, and robust remote desktop solutions were available. Cloud adoption reconfigured tablets from standalone devices into gateways to powerful remote infrastructures—shifting bottlenecks from device specs to network reliability. Tasks that had been poorly supported (editing documents, accessing business-critical databases) became feasible, improving the perceived value for roles that had previously written tablets off.

This evolution was not merely additive—new capabilities dissolved previous boundaries and created new use possibilities. The device’s fit was redefined both by technical improvements and radical changes in workflow (e.g., remote work, e-signature, or using cloud capabilities).

7.2.7 Synthesis – PE

The integrated evidence from quantitative patterns and qualitative accounts supports dominant-task anchoring as the cognitive mechanism underlying global PE ratings. The quantitative evidence shows both a strong PE→CI relationship and meaningful variation in how employees evaluated tablet usefulness. The qualitative evidence helps explain this pattern by suggesting that employees evaluated tablets through their most frequent, or important work contexts, rather than by averaging utility across all tasks. Dominant-task anchoring is therefore treated as an abductive integration of the 2014–15 quantitative PE pattern with the 2021 qualitative evidence on task-specific tablet fit.

Three qualitative mechanisms were available as candidate explanations for the PE→CI relationship: ecosystem maturation (Theme 2.1), role-specific task-technology fit (Themes 1.1–1.4), and discontinuous usage patterns (Theme 2.3).

Ecosystem maturation was not selected as the primary integration mechanism because it is mainly a population-level temporal shift. Such a shift can help explain how the range of high-fit tablet tasks expanded over time, but it cannot alone explain between-person variance in PE and CI observed within the 2014–15 cross-section, where respondents operating in broadly similar technological environments reported different PE levels.

Role-specific task-technology fit and discontinuous usage patterns together provide a stronger within-person, within-organisation account. PE appears to be anchored to the employee's dominant task context rather than averaged across the full task portfolio. CI is best understood as a context-dependent readiness state rather than a stable linear commitment. In other words, employees seem to form performance expectations in relation to the tasks where tablets matter most, and their intention to continue fluctuates with how well tablets support those focal contexts over time.

This mechanism also explains why employees exposed to the same broad tablet ecosystem could report different levels of performance expectation and continuance intention. Employees in high-fit roles, such as mobile, meeting-heavy, field-based, or client-facing work, had a stronger basis for positive PE and CI. Employees in low-fit or desktop-intensive roles could rationally report lower CI without necessarily abandoning the device. The qualitative evidence on discontinuous usage shows that dormancy often reflected task shifts, infrastructure constraints, or temporary ecosystem limitations rather than rejection of the technology itself.

For this reason, dominant-task anchoring provides the most plausible interpretation of the PE→CI pattern in this study. It connects the strong quantitative PE→CI pathway with qualitative evidence on task-specific fit and discontinuous usage, while avoiding the weaker explanation that ecosystem maturation alone produced the observed relationship. The resulting meta-inference is that continuance intention in tablet-enabled SME work should be understood less as a binary or linear construct and more as a context-dependent readiness to re-engage when task conditions and infrastructure make tablet use valuable.

The integrated evidence challenges the implicit assumption in continuance intention (CI) models that adoption success requires stable, continuous usage. Tablet adoption in organisational contexts operates through context-dependent cycles where dormancy periods do not signal rejection but rather reflect:

- Task-anchoring shifts: Role transitions or task-portfolio fluctuations move employees in and out of high-fit contexts, triggering rational usage oscillation.

- Infrastructure disruptions: Technical constraints (connectivity, device lifecycle, platform updates) create forced dormancy independent of PE or motivation.
- Ecosystem maturation lags: Temporal gaps between deployment and ecosystem readiness create extended dormancy periods that resolve once technological capabilities catch up to task requirements.

Critically, employees experiencing discontinuous usage typically retain readiness to re-engage. They maintain device access, preserve operational familiarity, and exhibit rapid re-adoption when task contexts or infrastructure conditions shift favourably. This contrasts sharply with true abandonment, where employees discard tablets, migrate to competing devices (smartphones, laptops), or lose operational competence through prolonged disengagement.

The dominant-task anchoring mechanism explains why discontinuous usage is rational and predictable rather than anomalous. PE assessments are anchored to dominant tasks; when dominant tasks shift (role transitions, ecosystem maturation), PE reassessment triggers corresponding usage adjustments. Organisations and researchers must distinguish between:

- Active engagement: Dominant tasks have high tablet fit; PE anchored to high-utility contexts
- Rational dormancy: Dominant tasks have low tablet fit; PE anchored to low-utility contexts, but readiness-to-re-engage preserved
- Infrastructure-enforced dormancy: Technical constraints prevent usage; PE and readiness remain unchanged
- True abandonment: Employee has migrated to competing devices; tablet discarded; operational competence lost

This discussion, grounded in the integration of quantitative PE→CI pathways and qualitative discontinuous usage patterns, reframes continuance intention from a binary or linear construct into a context-dependent readiness model (Table 7.4). The Conclusions section translates these findings into theoretical, practical, and research implications.

Table 7.4 Joint display 1: PE

Quantitative Finding (2014-15)	Qualitative Evidence (2021)
• PE → CI: total effect: $\beta = 0.539$ • PE → ATT: total effect: $\beta = 0.600$ • PE → ITIB: total effect: $\beta = 0.409$	1. Task-Technology Fit and Use Contexts 2.1 Technology and Device Maturation 2.3 Discontinuous usage patterns

Quantitative Finding (2014-15)	Qualitative Evidence (2021)
Interpretation: Performance Expectancy is the strongest predictor in the entire model. It not only drives Continuance Intention, but it is of core importance for the Attitude and IT-enabled Innovative Behaviour. PE operated through multiple pathways described below. CI • Direct PE→CI: $\beta = 0.135$ • Indirect PE→ATT→CI: $\beta = 0.255$ • Indirect PE→ITIB→CI: $\beta = 0.114$ • Indirect PE→ATT→ITIB→CI: $\beta = 0.035$ ATT • Direct PE→ATT: $\beta = 0.600$ ITIB • Direct PE→ITIB: $\beta = 0.315$ • Indirect PE→ATT→ITIB: $\beta = 0.093$ The 2014-15 PE assessments occurred during early adoption with an immature technology environment (e.g., cloud infrastructure). The model captured a snapshot of intention at a single time point during the early tablet maturity phase (2014-15).	PE assessments are not device-global but task-specific. Employees assess tablet performance relative to specific work activities—reading, meetings, field workflows—rather than forming uniform judgments. By 2021, task-technology pairings implied improved PE, reflecting ecosystem evolution. This suggests that temporal context (technology maturity) may moderate the PE→CI pathway strength, a question requiring longitudinal measurement.

7.3 Joint Display 2: Personal Innovativeness in IT

7.3.1 Introduction

Personal Innovativeness in the domain of Information Technology (PIIT) represents a trait-based construct capturing an individual's willingness to try out new information technologies independently of external influences (Agarwal & Prasad, 1998). PIIT is defined as "the willingness of an individual to try out any new information technology" and is positioned as a domain-specific adaptation of the broader Domain Specific Innovativeness (DSI) construct (Agarwal & Prasad, 1998).

Within the technology acceptance literature, PIIT has been theorised and tested as both a moderating variable and a direct antecedent to key constructs in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Lewis et al., 2003; Rosen, 2005; Yi et al., 2006). The theoretical rationale posits that individuals high in PIIT are more likely to experiment with novel technologies, tolerate uncertainty during initial use, and explore emergent features beyond prescribed workflows.

However, empirical findings surrounding PIIT have been mixed, with limited effects or even non-significance (Yi et al., 2006). More recently, PIIT was again tested both as a direct antecedent in health technology (Gu et al., 2021) and as a moderator in the wearables and educational context (Almusawi & Durugbo, 2024), confirming the impact of PIIT on behavioural intention and technology acceptance. Investigating PIIT in innovative work behaviour, research confirmed that PIIT shapes post-adoption behaviours as well (Wu & Yu, 2022). Recent meta-analyses and systematic reviews continue to report that the inclusion of individual difference variables like PIIT in the UTAUT model often yields modest effect sizes and context-dependent significance (Xue et al., 2024).

In this study, the quantitative findings revealed a paradox:

- Positive indirect effect (+0.064, sig.): innovation-oriented individuals engage in more IT-enabled innovative behaviours (ITIB), which then drive continuance.
- Negative direct effect (−0.086, sig.): innovation-oriented individuals simultaneously exhibit lower direct continuance intention, independent of their innovative behaviours.
- Net total effect (−0.022, n.s.): These forces cancel out, masking the underlying competitive dynamic.

And those quantitative results represent the central puzzle for this joint display (Table 7.5). It may be phrased as: “Why would personal innovativeness—a construct typically associated with early adoption enthusiasm and positive technology attitudes—directly suppress continuance intention?”

The quantitative findings (2014-15) revealed competitive mediation; the qualitative interviews (2021) illuminate theoretically plausible mechanisms. These mechanisms likely operated in both periods, though with changing relative strength as technology and organisational contexts evolved and will be discussed in the next sections (Table 7.5).

7.3.2 Mechanism 1: Positive Indirect Path

Evidence from Theme 4.1 Peer-Driven Innovation Diffusion shows that innovation-oriented participants consistently identified themselves as early adopters and opinion leaders who:

- Experimented ahead of others: Acquired tablets before organisational rollouts, explored features independently, discovered novel use cases.
- Shared discoveries through informal peer networks: Demonstrated tricks, shared apps via WhatsApp groups, and provided show-and-tell sessions.

This mechanism follows classic innovation diffusion dynamics:

- Discovery: Individual encounters a problem or explores tablet capabilities playfully (4.1 Peer-Driven Innovation Diffusion & 4.2 Emergent Innovation Processes)
- Prototyping / Demonstration: A working solution is developed & shared
- Demonstration: The solution is shared informally (meetings, chats, peer observation)
- Adoption: Colleagues trial the innovation; if successful, it spreads and becomes routinised
- Collective value: Visible innovations improve work outcomes, creating positive Performance Expectancy for the broader group

As discussed in Chapter 6, the discovery may be based on recombining available resources (bricolage) (Senyard et al., 2014), or may be based on the ludic pathway (Bateson & Martin, 2011; Scharp et al., 2022).

7.3.3 Mechanism 2: Negative Direct Path

Based on the interviews, the same innovation-oriented disposition that drives innovation also predisposes individuals to frustration when constraints block creative appropriation. Innovation-oriented individuals sought to experiment with new apps, sideload tools, or customise workflows. When technology immaturity or organisational governance limited innovation, they became frustrated, or at least less enthusiastic. The interviews showed that experiments may be blocked by 2.1 Technology and Device Maturation or Theme 4.3 Constraints on Innovation. One participant from an ICT firm with strong technical sophistication captured this evolution:

“We did some... let’s call it “creative enablement” early on—jailbreaking and sideloading—so we could run the apps we needed. Later Android and iOS got stricter, and we moved to proper mobile device management with signed builds. Less fun, more secure.” [SME14_B01_11]

When governance policies prioritise security and standardisation (rational from an IT perspective), they create friction for innovators. Low-PIIT users, who rely on standard apps and approved

workflows, likely experience minimal impact. Innovation-oriented users, who seek to push boundaries, encounter repeated permission denial—a micro-aggravation that may accumulate into disengagement.

Even where formal policies allowed experimentation, organisational cultures that punished failure suppressed innovation and (possibly) alienated innovation-oriented individuals, as described in Theme 4.3 Constraints on Innovation.

Finally, the ecosystem was immature in 2014-15 (Theme 2.1 Technology and Device Maturation). For low-PIIT users, this immaturity was invisible—they used tablets for basic tasks (reading, email) that worked adequately. For innovation-oriented users, immaturity was acutely visible—they explored the ecosystem, discovered its limits (poor multitasking, limited enterprise apps, weak cloud integration), and experienced capability disappointment. Innovation-oriented individuals are drawn to novelty: once they had explored the tablet's capabilities and found them constrained, the novelty wore off.

Disentangling the exact reason from these 2021 accounts referring back to 2014-15 is simply not possible. But it is clear that these elements, back in 2015, even after 3 months of usage, impacted high PIIT individuals, resulting in the negative edge of the sword.

These negative pathways operate even when innovations are successfully generated, suggesting that for innovation-oriented individuals, the experience of constraint itself—independent of whether workarounds succeed—erodes commitment. Even an innovation-oriented user who successfully creates workarounds may still experience low continuance intention because:

- The effort required to work around constraints (MDM approval delays, governance friction) exceeds the perceived benefit.
- They become restless and seek alternatives (newer devices, different platforms, reverting to laptops).
- Their critical lens—the same analytical mindset that enables innovation—also makes them hyper-aware of the device's limitations.

7.3.4 Synthesis – PIIT

Considering the temporal gap, it should be again highlighted that the competitive mediation was identified in the 2014-15 quantitative model. By 2021, the qualitative interviews discussed a number of changes, and these changes might have affected the competitive mediation:

Ecosystem maturation (Theme 2.1) likely weakened the negative direct path:

- In 2014-15, ecosystem immaturity (e.g., limited enterprise apps, poor multitasking, weak cloud integration) (likely) created capability disappointment for innovation-oriented users who explored boundaries.
- By 2021, maturation (robust app ecosystems, cloud integration, stylus support) expanded what innovators could accomplish → less frustration from hitting capability ceilings.

Governance constraints (Theme 4.3) likely persisted or intensified:

- MDM policies, app approval workflows, and risk-averse cultures were mentioned frequently in 2021, suggesting these constraints were stable or worsening.
- If governance friction increased over time, the negative direct path may have remained active even as ecosystem constraints eased.

The peer diffusion mechanism (Theme 4.1) likely remained stable:

- Innovation-oriented individuals acting as opinion leaders is a general social process that operates whenever innovations diffuse through informal networks.
- This mechanism likely operated in both 2015 and 2021, though the content of innovations shifted (2015: basic app discovery; 2021: cloud-enabled workflows, stylus creativity).

The above mechanisms probably interacted across these years. As an example, for Android devices, “mystery builds” were relatively easily managed at the beginning – but as the ecosystem matured, several manufacturers (e.g. Samsung) started locking down their tablets more and more (e.g. Knox system – installing a non-official build became more complicated). This technological hardening (for security purposes) constrained the experimental freedoms that innovation-oriented users had enjoyed in 2015, suggesting that ‘ecosystem maturation’ masked a concurrent shift toward stricter governance at the device level.

The competitive mediation structure - positive indirect PIIT→ITIB→CI ($\beta = +0.064$) and negative direct PIIT→CI ($\beta = -0.086$) - requires two separate mechanism-level explanations, one for each path.

For the positive indirect path, Theme 4.2 (emergent innovation processes) was considered but not selected as the primary integration mechanism. It explains how individual innovation ideas arise through pragmatic problem-solving or playful exploration, but it does not fully explain why individual ITIB converts into sustained CI reinforcement. In particular, it does not explain the social amplification process through which personal experimentation becomes visible collective value. Theme 4.1 (peer-driven innovation diffusion) is selected because it explains how innovation-

oriented individuals convert personal exploration into visible, socially shared value, thereby reinforcing continuance through the ITIB pathway.

For the negative direct path, ecosystem immaturity (Theme 2.1) was considered but not selected as the sole explanation. Ecosystem limitations may have contributed to frustration, particularly in 2014–15, but they would be expected to affect users more broadly and therefore cannot, on their own, explain why higher PIIT remains associated with lower CI after accounting for the positive indirect route through ITIB. Theme 4.3 (constraints on innovation) is selected because it identifies the specific asymmetry: device governance, time scarcity and risk-averse management approaches impose disproportionate frustration costs on individuals who actively seek to push boundaries, while users relying mainly on approved applications and standard workflows experience fewer such constraints.

Both themes (Theme 2.1 and 4.3) likely contributed to the negative path, but the within-firm, between-person variation is more plausibly accounted for by constraints on innovation. Theme 4.3 explains why the same organisational setting can be merely inconvenient for routine users but actively frustrating for users engaging in innovative work practices. These two selected mechanisms are therefore the most plausible explanations because they map directly onto the opposing signs and directions of the two competing paths, providing a structural account of the PIIT duality shown in Table 7.5.

Table 7.5 Joint display 2: PIIT

Quantitative Finding (2014-15)	Qualitative Evidence (2021)
Competitive Mediation Pattern: Direct path: PIIT → CI $\beta = -0.086$ ($p < 0.001$) $R^2 = 0.017$ (small/borderline) Indirect path: PIIT → ITIB → CI $\beta = +0.064$ ($p < 0.001$) Total effect: PIIT → CI $\beta = -0.022$ ($p = 0.404$, n.s.) Interpretation: Personal innovativeness simultaneously increases continuance indirectly (by fostering innovative IT behaviours that others value and adopt)	Theme 4.1: Peer-Driven Innovation Diffusion (Positive Edge) Theme 2.1 Technology and Device Maturation Theme 4.3: Constraints on Innovation (Negative Edge) Pattern: Even enthusiastic innovators encountered structural constraints—MDM restrictions, time scarcity, risk-averse culture, and budget limits—that blocked experimentation and creative appropriation, leading to frustration-driven disengagement.

Quantitative Finding (2014-15)	Qualitative Evidence (2021)
while decreasing continuance directly. These opposing forces cancel out, yielding a null total effect—revealing a 'double-edged sword.' This masking of dual mechanisms emphasises why aggregate regression coefficients alone are insufficient for understanding individual-level technology continuance in mandated-use organisational contexts.	The (im)maturity of the technology may have also contributed to their frustration.

Prior PIIT literature has reported positive effects on adoption (Agarwal & Prasad, 1998), null effects (Yi et al., 2006), and occasionally negative associations with UTAUT constructs (Jackson et al., 2013). These inconsistencies have typically been attributed to measurement variation, sample differences, or context effects. The competitive mediation structure identified in this study offers a different interpretation: the inconsistency is not merely noise, but may be theoretically meaningful.

PIIT is not a uniformly positive predictor of continuance. Rather, it operates as a context-contingent amplifier whose net effect depends on the organisational and technological conditions. Under supportive conditions, where innovative behaviour can be socially shared and practically applied, the positive indirect path (PIIT→ITIB→CI) becomes consequential: innovativeness is channelled into visible IT-enabled innovative use that reinforces continuance. Under constraining conditions, such as governance rigidity, time scarcity or limited permission to experiment, the negative direct path (PIIT→CI) becomes theoretically meaningful: innovativeness amplifies frustration and weakens continuance commitment. The non-significant total effect of PIIT on CI ($\beta = -0.022$, n.s.) is therefore not evidence that PIIT is unimportant; it reflects the simultaneous operation of two opposing pathways that cancel each other in aggregate.

A simple linear model would interpret this as “PIIT does not matter”. The integrated analysis suggests that “PIIT matters in two opposing directions at once”. This reframing advances PIIT theory by moving beyond a main-effect interpretation. It positions PIIT as a dual-path, context-contingent post-adoption construct whose contribution depends on whether organisational conditions convert innovativeness into IT-enabled innovative behaviour or into frustration. Future studies that model PIIT only as a direct antecedent may therefore underestimate its theoretical importance and reproduce inconsistent empirical results.

7.4 Joint Display 3: IT-enabled Innovative Behaviour

7.4.1 Introduction

A central element of this study was to introduce IT-enabled Innovative Behaviour (Jasperson et al., 2005), and the following joint display reviews this element of the model (Table 7.6). There are two constructs linked to ITIB as organisational enablers: IS and IF. The 2014-15 quantitative model measured Innovation Support (IS) as a formative construct with four indicators:

- IS1: "We have a very open communications environment."
- IS3: "Experimental mind-sets and risk-taking is encouraged."
- IS4: "Employees at all levels are rewarded for learning new skills."
- IS5: "New ideas are easy to be implemented."

IS operated through Involvement Facilitation (IF), which represents the operational translation of cultural support into concrete enablers:

- IF1: "Employees are encouraged to try out new technologies."
- IF2: "Employees are rewarded for using new technologies."
- IF4: "Employees are involved in technology change and/or implementation."

The key finding: $IS \rightarrow IF$ is the critical pathway ($\beta = 0.723$, $f^2 = 1.085$ —the largest effect size in the entire model). The surprising quantitative finding that IS does not directly predict ITIB ($\beta = 0.067$, $p = 0.055$, $f^2 = 0.008$) initially appeared counterintuitive—wouldn't a supportive innovation culture directly foster innovative behaviour?

The 2021 qualitative evidence reveals three mechanisms through process tracing which may explain why mediation is necessary, and these will be reviewed in the next sections.

7.4.2 Mechanism 1: Operational Translation

The primary pathway focuses on the $IS \rightarrow IF \rightarrow ITIB$ path. The strongest indirect path ($IS \rightarrow IF \rightarrow ITIB$, $\beta = 0.178$) translate abstract cultural support into concrete enablers. Participants distinguished sharply between:

- Symbolic support (IS) – managers saying "we value innovation," open communication norms, and general encouragement.
- Material provisioning (IF) – actual training, dedicated time, app budgets, fast-track approvals, peer-learning structures.

The mechanism: IS creates cultural permission for innovation ("it's okay to try new things"), but IF provides the structural capacity (time, tools, training, budget) to act on that permission. Without IF, IS remains rhetorical—employees know they're "allowed" to innovate but lack the resources to do so. In effect, IF is the operational translation of IS into actual innovative behaviour.

The qualitative data specified three barriers (Theme 4.3: Constraints on Innovation and Theme 3.3: Failed Organisational Rollouts):

- Barrier 1: Time Scarcity (Theme 4.3). IS creates cultural permission, but time is a rival resource. Under workload pressure, employees satisfice—using tablets "well enough" (Cristofaro, 2017) for routine tasks, avoiding the cognitive overhead of exploration. IS cannot directly generate ITIB because temporal slack is a necessary precondition, and temporal slack is provisioned through IF.
- Barrier 2: Governance and MDM Constraints (Theme 4.3). Restrictive IT policies blocked innovation even in supportive cultures.
- Barrier 3: Resource Scarcity (Theme 3.3). Innovation requires material resources—app licenses, device upgrades, etc. IS creates normative legitimacy for innovation ("your ideas are valued"), but budget allocation is a managerial decision enacted through IF (e.g., discretionary innovation budgets).

7.4.3 Mechanism 2: Motivational Amplification

The secondary option operates through two pathways: $IS \rightarrow PE \rightarrow ITIB$ ($\beta = 0.083$) and $IS \rightarrow PE \rightarrow ATT \rightarrow ITIB$ ($\beta = 0.025$) and it is focused on motivational mechanisms:

- $IS \rightarrow PE$: Supportive climates raise performance beliefs. When organisations visibly endorse tablets (management use, budget allocation), employees infer higher performance potential: "If management invests, there must be value here." This effect by itself directly impacts ITIB.
- $PE \rightarrow ATT$: Higher performance beliefs foster positive attitudes. The belief that tablets improve work generates enthusiasm and willingness to engage.
- $ATT \rightarrow ITIB$: Positive attitudes lower psychological barriers to experimentation. Theme 4.2 (Emergent Innovation Processes) revealed that innovation often starts through ludic exploration—playful tinkering driven by curiosity, not task pressure. Positive attitudes create psychological safety for non-instrumental play.

The mechanism: IS signals organisational commitment, which raises PE ("this technology is worth learning"), which then supports ITIB either directly or through ATT ("I enjoy using tablets"). These

pathways are weaker than IS→IF→ITIB ($\beta = 0.025$ and $\beta = 0.083$ vs. $\beta = 0.178$) because motivation alone cannot overcome structural barriers—without time, tools, or training (IF), even enthusiastic employees cannot innovate effectively. An employee may be highly motivated to innovate (high PE, high ATT) but still unable to generate ITIB if they lack time to experiment, cannot access necessary apps due to MDM restrictions, or face punishment for failed attempts. This explains why the motivational pathways are 3-7x weaker than the operational pathway—structural enablement (IF) is the binding constraint.

This finding also aligns with organisational innovation literature: even motivated employees cannot enact innovation without practical enablers (Amabile & Pratt, 2016; Johnsson, 2017; Katila & Scott, 2005). While organisational literature traditionally treated IS as a direct predictor of ITIB, recent studies advocate the importance of mediation (e.g., Fan et al., 2022).

7.4.4 Synthesis – ITIB

The combined strands show that organisational culture must be rendered actionable to foster IT-enabled innovative behaviour. IS creates a supportive climate for experimentation, but this climate does not appear to translate directly into ITIB unless it is operationalised through concrete IF. Organisations therefore cannot rely on encouragement alone. They must translate that support into actionable capacity through mechanisms such as training, time, budgets, governance flexibility and peer-learning structures (Table 7.6).

The key quantitative finding in Joint Display 3 is that IS has no significant direct effect on ITIB. Its strongest and substantively primary route operates through IF, forming the IS→IF→ITIB chain. Weaker motivational routes through PE and ATT are also present, but the operational pathway through IF carries the main explanatory weight. For the IS→IF step, three qualitative candidate mechanisms were available: Theme 3.1 (organisational support mechanisms: training and peer learning), Theme 3.3 (failed organisational rollouts), and Theme 3.4 (successful organisational rollouts).

Themes 3.3 and 3.4 were considered as a contrasting mechanism, but they are not selected as the primary integration vehicle because they describe outcomes of IS–IF alignment or misalignment. In other words, they show what happens when the chain works or breaks, rather than the process by which IS is translated into actionable support for ITIB. They are consequences and not the mechanism itself.

Theme 3.1 is selected for the IS→IF step because participants consistently and spontaneously distinguished between symbolic encouragement ("management says innovation is welcome") and

concrete facilitation ("we were given time, and access to tools"). This distinction closely mirrors the conceptual boundary between IS and IF in the quantitative model. The qualitative evidence therefore supports the mediation structure rather than merely illustrating it.

Theme 4.2 (emergent innovation) is selected for the IF→ITIB step because it documents the activation mechanism. Protected time, peer infrastructure and practical access to tools enable both the pragmatic pathway of opportunistic problem-solving and the ludic pathway of playful discovery. Without these concrete IF resources, both pathways may stall regardless of how supportive the broader IS climate appears to be.

The resulting meta-inference is that IS appears to be insufficient on its own; its contribution to ITIB depends mainly on whether it is translated into concrete IF. This conclusion could not have been derived from the quantitative model alone, which shows the path structure but not the organisational process behind it, nor from the qualitative data alone, which explains the process but does not quantify the relative strength of the indirect pathways or the non-significance of the direct IS→ITIB path.

Table 7.6 Joint display 3: ITIB

Quantitative Finding (2014-15)	Qualitative Evidence (2021)
Final Model Pathways (Indirect-Only Mediation): Path 1: IS → IF → ITIB IS → IF: $\beta = 0.723$ ($p < 0.001$), $r^2 = 1.085$ (large) IF → ITIB: $\beta = 0.246$ ($p < 0.001$), $r^2 = 0.031$ (small) Specific indirect: $\beta = 0.178$ ($p < 0.001$) Path 2: IS → PE → ATT → ITIB IS → PE → ITIB IS → PE: $\beta = 0.262$ ($p < 0.001$), $r^2 = 0.092$ (small) PE → ITIB: $\beta = 0.315$ ($p < 0.001$), $r^2 = 0.075$ (small) Specific indirect: $\beta = 0.083$ ($p < 0.001$) PE → ATT: $\beta = 0.600$ ($p < 0.001$), $r^2 = 0.611$ (large)	3.1 Organisational support mechanisms 4.2 Emergent Innovation Processes Successful innovation required concrete operational support—training programs, peer-learning structures, visible management endorsement. Innovations spread through informal & formal channels. Innovation-oriented individuals acted as opinion leaders, but diffusion required organisational scaffolding (time to tinker, fast prototyping tools, permission to experiment). 4.3 Constraints on Innovation Without proper time/budget for experimentation, generic "supportive culture" (IS) alone was insufficient. The qualitative narrative shows the consequences:

Quantitative Finding (2014-15)	Qualitative Evidence (2021)
ATT → ITIB: $\beta = 0.157$ ($p < 0.001$), $R^2 = 0.019$ (small/borderline) Specific indirect: $\beta = 0.025$ ($p < 0.001$) Direct path: IS → ITIB (non-significant) $\beta = 0.067$ ($p = 0.055$, non-significant) $R^2 = 0.008$ (non-significant) Interpretation: Innovation Support (IS) does not directly drive IT-enabled innovative behaviour. Instead, IS operates exclusively through mediators—primarily via Involvement Facilitation (IF), which provides the operational mechanisms (training, time, rewards) that translate cultural support into experimentation, and secondarily via Performance Expectancy and Attitudes, which enhance motivation and openness to innovation. The model predicts the propensity to ideate.	Theme 3.3 – Failed Organisational Rollouts: In problematic cases (failed rollouts), symbolic support (IS) wasn't backed by operational resources (IF)—no training budget, no app licenses, no time for exploration, no device lifecycle management – ITIB was not operational in these organisations.

The finding that ITIB partially mediates the ATT→CI relationship builds on and extends Torkzadeh et al. (2005), who conceptualised IT-enabled ideation as an important technology-enabled behavioural outcome. It also aligns with post-adoption research on trying to innovate with IT and emergent use, where users move beyond routine operation toward finding novel and work-relevant applications of technology (Ahuja & Thatcher, 2005; Kim & Gupta, 2014; Wang et al., 2013).

In the present study, ITIB is not only treated as an outcome of positive affect toward the technology, but also as an active mediating mechanism through which attitude is translated into continuance intention. This is consistent with Bhattacharjee and Premkumar's (2004) argument that post-adoption continuance is shaped not by initial utility beliefs alone but by experience-based evaluation. In this study, the significant ITIB→CI path suggests that employees' engagement in innovative work practices may reinforce their intention to continue using the technology.

The qualitative evidence adds a socio-technical dimension that is not fully specified in prior quantitative models. The mechanisms through which ITIB reinforces CI, such as motivational

amplification through ludic and pragmatic exploration, are organisationally contingent rather than purely individual-level constants. This extends the post-adoptive behaviour perspective associated with Jasperson et al.'s (2005) by showing that innovative use depends not only on individual motivation but also on the organisational scaffolding that allows experimentation to translate into innovative practice in the SME tablet context.

Looking at the timeframe, the IS→IF→ITIB pathway likely operated in both 2014-15 and 2021, but the operational content of IF evolved:

- 2014-15 (Early Adoption Phase): IF possibly focused on basic enablement: Initial training, device provisioning, establishing MDM infrastructure. Innovation was mostly exploratory: early adopters (innovation-oriented individuals) experimented with novel use cases, discovering what tablets could do.
- 2021 (Maturation Phase): IF became routinised: Established training programs, formalised peer-learning sessions (WhatsApp groups, stand-ups), streamlined governance (fast-track approvals). Innovation became incremental: Focus shifted from "can we use tablets?" to "how can we optimise tablet workflows?" (e.g., integrating with CRM, automating data capture).

Theme 2.1 (Ecosystem Maturation) and Theme 2.2 (COVID Cloud Transformation) likely amplified the IS→IF→ITIB pathway over time:

- Mature app ecosystems (2021) expanded the range of viable innovations, increasing IF's payoff
- Cloud infrastructure (post-COVID) enabled more complex workflows (remote desktop, database access), raising the innovation ceiling

This suggests that the IS→IF→ITIB pathway may be stronger in 2021 than 2015, though the 2015 cross-sectional model cannot capture this temporal evolution. These findings also suggest that organisations should continually update operational enablers to reflect the changing digital landscape, rather than assuming initial supports will remain effective.

7.5 Attitude as the Affective Bridge

Drawing on Joint Displays 1–3, this section synthesises how the Attitude construct functions as an affective bridge between cognitive beliefs (PE, EE), innovative behaviours (ITIB) and continuance intention (CI) in the Hungarian SME context.

A pivotal theoretical decision in this thesis is the reinstatement of the Attitude construct within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. While the original UTAUT model excluded attitude in the interest of parsimony, arguing that its effect was fully mediated by performance expectancy (PE) and effort expectancy (EE), this thesis argues for its inclusion in post-adoption contexts.

Positive attitudes toward tablets drive continuance through two simultaneous pathways: a strong direct commitment ("I like it, so I'll keep using it") and a moderate indirect behavioural deepening ("I like it → I experiment with it → innovations strengthen my commitment").

This serial mediation—ATT → ITIB → CI—reveals a cognitive-affective-behavioural progression. This mediation operates through three mechanisms: (1) task-technology fit generates positive attitudes by delivering satisfying user experiences; (2) positive attitudes lower psychological barriers to playful experimentation, enabling the ludic-to-pragmatic innovation pipeline; and (3) innovations create collective value through peer diffusion and network effects, strengthening continuance beyond mere hedonic enjoyment.

The reinstatement of Attitude as a significant predictor of both ITIB and CI in this study contributes to an ongoing debate in the UTAUT literature. Venkatesh et al. (2003) deliberately excluded Attitude from the original UTAUT for parsimony, arguing that ATT was fully mediated by Performance Expectancy and Effort Expectancy in their multi-organisational dataset. However, subsequent continuance research has found that ATT can re-emerge as an independent predictor once users have accumulated experience with a technology (Liao et al., 2009; Nabavi et al., 2016). The present findings align with this reinstatement stream.

In a mandated post-adoption context, Attitude captures an evaluative stance that is qualitatively different from PE. PE concerns whether the tablet is perceived to improve task performance, whereas ATT captures the employee's broader affective and evaluative orientation toward using the tablet in work. This distinction matters because ATT predicts ITIB independently of PE, suggesting that affective engagement, not just utility assessment, supports innovative appropriation. This is consistent with Brown et al.'s (2002) argument that, in mandatory-use environments, ATT helps distinguish ritualistic compliance from more genuine internalisation and appropriation of the technology.

The rationale is robust: in these usage settings, affective evaluation becomes a distinct predictor of discretionary behaviours such as ITIB. The quantitative analysis in Chapter 5 supports this theoretical choice. The path from ATT to CI is significant ($\beta = 0.424$), the path from ATT to ITIB is

also significant ($\beta = 0.157$), and ATT serves as a significant mediator between PE and ITIB ($\beta = 0.094$ for the specific indirect effect). This suggests that, in post-adoption use, cognitive assessment of utility is partly translated into innovative engagement through affective evaluation. The finding therefore offers a nuanced view of the “affective bridge” required for deeper technology infusion.

7.6 Effort Expectancy: The Forgotten Enabler

The integrated quantitative–qualitative evidence also reveals that effort expectancy operates as a threshold enabler that shapes performance beliefs, attitudes and ultimately both continuance and IT-enabled innovative behaviour. The quantitative findings from 2014-15 reveal that EE plays a crucial, albeit indirect, role in shaping post-adoption continuance and IT-enabled innovative behaviour. The qualitative phase yielded limited direct commentary on EE: participants largely dismissed usability concerns by stating that “tablet usage is basic”.

The structural model demonstrates that EE operates through multiple significant pathways, establishing it as a foundational enabler in the post-adoption ecosystem. EE exerts a strong positive effect on Performance Expectancy (EE→PE $\beta=0.402$, $p<0.001$, $f^2=0.213$ medium effect size), indicating that perceived ease of use directly enhances performance beliefs. This pathway aligns with cognitive load theory: when systems demand less mental effort, users can allocate cognitive resources toward recognising and appreciating performance gains rather than struggling with operational mechanics.

Beyond this direct relationship, EE influences Attitude (EE→ATT $\beta=0.223$, $p<0.001$), demonstrating that ease of use contributes independently to affective evaluations. Together, these dual pathways—through both PE and directly to ATT—position EE as a critical antecedent that shapes the cognitive-affective foundation upon which continuance decisions rest. The total effect of EE on CI ($\beta=0.327$) and on ITIB ($\beta=0.200$) confirms that usability perceptions were important in 2014-15.

The significant EE→ATT path (H3 supported), the stronger EE→PE path (H4 supported), and the indirect contribution of EE to CI and ITIB are noteworthy in the context of the broader UTAUT literature. A consistent finding across post-adoption studies is that effort-related effects often weaken as users gain experience, habituate to system interactions, and begin to take ease of use for granted (Bhattacharjee, 2001; Venkatesh et al., 2003). The present study, conducted after a minimum three-month use period, might therefore have been expected to show a weakened EE

effect. Instead, EE remains significant through both cognitive and affective pathways: it strengthens PE and also contributes independently to ATT.

This finding can be explained by the general-purpose nature of tablets. In contrast to narrowly defined enterprise systems, tablets can be used across multiple applications, workflows and collaborative settings. Employees may therefore become familiar with the device interface while still encountering new local learning thresholds as task contexts change. Tablet-specific UTAUT research also suggests that ease of use remains relevant when mobile devices are incorporated into varied everyday practices (Magsamen-Conrad et al., 2015). In the tablet context, the implication is that EE should not be treated only as a one-time learning threshold. For SMEs deploying general-purpose technology across diverse roles, EE is better understood as a moving target that may be reactivated whenever users encounter new applications, workflows or task demands.

The relative absence of EE-related concerns in the 2021 qualitative interviews should therefore be interpreted as a later-stage development, not as a contradiction of the 2014–15 quantitative findings. By 2021, participants characterised tablet interfaces as "basic" and "intuitive," suggesting that ecosystem maturation (Theme 2.1) and repeated use reduced the usability challenges that were encountered during the earlier period. This trajectory is consistent with Limayem et al.'s (2007) habituation argument: with repeated use, technology interactions become automatic, and deliberate ease-of-use assessments recede from conscious awareness as behaviour shifts from effortful execution to routinised habit. Similarly, Jasperson et al.'s (2005) post-adoptive use perspective suggests that deeply appropriated technology may become part of the background infrastructure of work: users attend to what the technology enables rather than how it operates.

This positions EE less as a direct driver of continuance and more as a threshold enabler. Organisations cannot compensate for poor usability through high IS or strong IF alone; if employees lack the skills access to operate devices fluidly, the downstream system of attitude formation, experimentation and innovative use is likely to underperform. Conversely, once EE surpasses a usability threshold, its constraining effect may diminish and it may disappear from active deliberation. The "forgotten" status of EE in mature adoption contexts is therefore not necessarily a theoretical absence, but a theoretical signal: it may mark the point at which usability has been successfully internalised.

7.7 Between-Method Triangulation: Convergence and Divergence

7.7.1 Introduction

The explanatory sequential design employed in this research generated systematic between-method triangulation—the purposeful use of quantitative survey data and qualitative interview data on overlapping aspects of tablet use, innovativeness and organisational support in Hungarian SMEs. Following Denzin's framework, this methodological triangulation aimed not only at corroboration but also at leveraging productive divergences where they emerged (Denzin, 2009).

7.7.2 Areas of Convergence

As shown through the joint displays, the quantitative and qualitative phases substantially reinforced core findings. The structural model identified Innovation Support and Involvement Facilitation as powerful antecedents to IT-enabled innovative behaviour (total effects: IS→ITIB, $\beta=0.285$ through IF). Interview data confirmed this pattern: successful organisational rollouts (Theme 3.4) consistently involved training, peer-learning networks, and management encouragement—the operational enactments of IS and IF. When these mechanisms were absent, respondents reported routine use or discontinuance (Theme 3.3: Failed Organisational Rollouts). This alignment across methods strengthens confidence in the inference that organisational support is not merely predictive but mechanistically central to innovation enablement.

Performance Expectancy emerged as the dominant predictor in the quantitative phase (PE→Attitude, $\beta=0.600$; PE→Continuance, $\beta=0.538$). Interview accounts aligned with this finding: respondents who perceived tablets as genuinely useful for their specific workflows (Task-Technology Fit, Theme 1) reported sustained engagement, whereas those perceiving a mismatch (Theme 1.4: Boundaries for Complex Work) exhibited discontinuous or dormant use. This convergence underscores the psychological centrality of perceived usefulness in tablet appropriation.

7.7.3 Productive Divergences

Equally instructive were points of divergence. The quantitative model revealed a competitive mediation effect for Personal Innovativeness in IT: a positive indirect path (PIIT→Attitude→ITIB, supporting innovation when support was high) and a negative direct path (PIIT→Continuance, suggesting that highly-innovative individuals experience frustration where support is lacking). Interview data enriched this finding by revealing the lived experience behind the statistic: highly innovative respondents functioned as "double-edged swords." In well-supported environments

(SMEs 16, 19), they drove emergent innovation processes (Pragmatic and Ludic Pathways, Theme 4.2). In constrained environments, however, they encountered structural and temporal obstacles (Theme 4.3) that frustrated their initiative—not because they lacked ability but because organisational conditions prevented experimentation. This divergence did not contradict the model; rather, it localised and contextualised the boundary conditions.

Another revealing divergence concerned ecosystem maturation (Themes 2.1 and 2.2). The quantitative survey captured a single cross-sectional moment (2014-15) during early tablet adoption; the device-software ecosystem was immature, and many cloud-based workflows were nascent. Interview retrospection revealed that perceived usefulness, effort, and continuance had themselves evolved across the intervening years (2014-2021). Discontinuous usage patterns (Theme 2.3)—periods of dormancy interspersed with active use—were explained not by individual factors alone but by the maturation of the ecosystem and the evolution of cloud infrastructure. This temporal dimension, invisible in the quantitative model, did not overturn its findings but demonstrated that the strength and salience of relationships change as technology and organisational context evolve.

7.7.4 Integration Implications

The between-method triangulation in this study does not merely corroborate the findings; it produces richer insights than either strand could yield independently. To assess integration quality systematically, the patterns documented in Sections 7.7.2 and 7.7.3 are interpreted by drawing on Venkatesh et al.'s (2013) discussion of mixed-methods integration outcomes in IS research, particularly confirmation, expansion and divergence.

Confirmation occurs where qualitative evidence directly supports and elaborates quantitative findings. The IS→IF→ITIB serial chain is the clearest example: the non-significant direct IS→ITIB path in the structural model is consistent with and explained by Theme 3.1's operational translation evidence. In these interviews participants consistently distinguished between symbolic organisational encouragement and the concrete facilitation resources that actually enable innovative use. This confirmation is theoretically important because it transforms a statistical mediation result into a mechanism-based explanatory inference: IS does not appear to translate into ITIB directly, but through IF as its operational arm.

Expansion occurs where qualitative findings extend beyond what the quantitative model could reveal. The dominant-task anchoring mechanism and the discontinuous usage trajectories documented in Themes 1.1–1.4 and 2.3 represent this type of outcome. The cross-sectional

structural model captures the strength of the PE→CI relationship but is structurally silent on the cyclical, task-contingent nature of continuance. The qualitative evidence therefore expands the theoretical account from a static prediction to a dynamic process interpretation, revealing that continuance is not simply a one-off decision but a context-dependent readiness state that shifts as roles, tasks and ecosystems evolve.

Divergence occurs where findings are not directly aligned and require interpretive reconciliation. The qualitative evidence of ecosystem maturation post-2015 (Theme 2.1) cannot be mapped directly onto the 2014-15 structural model. Similarly, the 2021 accounts of reduced EE salience cannot be treated as direct explanations of 2014-15 quantitative patterns. Rather than undermining the integration, this divergence strengthens inference quality by making the study's boundary conditions explicit. The interpretive caution exercised is a product of taking divergence seriously rather than suppressing it.

Together, these three integration outcomes produce three overarching meta-inferences (Tashakkori & Teddlie, 2010):

- First, the core quantitative relationships — particularly PE as a dominant predictor of continuance, and IS and IF as central organisational antecedents of ITIB — are robust and mechanism-rich: they are supported by plausible cognitive and organisational mechanisms, rather than remaining merely statistical associations.
- Second, individual dispositions such as innovativeness are not fixed drivers of outcomes but context-contingent amplifiers: where organisational support and usable ecosystem conditions allow innovativeness to be enacted, it can become an asset; where constraints are active, it can become a liability. This finding calls for context-sensitive intervention approaches rather than trait-based recruitment strategies alone.
- Third, the temporal distance between phases revealed that adoption is not a static event but an evolving process: models calibrated at one organisational and technological moment require periodic reassessment as contexts, ecosystems, and role configurations shift.

This tripartite integration pattern demonstrates that the mixed-methods design is doing genuine analytical work (Creswell & Plano Clark, 2018). It produces not just corroboration but a theoretically richer and more actionable picture of post-adoption dynamics than either strand alone could supply. These integrated inferences directly inform the subsequent framing through the digital divide lens in Section 7.8 and strengthen the contributions (Section 7.9) and implications (Section 7.10).

7.8 Framing Through the Second-Level Digital Divide

7.8.1 Introduction

The mechanisms documented in Sections 7.2-7.7 can now be read through a specific theoretical lens: the second-level digital divide. Van Dijk (2019) distinguishes four successive forms of access: material access (physical possession of devices and connectivity), motivational access (willingness to engage with digital technologies), skills access (operational and strategic competences required to use ICT effectively), and usage access (opportunities to apply ICT in meaningful, value-creating tasks). Following Hargittai's (2002) influential distinction, the first level of the digital divide concerns physical access, while the second level concerns the skills and usage inequalities that persist once material access is resolved.

The application of this framework to organisational and SME contexts is not without precedent. Riggins and Dewan (2005) explicitly distinguish a first-order divide (access barriers) from a second-order divide (differences in ICT use intensity and value realisation among those with access) in an organisational extension of the framework. This distinction maps directly onto the design of the present study, in which material access was resolved by tablet provisioning and the inequalities concern use quality and innovative appropriation. Arendt (2008) reaches a similar conclusion in a Polish and Czech SME context: skills and motivational deficits are key constraints on ICT use in small firms, and training intensity emerges as an important differentiator between digitally capable and digitally stagnant SMEs. Wielicki and Cavalcanti (2006) find that the SME digital divide is more related to the knowledge of employees than to lack of financial funds. De Souza et al. (2017) replicate this mechanism in a large-scale PLS-SEM study of Brazilian SMEs: using constructs measuring IT knowledge and managerial IT capability alongside structural support variables, they find that human capital is the primary constraint on digital value creation. These firm-level studies collectively establish that the second-level divide is the operative inequality in digitally equipped SME populations. They operate, however, at the firm level of analysis. The present study descends one level further to provide individual-level evidence of how second-level barriers are experienced and reproduced within organisations.

The argument developed in this section is that the integrated evidence positions Hungarian SMEs in this study firmly at the second level: material access was resolved by design (all respondents were provisioned with tablets), while skills and usage access emerged as the recurring structural bottlenecks. The Hungarian context reinforces this positioning. Endrődi-Kovács and Stukovszky (2022), examining Hungarian SME digitalisation through the Digital Economy and Society Index

and EU SME Performance Review data, document that Hungary ranks 21st of 28 EU member states, with business digitisation and e-commerce its single worst-performing component. Critically, they find that this underperformance is not driven by infrastructure deficits: Hungary's connectivity scores and digital public services are at or near EU average. This macro-level pattern establishes the context within which the present study is situated: the binding constraints lie upstream of infrastructure, in the skills and usage dimensions of the second-level divide.

7.8.2 Motivational Access Mechanisms

One aspect of the micro-level translation in a mandated-use situation requires theoretical reconsideration. In van Dijk's (2019) original causal sequence, motivational access precedes material access: the willingness to engage with digital technology determines whether individuals seek out and acquire devices. This sequence reflects a voluntary consumer context. In the mandated-use context of this study, however, device provision is an employer decision; employees enter the post-adoption phase already in possession of tablets, irrespective of their initial motivational orientation.

Motivational access therefore reappears downstream rather than upstream. It does not determine whether employees obtain the device; instead, it shapes whether device possession is converted into meaningful use and innovative appropriation. This is consistent with van Deursen and van Dijk's (2015) empirical finding that attitude is associated with all stages of digital technology appropriation and directly affects the development of skills and usage diversity. In this study, motivational access in its mandated-use form is captured through ATT, which mediates the PE→ITIB pathway and, as established in Section 7.5, functions as the affective bridge between cognitive utility beliefs and innovative appropriation. The contribution is therefore to show that, in employer-provisioned technology settings, motivational access may operate post-provision rather than as a pre-acquisition condition.

7.8.3 Skills Access Mechanisms

Skills access operates through two analytically distinct channels in the integrated evidence.

The first is formal training and peer learning (Theme 3.1, Section 6.6.2). Successful SMEs in the qualitative phase described institutionalised peer-learning structures and ongoing training sessions rather than one-off rollout sessions. Where training was absent or discontinued, employees likely remained locked into basic uses (e.g., reading, email, light note-taking), unable to appropriate tablets for complex or innovative workflows. Arendt (2008), based on audit-based Central European SME data, also finds that training intensity is a key operative differentiator

between digitally capable and stagnant firms; his conclusion is that the skills gap is primarily an organisational investment problem rather than an individual capability problem. In the Hungarian context, this pattern has a macro-level analogue: Endródi-Kovács and Stukovszky (2022) identify training intensity as the key differentiator between Hungarian SMEs capturing digital value and those that are not, corroborating the qualitative evidence that the skills constraint in this study is organisationally reproduced rather than individually determined.

The second channel is Effort Expectancy as a skills proxy, analysed in detail in Section 7.6. The quantitative finding that $EE \rightarrow PE$ ($\beta = 0.402$) and $EE \rightarrow ATT$ ($\beta = 0.223$) demonstrates that effort expectancy directly shapes both performance assessments and affective evaluations. Employees who found tablets difficult to operate would therefore be expected to develop lower performance expectations and more negative attitudes, suppressing both continuance and innovative use through the $PE \rightarrow CI$ and $ATT \rightarrow ITIB$ pathways. Based on the interviews, this issue largely resolved over time, partly as a consequence of ecosystem and platform maturation (Theme 2.1). However, the discontinuous usage patterns (Theme 2.3) suggest that skills access is not a fixed threshold but a moving target that may require ongoing organisational investment in capability maintenance.

7.8.4 Usage Access Mechanisms

In the SME context, usage access is interpreted as the provision of structural resources (time, training, governance permissions, peer infrastructure) that convert material access (device ownership) into value-creating behaviours. The ability to appropriate technology for value-creating non-routine work emerged as the binding constraint across the integrated evidence. Three mechanisms illuminate how this operates.

Task-technology fit as usage enabler (Joint Display 1, Section 7.2). Usage access is not device-global but task-specific. As demonstrated through the dominant-task anchoring interpretation of PE (Section 7.2), employees form usage access judgements anchored to their most important task context. Employees did not necessarily fail to adopt or abandon tablets altogether. Rather, they engaged in context-dependent cycles of use and dormancy driven by task-anchoring shifts. This reframes usage access not as binary (use / non-use) but as a dynamic readiness: a capacity to appropriate technology when contextual conditions align, and to disengage when they do not. Van Dijk's (2019) usage access concept treats usage access primarily as a structural condition (having the opportunity to use) rather than a dynamic state that fluctuates with task context. The present findings extend this concept by demonstrating that usage access can be intermittently present and absent for the same individual across different task

contexts within the same organisation: a granularity that the macro-societal framing of digital divide theory does not capture.

Organisational support as usage infrastructure (Joint Display 3, Section 7.4). The IS→IF→ITIB serial chain is the most direct empirical demonstration that symbolic encouragement alone cannot create usage access. As established in Section 7.4, IS has no significant direct effect on ITIB; its strongest and most substantively important route operates through facilitation: through the concrete provision of time, governance flexibility, peer structures, and experimentation budgets. The IPMA analysis (Section 5.6.2) confirms the practical significance of this finding: IF has an importance of 0.245 for ITIB and a performance score of only 48.3 out of 100, making it (alongside IS: importance = 0.279, performance = 48.0) the highest-priority and most underdeveloped lever for innovative behaviour in the model. This IS→IF translation step maps onto van Dijk's (2019) usage access barrier. The qualitative evidence (Themes 3.1, 4.3) shows that this translation had problems in the studied Hungarian SMEs: managers expressed support for innovation in principle but did not operationalise it through dedicated time allocations, governance flexibility, or protected experimentation. The expectation-reality gap in SMEs with high IS but low IF is the intra-organisational analogue of an access trap: IS signals create willingness to engage, but without IF operationalising structural access, actual innovative use is suppressed.

Personal innovativeness as a usage-access demand signal (Joint Display 2, Section 7.3). The competitive mediation finding demonstrates that usage access barriers are most acutely experienced by those most motivated to appropriate technology. Innovation-oriented employees likely seek structural experimentation conditions; when usage access is denied through various conditions (Theme 4.3: Constraints on Innovation), they withdraw continuance commitment, as reflected in the small but significant negative direct PIIT→CI path ($\beta = -0.086$). This pattern was visible in both strands: quantitatively, the competitive mediation establishes the structural dynamic; qualitatively, participants describing exploratory use also described frustration with organisational constraints as a driver of disengagement. In the Hungarian SME context, where Endrődi-Kovács and Stukovszky (2022) document that even digitally oriented firms struggle to provide structured innovation support, the implication is that the cost of this usage-access denial falls on the employees most capable of generating digital value. Personal innovativeness thus magnifies both the benefits of adequate facilitation and the costs of its absence.

7.8.5 Synthesis: Closing the Second-Level Digital Divide

The integrated quantitative and qualitative evidence produces a coherent and convergent argument: Hungarian SMEs in this study face a second-level digital divide whose binding constraints lie in skills and usage access, not in material infrastructure. In simple terms, closing the first-level divide (provisioning devices) was necessary but insufficient; the operative barriers were skills and usage access.

The case for this conclusion rests on the convergence of methodologically distinct evidence streams. In this study, tablet access was already present by design, since respondents were employees who had been provisioned with tablets. This mirrors the broader contextual pattern that the primary bottleneck in Hungarian SME digitalisation is not simply material access or basic infrastructure, but the organisational and human conditions that convert access into productive use (Endrődi-Kovács & Stukovszky, 2022). Qualitatively, the interviews did identify local infrastructure frictions, especially Wi-Fi reliability and device lifecycle management, but these did not amount to a first-level access deficit in the sense of lacking devices or basic connectivity. Rather, they operated as organisational usage-access conditions: when connectivity, refresh cycles, support, or governance were weak, tablets remained available but could not be reliably converted into innovative work. Quantitatively, the IS→IF→ITIB serial chain demonstrates that organisational support must be operationalised into concrete facilitation resources before it is associated with innovative behaviour; climate without structure does not constitute usage access. During the interviews, participants repeatedly named temporal, structural, and social constraints: time scarcity, governance rigidity, risk-averse culture, and the absence of peer-learning structures. Both strands, despite using different forms of evidence and analysis, identify the same bottleneck. This is not a case of one strand merely illustrating the other; different data sources and analytical methods converge on the same structural conclusion. In Venkatesh et al.'s (2013) criterion of inferential quality in mixed-methods integration, this convergence supports confidence in the core meta-inference. Due to the temporal gap between the quantitative and qualitative phase, the integration focuses on conceptually durable mechanisms, consistent with the integration logic established in Section 1.5.4.

The theoretical extension this convergence enables is threefold. First, it translates van Dijk's (2019) four-level access model from its original societal level into an intra-organisational unit of analysis: van Dijk conceived motivational, material, skills and usage access as population-level inequality dimensions. The present findings suggest that a comparable hierarchy also operates within SMEs, producing differential digital value realisation across employees working within the

same organisation and under broadly similar device-provision conditions. The access hierarchy is therefore not merely a macro-societal phenomenon; it can also be reproduced at the micro level of individual work practices. Second, the study operationalises van Dijk's abstract categories through specific organisational and behavioural constructs: IF captures the organisational-resource dimension of usage access, while ITIB captures the innovative appropriation that usage access is intended to enable. This operationalisation moves the digital divide concept from a descriptive inequality framework toward a testable, mechanism-level model applicable to intra-organisational research. Third, the mandated-use context reveals a variant form of motivational access, that is less visible in consumer-oriented digital divide theory.

This extension also responds to Hargittai's (2002) foundational argument that the second-level digital divide is fundamentally about what people do with access rather than whether they have it - but repositions that argument at the organisational level. In Hargittai's original framing, the relevant unit is the individual and the relevant predictor is digital skill. In the present study, the relevant unit is the employee-in-organisation and the key predictor is the organisational scaffolding - training intensity, governance flexibility, peer learning infrastructure - that determines whether individual skill and motivation can convert into innovative appropriation. Individual competence is necessary but not sufficient; the organisation must provide the structural conditions for usage access to materialise. Selwyn's (2004) argument that digital divide analysis must move beyond access metrics to examine the quality and purposefulness of use in specific social and workplace contexts provides theoretical backing for this task-contingent within-SME interpretation of usage access. The present study gives Selwyn's programme empirical content at the employee level: it identifies the specific organisational mechanisms through which the quality and purposefulness of use is produced or suppressed.

Collectively, these findings operationalise a micro-level theory of the second-level digital divide in Hungarian SMEs: hardware provision is necessary but insufficient without concurrent attention to the cognitive, affective, and organisational conditions that enable productive technology use. The specific levers the integrated evidence identifies - training intensity, governance flexibility, peer-learning infrastructure, task-technology alignment, and periodic re-engagement monitoring - translate this theoretical framework into actionable diagnostics for SME managers and policymakers. These implications are developed in Section 7.10.

7.9 Contributions

7.9.1 Academia

For academia, this thesis advances understanding of post-adoption information technology use by integrating individual, organisational, and temporal perspectives. It demonstrates that employees' beliefs about technology usefulness, and their intentions to continue using it are anchored in specific work tasks and may evolve over time.

The competitive mediation finding also advances PIIT theory beyond the linear-effect framing that dominates much of the adoption literature. Where prior work has often treated inconsistent PIIT findings as measurement or sampling artefacts, this study suggests that such inconsistency may reflect a genuine structural duality: PIIT strengthens continuance indirectly by enabling IT-enabled innovative behaviour, while also exerting a negative direct effect on continuance when organisational and technological constraints limit the enactment of innovativeness.

This is not a moderation finding in the conventional statistical sense; it does not show that PIIT is simply stronger or weaker under different conditions. It is a decomposition finding: the construct operates through two theoretically distinct pathways that are empirically distinguishable through competitive mediation analysis. The integrated mixed-methods evidence is essential here. The quantitative model identifies the competing paths, but without the qualitative mechanisms — peer diffusion as the positive mechanism and constraint-driven frustration as the negative mechanism — the decomposition would remain a statistical pattern rather than a theoretical explanation. Together, the two strands produce a coherent account of why PIIT functions as a double-edged sword in post-adoption SME technology use.

Finally, the mixed-methods design and SME context extend existing work on the second-level digital divide by illustrating how access, skills, organisational support, and usage conditions interact in practice.

7.9.2 Industry

For the industry, the thesis contributes a broad framework for transforming device deployment into meaningful, innovation-oriented change. It distinguishes clearly between basic use and value-creating innovative use. The findings emphasise that digital tools generate benefits when they are matched to appropriate tasks and embedded in everyday workflows. These tools need to be supported by time, training, and management practices that encourage experimentation. Rather than relying solely on simple adoption indicators such as log-ins or device counts, the findings encourage managers to focus on whether technology is helping employees solve problems,

improve services, and develop new ideas. They also highlight that fluctuations in usage can be a rational response to changing roles, workloads, and infrastructures.

7.9.3 Policymakers

For policymakers, the thesis offers a micro-level perspective on SME digitalisation that complements high-level indicators and strategies. In contexts where connectivity and devices are already in place, the findings show that the main barriers to productive technology use lie in skills, confidence, task relevance, and organisational capacity to support innovation. The study, therefore, suggests that digital policy should move beyond a narrow focus on infrastructure provision. It should promote programmes that build digital capabilities within firms, strengthen peer networks, and support the ongoing alignment between technology, work processes, and employee development. These issues are especially salient in resource-constrained and transitional economies.

7.10 Implications

7.10.1 Academia

For academic research, the findings encourage a shift in how post-adoption behaviour is conceptualised and studied. Rather than treating constructs such as expected usefulness, continuance intention and individual innovativeness as fixed, general properties, future work should examine how they are shaped by specific task contexts, by the maturity of the technological environment and by organisational support conditions. The study also underlines the value of mixed-methods and longer-term designs that can capture cycles of use, dormancy and re-engagement. It encourages researchers to distinguish clearly between high-level signals of support for innovation and the concrete mechanisms through which organisations make experimentation and change possible.

7.10.2 Industry

For managers in SMEs and similar organisations, the implications are to approach digital initiatives as ongoing socio-technical change processes rather than one-off implementations. Planning should consider not only which technologies to purchase, but also which tasks they are best suited to and how they will be integrated into everyday work. It should also address how training and peer learning will be organised, and how employees will be given time and autonomy to explore new ways of working. Monitoring should go beyond whether systems are being used to whether they are enabling innovation and performance improvement. Particular attention is

needed to support highly innovative employees, so that their motivation is channelled into constructive change rather than frustration or disengagement.

7.10.3 Policymakers

For policymakers, the key implication is that SME digitalisation strategies need to place as much emphasis on capabilities and organisational conditions as on hardware and connectivity. Funding and support instruments should therefore consider whether firms have access to relevant training, advisory services and peer networks. They should also assess whether interventions enable managers to create the time, structures and governance arrangements required for employees to experiment with new tools. The thesis further suggests that evaluation frameworks for digital policy, especially in transitional and peripheral economies, should include indicators of skills access, usage conditions and innovation-supportive climates, alongside traditional measures of adoption and infrastructure.

7.11 Summary

The integrated analysis in this chapter has shown how the structural relationships identified in the quantitative model are enacted through concrete mechanisms of task–technology fit, evolving usage trajectories and organisational support. Together, these mechanisms reproduce a second-level digital divide at the micro level in Hungarian SMEs. The joint displays and cross-cutting themes demonstrate that continuance and IT-enabled innovative behaviour are socio-technical achievements that depend on the alignment of beliefs, personal innovativeness, and organisational scaffolding over time, rather than on device provision alone. The main contributions and implications are outlined for academia, industry and policymakers, with extended contributions and implications developed and presented in Appendix N and Appendix O, respectively.

Building on this integrated account, the following section restates the research questions and draws out the main conclusions of the study, before moving to the limitations and directions for future research and closing with a personal reflection.

8 CONCLUSION

8.1.1 Overview of the Study

This thesis set out to examine how individual-level factors and organisational support mechanisms shape the post-adoption use and innovative appropriation of tablet devices by employees in Hungarian SMEs. The study responded to three interrelated gaps identified in Chapter 1: a contextual gap concerning post-adoption use in SME organisational settings rather than consumer or educational contexts; a theoretical gap around employee-level, IT-enabled innovative behaviour; and a methodological gap regarding the need for mixed-methods designs that connect the “what” of structural relationships with the “how” and “why” of underlying mechanisms.

To address these gaps, an explanatory sequential mixed-methods design was adopted. A large-scale quantitative survey conducted in 2014–15 ($n = 1,040$ tablet users across 21 SMEs) modelled structural relationships between personal innovativeness, performance beliefs, effort expectancy, attitude, organisational support and post-adoption outcomes (continuance intention and IT-enabled innovative behaviour). A qualitative interview study conducted in 2021 with 18 participants from nine SMEs then provided a retrospective, mechanism-focused account of how tablet use and innovation practices evolved over time in real organisational settings. The findings from both strands were integrated through joint displays in Chapter 7, yielding meta-inferences that link predictive patterns with socio-technical mechanisms.

The remainder of this section draws together the main findings in two steps. First, it revisits and answers the research questions. Second, it distils a set of key integrated conclusions that characterise how tablet technologies become embedded, routinised and used innovatively within the socio-technical context of Hungarian SMEs.

8.1.2 Reflecting on the Research Questions

The principal research question asked:

How do individual-level factors (cognitive, affective, and trait-based) and organisational-level support mechanisms interact to shape the post-adoption continuance and IT-enabled innovative behaviour of employees using tablet devices within the socio-technical context of Hungarian SMEs?

This was operationalised through three sub-research questions aligned with the quantitative, qualitative and integrative strands.

SRQ1: What are the structural relationships between individual perceptions, personal traits, organisational support, innovative use and post-adoption behaviours among tablet device users in Hungarian SMEs?

The structural model shows that continuance intention is predicted primarily by performance expectancy and attitude, with effort expectancy acting as a foundational enabler rather than a direct driver of continuance. Personal Innovativeness in IT exerts a double-edged influence: it strengthens IT-enabled innovative behaviour, but under constrained conditions it can weaken continuance intention. Innovation Support has no significant direct effect on IT-enabled innovative behaviour; rather, its influence is channelled mainly through Involvement Facilitation and, to a lesser extent, through performance beliefs and attitudes. Overall, the model demonstrates that post-adoption outcomes depend on a configuration of cognitive (PE, EE), affective (attitude), trait-based (PIIT) and organisational (IS, IF) factors.

SRQ2: What organisational, contextual, and task-related mechanisms shaped post-adoption outcomes (continuance, discontinuance, innovative use) over time, and how do these mechanisms relate to the structural relationships identified in the quantitative phase?

The qualitative findings reveal four aggregate dimensions that explain how structural relationships are enacted in practice. First, task–technology fit and use contexts matter: tablets are most successful in specific tasks (e.g. media consumption, note taking), and least effective for complex, high-intensity knowledge work. Second, technology maturation and adoption trajectories show that discontinuous usage patterns (phases of abandonment and re-adoption) are common, and that ecosystem developments (apps, accessories, connectivity) gradually resolve early usability barriers. Third, organisational context and support clarify why Innovation Support acts primarily through Involvement Facilitation: symbolic encouragement must be translated into time, tools, training and flexible governance before it can generate visible innovative behaviour. Fourth, innovation-oriented behaviours and emergent use demonstrate how peer learning, playful experimentation and local problem-solving gradually transform routine tablet use into IT-enabled innovations, but also how temporal and structural constraints can suppress these processes.

SRQ3: How do the qualitative findings (mechanisms, processes) explain, expand, and contextualise the quantitative results (predictive paths) to produce an integrated, actionable framework for fostering employee-driven digital innovation in resource-constrained environments?

The joint displays in Chapter 7 show that quantitative paths and qualitative mechanisms are mutually reinforcing. The strong PE and attitude effects on continuance are supported by narratives in which task-anchored, satisfying uses build positive affect and commitment over time. The double-edged role of PIIT is illuminated by accounts of highly innovative employees who either flourish when given autonomy and support, or become frustrated and disengaged when constrained. The mediated IS→IF→ITIB pattern is explained by the sharp distinction participants drew between “talk” and “tools”: only when innovation rhetoric is backed by concrete facilitation do employees sustain innovative use. Together, these integrated insights produce an actionable framework in which continuance and innovation are seen as outcomes of aligned task design, maturing technologies, organisational scaffolding and employee-level capabilities rather than of individual factors alone.

8.1.3 Key Integrated Conclusions

On the basis of these findings, five overarching conclusions can be drawn.

8.1.3.1 Conclusion 1

Post-adoption continuance is task-anchored and cyclical rather than device-global and linear.

The evidence shows that performance expectancy is formed and updated at the level of specific work tasks, not at the level of “the tablet” as a generic device. Employees maintain or abandon tablet use depending on whether particular tasks (e.g. client visits, warehouse checks, on-site presentations) continue to benefit from mobile access and visual display. Usage trajectories are frequently discontinuous, with phases of abandonment followed by renewed use when tasks, apps or organisational priorities change. This challenges models that treat continuance as a one-off decision and instead supports a view of continuance as an ongoing, task-contingent evaluation process.

8.1.3.2 Conclusion 2

Attitude is a critical affective bridge between cognitive appraisals and innovative behaviour.

Reinstating attitude within the UTAUT-based framework is empirically justified. The quantitative analysis shows that attitude has a strong direct effect on continuance intention and mediates the influence of performance expectancy on IT-enabled innovative behaviour. The qualitative evidence clarifies why: positive attitudes lower psychological barriers to experimentation, enable

playful exploration and foster willingness to invest effort in learning new uses. In this setting, sustained innovative engagement is not driven by utility assessments alone; it requires an affective bond in which employees feel that “the tablet works for me and I enjoy using it”.

8.1.3.3 Conclusion 3

Effort expectancy operates as a threshold enabler in mature adoption contexts.

Effort expectancy significantly shapes performance beliefs and attitudes, and through them influences continuance and innovative behaviour in the quantitative model. However, it is largely absent from participants’ qualitative narratives by 2021, as tablet interfaces came to be seen as “basic” and “intuitive”. This suggests that once a usability threshold is crossed, effort expectancy recedes from conscious attention and becomes a necessary but insufficient condition for post-adoption success. Poor usability can undermine adoption even in supportive contexts, but beyond a certain point, further ease-of-use gains yield diminishing returns relative to task fit and organisational support.

8.1.3.4 Conclusion 4

Personal innovativeness is a strategic resource that requires organisational scaffolding.

High PIIT employees act as early experimenters and local champions who search for new applications, configure workflows, and informally support their peers. Yet PIIT has a negative direct effect on continuance intention when organisational conditions are constraining. Qualitative accounts describe frustration, hidden workarounds and selective withdrawal when innovative employees encounter rigid governance, lack of time or absent management follow-through. Personal innovativeness thus functions as a lever that can amplify organisational support into visible innovation when adequately scaffolded, or convert organisational rhetoric into disengagement when left unsupported.

8.1.3.5 Conclusion 5

The second-level digital divide in Hungarian SMEs is primarily a skills and usage access problem, not a material access problem.

The Hungarian SMEs participating in this research possessed adequate material access to tablets and connectivity. The integrated findings show that in these cases, inequalities centre on skills access (competences, confidence, attitudes) and usage access (opportunities, time, organisational permission). Employees in better-resourced, supportive contexts develop richer repertoires of tablet-supported tasks and are more likely to sustain IT-enabled innovative

behaviour. Where skills development and usage opportunities are limited, tablets remain on desks as underused tools. This micro-level pattern mirrors broader European evidence that digital policy must move beyond infrastructure provision towards sustained investment in digital capabilities and meaningful usage.

Taken together, these conclusions portray post-adoption tablet use in Hungarian SMEs as a socio-technical achievement. Continuance and innovative behaviour emerge where task design, maturing technologies, organisational scaffolding and individual capabilities are aligned over time. Where any of these elements is absent or misaligned, technology risks sliding back into routine or symbolic use. The next sections consider the limitations of the research and directions for future inquiry.

8.2 Limitations

8.2.1 Temporal Gap and Ecosystem Changes (2014-15 vs. 2021)

The 6-7 year gap between quantitative and qualitative phases means the 2015 model operated under different ecosystem conditions than the 2021 reality. The integrative interpretation assumes mechanistic stability (processes like task-anchoring and peer diffusion operate in both eras) while acknowledging operationalisation shifts (mean PE levels likely increased due to platform maturation). This boundary cannot be definitively tested with current data—longitudinal model refitting would be required.

8.2.2 SME Context Specificity

Findings reflect small-to-medium enterprise dynamics in Hungary—resource constraints, flatter hierarchies, and tight-knit informal networks. Organisations with formal IT governance, extensive training infrastructure, and institutionalised change management may exhibit different patterns. The accordion model, for instance, may be less pronounced in enterprises with formal device lifecycle management and broader task portfolios.

8.2.3 Technology-Specific Dynamics

Tablets are mobile-hybrid devices (phone-laptop continuum). The task-fit boundaries, ecosystem interdependencies, and usage / replacement patterns may differ for other mobile technologies (smartphones, wearables) or different computing paradigms. Generalisation requires replication across technology contexts.

8.2.4 Self-Selection in Qualitative Sample

The 2021 interview cohort (9 organisations) represents companies that kept using tablets. Organisations that abandoned tablets entirely are absent. This survivor bias means the qualitative data may overrepresent persistence factors and underrepresent barriers to adoption. The rich discontinuance narratives come from dormancy (temporary non-use), not discontinuance (permanent exit). Individuals who rejected the technology entirely and (perhaps) left the organisation were not accessible. Consequently, the qualitative findings likely understate the severity of resistance and frustration, suggesting that the 'negative direct effect' of PIIT observed in the quantitative population might be even more pronounced in the total population.

8.2.5 Retrospective Measurement in Qualitative Phase

The 2021 interviews captured retrospective accounts of 2014-15 experiences. Recall bias, post-hoc rationalisation, and temporal distortion may affect accuracy. Role transitions ("got into design team") were more memorable than stable usage patterns, potentially skewing the narrative toward dramatic change rather than stability.

8.2.6 Self-Report and Single-Informant Data

As with most survey-based studies of technology use, the quantitative phase relies on self-report data from single informants within each organisation. The key constructs—performance expectancy, effort expectancy, attitude, personal innovativeness in IT, innovation support, involvement facilitation, continuance intention and IT-enabled innovative behaviour—are all measured from the perspective of individual employees. This raises the possibility of response biases and common method variance, even though procedural and statistical remedies were applied as outlined in Chapter 3. Employees' perceptions of organisational support and innovation climate may diverge from formal policies or objective resource allocations, and their self-reported innovative behaviour may not fully align with observable outcomes in organisational records. Future research could mitigate these risks by combining employee surveys with additional data sources, such as supervisor ratings, archival indicators of innovation activity, system usage logs, or independent assessments of organisational practices.

8.2.7 Positively phrased items across the instrument

All constructs in this study were measured through positively framed items. This is broadly consistent with common technology-acceptance survey practice and was also intended to reduce respondent confusion. During the pilot, a single reverse-coded PIIT item produced unreliable

response patterns, suggesting that respondents were not processing the negative framing consistently, and it was therefore rephrased to a positive orientation.

However, positive framing introduces a uniform directional constraint across the instrument. Exclusively positive keying means that the scales primarily capture the degree to which respondents endorse favourable evaluations. Low scores therefore indicate weak endorsement of positive statements, but they do not separately identify the presence, intensity, or source of negative affect, nor do they capture ambivalence, where employees may simultaneously recognise benefits and experience frustration. In a mandated-use context, this is particularly consequential: employees may comply with tablet use while privately resenting it, or perceive organisational support as superficial while rating it neutrally rather than explicitly negatively. The practical consequence may be a compression of the lower response range and potential attenuation of negative or conflicting relationships in the structural model.

This limitation was partially mitigated in the qualitative phase. The interview protocol invited participants to recount episodes where tablet use created friction, and attention was paid to negative and divergent cases during axial coding. This approach surfaced negative and mixed evaluations, including failed organisational rollouts (Theme 3.3), task-technology boundaries (Theme 1.4), and temporal and structural constraints on innovation (Theme 4.3). Future research in mandated settings would benefit from instruments that include bipolar or ambivalence-sensitive items, or that supplement Likert scales with open-response items capturing negative and conflicting evaluations.

8.2.8 Model Specification

The structural relationships in this thesis are estimated using PLS-SEM on cross-sectional survey data collected in 2014–15. Although the model is grounded in established theory and supported by robust fit and diagnostic checks, the interpretation of the paths remains inferential rather than experimental. Mediation findings (for example, PIIT→ITIB→CI; IS→IF→ITIB) are consistent with the hypothesised mechanisms but cannot conclusively rule out alternative orders or unmeasured confounders. The mixed-methods design and later qualitative phase strengthen the plausibility of the proposed mechanisms, yet they do not provide the kind of temporal ordering or experimental control that would be required for definitive causal claims. Longitudinal panel studies and intervention-based designs, as outlined in the recommendations for future research, would be better suited to disentangling dynamic feedback loops and testing whether changes in support structures or ecosystem maturity causally drive shifts in continuance and IT-enabled innovative behaviour.

8.3 Recommendations for Future Research

8.3.1 Introduction

Building on the implications discussed in Chapter 7, this thesis opens up several avenues for further inquiry into employee-driven digital innovation and continuance in SMEs. While the study has provided a theoretically and empirically grounded account in a particular tablet adoption context, many of the mechanisms identified are likely to extend beyond this specific setting. Future research could therefore build on the present work.

8.3.2 Replicating and Extending the Model in Other Contexts

A first priority is to examine the generalisability of the core relationships identified in this thesis beyond Hungarian SMEs and the specific tablet ecosystem studied here. The reconceptualisation of performance expectancy as dominant-task anchored (PE-DTC), the interpretation of continuance intention as readiness-to-re-engage, the contingent role of PIIT, and the mediated impact of innovation support via involvement facilitation are all theoretically portable propositions. Future studies could replicate the structural model and joint-display logic in other national contexts with different digital maturity levels, regulatory regimes and SME structures.

8.3.3 Longitudinal Designs and Usage Trajectories

A second avenue concerns the temporal dynamics of adoption, discontinuation and resumption. The present research relied on a time-separated design. Consequently, continuance had to be inferred from a combination of earlier survey measures and later retrospective accounts. The conclusion that continuance is best understood as cyclical readiness-to-re-engage, with “on–off” trajectories rather than uninterrupted usage, now warrants direct longitudinal investigation.

Panel studies that repeatedly measure PE, EE, ATT, PIIT, IS, IF, ITIB and CI, combined with objective usage logs where feasible, would make it possible to model how changes in roles, task portfolios, governance arrangements and ecosystem maturity trigger shifts in these constructs.

8.3.4 Refining Measures of Task-Specific Performance and Continuance

The integrated analysis suggests that conventional, device-level measures of performance expectancy and continuance intention obscure important task-level variation. Future research could therefore focus on developing and validating more granular, task-specific measures of PE and CI that explicitly anchor respondents’ judgements in clearly defined task families (for example, fieldwork, meetings, documentation, analysis, creative work). This would make it possible to test more directly whether continuance is indeed driven by high-fit “anchor tasks” rather than an

implicit aggregation across the task portfolio. Similarly, the concept of continuance as readiness-to-re-engage could be operationalised through new scales that distinguish between uninterrupted, routine usage; intermittent, situational usage; and dormant but recoverable usage. On the innovation side, further work could disentangle different forms of IT-enabled innovative behaviour (for example, local process tweaks, cross-team solution diffusion, formalised innovation projects). Such measurement refinement would not only enhance model precision but also support more targeted managerial interventions.

8.3.5 Multilevel Perspectives and Organisational Boundary Conditions

A fourth line of inquiry concerns the organisational and multi-level boundary conditions under which the mechanisms identified in this thesis operate. The present study has shown that innovation support functions as a climate-level signal which must be translated into practice through involvement facilitation. However, it did not explicitly model higher-level variables such as organisational structure, strategy or human resource policies. Future research could adopt multi-level designs that embed individual-level beliefs, attitudes and behaviours within team- and organisational-level constructs, such as innovation climate, digital strategy, governance philosophy, or learning orientation.

8.3.6 Second-Level Digital Divide, Policy and Intervention Studies

Finally, the thesis has argued that second-level digital divide issues cannot be reduced to individual skills deficits, but are shaped by task–technology fit, ecosystem maturity and organisational scaffolding. Future research could extend this perspective by explicitly linking micro-level continuance and innovation processes to meso- and macro-level policies and support schemes. For example, studies might investigate how regional or national programmes aimed at SME digitalisation influence the availability of time, training, advisory support and flexible governance at the firm level. Design-based intervention studies, in which specific support packages (such as structured experimentation time, peer-learning mechanisms or innovation sandboxes) are implemented and evaluated, would provide stronger causal evidence regarding the effectiveness of different combinations of IS and IF. Such work would not only deepen theoretical understanding of the second-level digital divide, but also generate actionable insights for policy-makers and intermediary organisations seeking to move SMEs from mere technology deployment towards sustained, innovative use.

8.3.7 Overview

Taken together, these directions suggest that the framework developed in this thesis is not a closed explanatory system, but a starting point for a broader research agenda on employee-driven digital innovation in SMEs. By extending it to new contexts, following trajectories over time, sharpening key constructs and adopting more explicitly multi-level and interventionist designs, future research can both test and elaborate the mechanisms proposed here and further inform practice and policy in this critical domain.

8.4 Personal Reflections

This research began with the simple observation of tablet devices lying unused on desks – devices bought with high hopes in a medium enterprise, quietly becoming digital paperweights. At the time, I framed this as a symptom of a “second-level” digital divide, but I did not yet fully appreciate how complex the underlying story would be. Over the course of this thesis, it has become clear that the difference between a paperweight and a tool of innovation is not the device itself, but the scaffolding of organisational support, individual beliefs and available time that surrounds it.

The journey from that initial puzzle to a completed PhD has been long and, at times, uneven. It has spanned several countries, jobs and institutional contexts. While the data for the quantitative phase were collected in 2014–2015, the work of understanding and making sense of them stretched over a longer time period. My own professional life changed substantially: I moved between roles and locations, and worked with a wide range of students and practitioners. These shifts were not simply background noise; they influenced how I read the data, which questions I found pressing, and how I came to think about SMEs, technology and innovation.

In parallel with the thesis, I became increasingly involved in teaching and case-based work on organisational life and technology use. I frequently use multi-level case studies and experiential teaching based on the Kolb cycle (Kolb, 1984). In some sense, the PhD itself became somewhat similar to a Kolb cycle. Starting from a practical experience, the quantitative phase offered a structured, abstracted view of patterns and relationships – an “abstract conceptualisation” that I was familiar with. The qualitative phase then brought me back to “concrete experience” and “reflective observation” as I listened to participants’ stories and traced their trajectories over seven years. As someone who identifies more readily as a quantitative person, the qualitative strand of this project was both challenging and enriching. The process reinforced, in practice, that different

methods illuminate different facets of the same phenomenon and understanding emerges from their systematic combination.

Finally, this thesis has been a test of perseverance as much as of analytical ability. It accompanied periods of professional uncertainty, institutional transition and personal change. There were long stretches when the project felt too large and too distant from completion. Looking back, what sustained it was not only formal supervision and institutional support, but also a continued sense that the core puzzle remained relevant: why some organisations manage to turn digital tools into vehicles of innovation, while others see them sink quietly into routine or disuse. The answer, as this thesis has tried to show, lies in the delicate and dynamic interplay of individual dispositions, organisational scaffolding and time.

In closing, the image of unused tablets on desks no longer represents, for me, a simple “failure to adopt” or a deficit on the part of users. It is a reminder that technology projects are, ultimately, human projects. Understanding them requires both rigorous models and careful listening, and it requires patience – from organisations, from researchers and, perhaps most of all, from doctoral students learning to navigate their own long adoption journeys.

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Appendix A Definitions and Acronyms

Table 9.1 Definitions / Acronyms

Term (Acronym)	Expression	Definition / Explanation (applicable to this study)
AI	Artificial Intelligence	Broad class of computational methods (e.g., Machine Learning) referenced in EU/HU digitalisation context.
API	Application Programming Interface	Set of rules and protocols that allow different software systems to communicate; referenced when tablet applications connect to back-end systems.
ATT	Attitude	Overall evaluative judgement toward using the focal ICT in work; reinstated as a proximal predictor of CI and ITIB in post-adoption, mandated contexts.
AVE	Average Variance Extracted	Convergent validity index in SEM indicating the average amount of variance that a construct explains in its indicators; used to assess reflective measurement quality.
BH	Benjamini–Hochberg	False-discovery-rate correction procedure applied to adjust p-values for multiple structural paths.
BI	Behavioural Intention	Intention to use (original UTAUT).
CA	Cronbach’s Alpha	Classical internal consistency reliability estimate for reflective scales; reported alongside composite reliability.
CB-SEM	Covariance-Based Structural Equation Modelling	SEM family that focuses on reproducing the sample covariance matrix; discussed as an alternative to PLS-SEM but not used empirically.
CI	Continuance Intention	Intention to continue using the focal ICT over time (dependent variable).
CMB	Common Method Bias	Potential bias arising when predictor and outcome variables are collected using the same method and source; assessed through diagnostics.
CMV	Common Method Variance	Portion of variance attributable to the measurement method rather than the constructs; monitored as a design and analysis concern.
CR	Composite Reliability	Reliability index in SEM that captures the internal consistency of latent constructs; preferred over Cronbach’s alpha for PLS-SEM.
CRM	Customer Relationship Management	Enterprise systems used as contextual examples of ICT supporting customer-facing processes in SMEs.
CoP	Community of Practice	Organisational learning forum; appears as an operational cue in DTCL (e.g., CoP notes).
DA	Digital Awareness	First DASAT phase: awareness, use-cases, demos, basic literacy.

Term (Acronym)	Expression	Definition / Explanation (applicable to this study)
DAI	Digital Adoption & Implementation	Third DASAT phase: pilots, training, configuration, initial usage.
DASAT	—	Four-phase organisational cycle: DA → DSR → DAI → DTCl; used to locate individual mechanisms within firm-level DT progression.
DESI	Digital Economy and Society Index	EU composite index used to benchmark national-level digitalisation and SME ICT uptake.
DOI	Diffusion of Innovations	Theory explaining innovation spread; reviewed for background context.
DSI	Digital Skills Indicator	EU indicator set capturing levels of digital skills; used to contextualise skills-related aspects of the digital divide.
DSR	Digital Strategy & Roadmap	Second DASAT phase: prioritisation, resourcing, governance, policy.
DT	Digital Transformation	Firm-level, capability-building change leveraging digital technologies; in this study, mapped to DASAT phases.
DTCl	Digital Transformation – Continuous Improvement	Fourth DASAT phase: routinisation, metrics, upskilling, diffusion.
ECM / ISCM	(Information Systems) Expectation–Confirmation Model	Post-adoption satisfaction/confirmation account of continuance; not measured here (informative background only).
ECT	Expectation–Confirmation Theory	Consumer-behaviour theory underpinning ECM; used as background.
EDI	Employee-Driven Innovation	Bottom-up innovation driven by employees' ideas and initiatives; used conceptually to frame IT-enabled Innovative Behaviour.
EDMS	Electronic Document Management System	Class of systems providing digital storage and workflow for documents; referenced as example of organisational ICT.
EE	Effort Expectancy	Perceived ease of use (UTAUT belief) adapted to the focal ICT.
EFA	Exploratory Factor Analysis	Multivariate technique used during scale development to explore factor structure prior to confirmatory modelling.
ERP	Enterprise Resource Planning	Integrated suite of business applications; referenced as example of enterprise-level ICT adopted by SMEs.
EU-27 / EU-28	European Union (27 / 28)	Statistical groupings used for comparability across pre-/post-Brexit datasets.
FC	Facilitating Conditions	Degree to which an individual believes that organisational and technical infrastructure exists to support system use; discussed in the conceptualisation of UTAUT but not directly modelled in the final PLS-SEM.

Term (Acronym)	Expression	Definition / Explanation (applicable to this study)
FDR	False Discovery Rate	Expected proportion of false positives among rejected hypotheses; controlled via BH correction.
HTMT	Heterotrait–Monotrait Ratio	Discriminant validity index in SEM; values below recommended thresholds indicate adequate construct distinctiveness.
IB	Innovative Behaviour	Individual actions (idea generation → championing → application); here, operationalised via ITIB (ideation focus).
ICT or IT	Information and Communication Technology	Digital tools/services enabling information processing and communication. These terms are used interchangeably; both include all communication by now.
IF	Involvement Facilitation	Organisational practices that create opportunities for employees to participate, co-configure, and try features (contextual enabler).
IPMA	Importance–Performance Map Analysis	PLS-SEM extension that maps the importance (total effects) and performance (latent variable scores) of constructs to prioritise managerial interventions.
IS	Innovation Support	Perceived organisational support/encouragement for innovative activity (contextual enabler).
IT	Information Technology	General term for digital systems; umbrella for the focal ICT.
ITIB	IT-enabled Innovative Behaviour	Employee idea-generation behaviours enacted with/through the focal ICT (measured; ideation-only in this study).
InT	Institutional Theory	Firm-level lens referenced for context; not modelled.
KPI	Key Performance Indicator	Metrics referenced as cues in DTIC (dashboards, reviews).
LOFO	Leave-One-Firm-Out	Sensitivity analysis where the structural model is re-estimated repeatedly, each time omitting all observations from one firm to test robustness.
MCD	Minimum Covariance Determinant	Robust estimator used for multivariate outlier detection in data screening.
MGA	Multi-Group Analysis	PLS-SEM procedure comparing structural path coefficients across groups (e.g., gender, age).
MICOM	Measurement Invariance of Composite Models	Procedure used in PLS-SEM to assess whether measurement models are equivalent across groups before MGA.
PCA	Principal Component Analysis	Data reduction technique related to factor analysis; used in early exploratory analysis.
PE	Performance Expectancy	Perceived performance gains from using the focal ICT (UTAUT belief).
PIIT	Personal Innovativeness in IT	Trait-level willingness to try out new IT; modelled as an individual antecedent.

Term (Acronym)	Expression	Definition / Explanation (applicable to this study)
PLS	Partial Least Squares	Variance-based estimation method underlying PLS-SEM.
PLS-MGA	PLS-based Multi-Group Analysis	Non-parametric MGA procedure implemented in PLS-SEM software to test group differences in paths.
PLS-SEM	Partial Least Squares Structural Equation Modelling	Variance-based SEM technique used as the main quantitative analysis method in this thesis.
PRQ	Primary Research Question	Overall guiding research question of the thesis, focusing on tablet-enabled post-adoption and innovative behaviour in Hungarian SMEs.
RAA	Reasoned-Action Approach	Attitude–intention framework; reviewed for background.
SEM	Structural Equation Modelling	Family of multivariate techniques that estimate measurement and structural models simultaneously; includes CB-SEM and PLS-SEM.
SI	Social Influence	Perceived social pressure to use; excluded here due to post-adoption, mandated context.
SME	Small and Medium-sized Enterprise	Organisational context of the study (EU definition adopted).
SRMR	Standardised Root Mean Square Residual	Model fit index reported for PLS-SEM structural models.
SRQ	Sub-Research Question	Component questions (SRQ1–SRQ3) that operationalise the PRQ within the mixed-methods design.
TAM	Technology Acceptance Model	Classic acceptance model; referenced for lineage/parsimonious benchmarks.
TCM	Two-stage Continuance Model	UTAUT-based pre/post continuance framing; not measured here (background only).
TOE	Technology–Organisation–Environment	Firm-level framework used for contextualisation; not modelled.
TPB	Theory of Planned Behaviour	Intention model; reviewed for background.
TRA	Theory of Reasoned Action	Precursor to TPB/RAA; background only.
TTF	Task–Technology Fit	Fit between tasks and system capabilities; cited briefly, not modelled.
UTAUT	Unified Theory of Acceptance and Use of Technology	Core individual-level backbone used in this study (PE, EE, Attitude → CI), adapted for post-adoption.
UTAUT2	UTAUT (consumer extension)	Adds hedonic motivation, price value, habit; not used given employee/mandated context.
VHCN	Very High-Capacity Network	High-speed broadband infrastructure indicator used to contextualise national-level connectivity.

Term (Acronym)	Expression	Definition / Explanation (applicable to this study)
VIF	Variance Inflation Factor	Collinearity diagnostic in regression/SEM; values above thresholds signal multicollinearity.
VPN	Virtual Private Network	Secure connectivity mechanism mentioned when describing remote access and security in SME tablet use.
WLAN	Wireless Local Area Network	Local wireless network technology underpinning tablet connectivity within SMEs.
Wi-Fi	Wireless Fidelity	Common commercial term for IEEE 802.11-based wireless networking; referenced in everyday descriptions of connectivity.

Appendix B Context Overview

Appendix B1. SME Definition

The term SME may be defined in several ways, typically by headcount and financial values (e.g. Carter & Jones-Evans, 2006; Nandan, 2009). However, as this research focuses on a member country of the EU, the European Commission definition is used as a starting point. This specification is detailed in the European Commission User Guide and Model Definition (European Commission, 2005 Art. 2). In addition to the headcount, either Annual turnover or Annual balance sheet total may be selected for full specification. The EU Definition also clarifies autonomous, partner and linked enterprises (European Commission, 2005 Art. 3.1, 3.2 and 3.3).

Table 9.2 SME Definition European Commission (European Commission, 2005)

Enterprise Category	Headcount: Annual Work Unit	Annual Turnover	Annual balance sheet total
Medium-sized	<250	≤€50 million	≤€43 million
Small	<50	≤€10 million	≤€10 million
Micro	<10	≤€2 million	≤€2 million

However, both researchers and policy makers frequently use exclusively the headcount limitation (Ayyagari et al., 2007; Gagliardi et al., 2013), and this research follows the same rule (headcount is less than 250).

Appendix B2. Hungarian SMEs Overview

This data is representative of the year (2013) when the study started. SMEs' economic centrality in Europe is well established ((Ayyagari et al., 2007). However, it should be noted that these numbers fluctuate and recent EU-27 SME economic performance (relative to the 2013 data) shows EU-wide value added contributions dropping to 53.1% and SME employment to 65.2% in 2023 (Bella et al., 2023, 2024).

Table 9.3 Enterprises in the EU-28 in 2013 (Muller et al., 2014)

	Number of Enterprises		Employment		Value Added	
	Number	%	Number	%	Million Euros	%
Micro	19,969,338	92.4%	38,629,012	29.1%	1,362,336	21.6%
Small	1,378,374	6.4%	27,353,660	20.6%	1,147,885	18.2%
Medium	223,648	1.0%	22,860,792	17.2%	1,156,558	18.3%

	Number of Enterprises		Employment		Value Added	
SMEs Σ	21,571,360	99.8%	88,843,464	66.9%	3,666,779	58.1%
Large	43,517	0.2%	44,053,576	33.1%	2,643,795	41.9%
Total	21,614,877	100.0%	132,897,040	100.0%	6,310,574	100.0%

Despite their contribution, SMEs are vulnerable to external shocks; smaller firms are disproportionately affected due to limited slack resources and bargaining power (Eggers, 2020; Miklian & Hoelscher, 2021; Muller et al., 2014).

SMEs in Hungary

Hungarian SMEs constitute a particularly relevant subgroup with a distinct recovery path and capability profile relative to EU averages. While their role in the economy is comparable to EU peers (European Commission, 2014; Papanek, 2010), productivity lags. In 2013, SME value-added share was 53.9%. Medium enterprises perform comparably to EU peers, whereas small and micro enterprises are less developed.

Table 9.4 Enterprises in Hungary in 2013 (European Commission, 2014)

	Number of Enterprises		Employment				Value Added		
	Hungary		EU-28	Hungary		EU-28	Hungary		EU-28
	Number	%	%	Number	%	%	Million Euros	%	%
Micro	497,947	94.5%	92.4%	867,316	35.7%	29.1%	8,570	18.5%	21.6%
Small	23,906	4.5%	6.4%	447,932	18.4%	20.6%	7,528	16.2%	18.2%
Medium	4,064	0.8%	1.0%	404,374	16.7%	17.2%	8,874	19.2%	18.3%
SMEs Σ	525,917	99.8%	99.8%	1,719,622	70.8%	66.9%	24,972	53.9%	58.1%
Large	829	0.2%	0.2%	708,457	29.2%	33.1%	21,365	46.1%	41.9%
Total	526,746	100%	100%	2,428,079	100%	100%	46,337	100%	100%

The sector stagnated through the mid-2000s, with the 2008/2009 crisis deepening the downturn (European Commission, 2014). Only IT-sector SMEs went against the stagnation / downturn trend with ~13% value-added growth between 2009–2010 (European Commission, 2014; Szern, 2010). These SMEs present an exception: typical examples are Kürt (unique data recovery solutions), Graphisoft (software company), or Prezi (online presentation delivery). By 2023, employment in SMEs recovered to 70.9%, while value added increased to 55.5% (Bella et al., 2024).

A brief historical note helps contextualise the Hungarian SME situation: prior to the communist regime takeover (1950s) Hungarian SMEs developed in a similar way to their counterparts in

other European countries (e.g. Austria) (Román, 2002). Under the planned economy, SMEs were largely absorbed into state enterprises. SMEs were only allowed to exist as marginal players in contrast to the state-owned sector (Cieřlik & Stel, 2014): approximately two-third of the employees were working in large, state-run enterprises – the total number of registered enterprises were 359,997 (Román, 2002). Post-1989 reforms triggered a rapid surge in firm registrations, later stabilising around 0.5–0.6 million by the 2010s, with 60–70% of employment now in SMEs. Hungarian SMEs remain affected by structural challenges, such as limited access to financing, uneven managerial competencies, and relatively slow adoption of innovative practices, which potentially inhibit rapid economic recovery and growth (Keszey & Zsukk, 2017; Kovács & Nemeslaki, 2024; Rahman et al., 2017). Targeted interventions—robust ICT initiatives and strengthened managerial capabilities—are therefore very important (Kovács & Nemeslaki, 2024). Hungarian SMEs are frequently identified through the enterprise typology introduced by Vecsenyi (1999), where SMEs are commonly classified into ant, gazella or tiger groups.

Table 9.5 Enterprise typology in Hungary (adapted from Vecsenyi 1999 p 49)

	Ant	Gazella	Tiger	Dinosaur
Strategic directions	Stable, no desire to grow	Fast growth	Continuous growth, searching for business opportunities	Minimal growth, trying to preserve status quo
Organisational structure	Unstructured, very few layers	Unstructured, but moving towards a structured approach	Divisional / structural setup of business units	Hierarchical, usually sector-based
Management	Owner directs everything	Progressing towards business leaders	Business leaders	Sector-based professionals, minimal market knowledge
Decision making, control	No structure, individual, owner-specific	Developing autonomy	Level of autonomy provided to managers	Centralised
Leadership style	Owner dependent	Charismatic, motivating	Positive, team-spirit	Autocracy
Culture	Owner dependent	"We are the champions"	Entrepreneurial, looking for opportunities	Negative and disruptive, employees are not motivated

	Ant	Gazella	Tiger	Dinosaur
Planning	Minimal	Key strategy well defined, developing business plans	Business plans at the level of divisions	Top-down planning

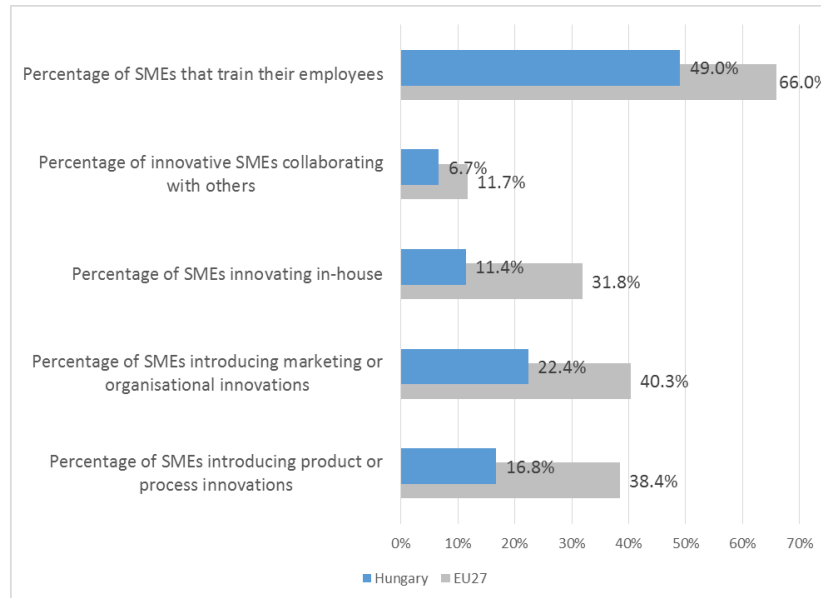
Digitalisation Level in Hungary

The digitalization level of SMEs in Hungary is persistently below the EU average. Hungary ranked 21/28 on the Digital Economy and Society Index (DESI) in 2020, signalling low SME digital uptake. Only 10–20% of Hungarian SMEs are digitalised, placing Hungary 26/28 on business digitisation and e-commerce. The gap between Hungary and the EU average has widened despite modest post-2015 gains (Endrődi-Kovács & Stukovszky, 2022).

In a 2016 study, Hungarian SMEs exhibited low ICT adoption compared to their EU counterparts, ranking second to last in hardware usage and business information systems. Hungarian small-sized enterprises rarely used management information systems (MIS), with only ~15% using customer relationship management (CRM) systems. In contrast, Italian and Portuguese SMEs showed significantly higher adoption rates, highlighting a disparity in ICT development and utilisation within the EU, particularly between Eastern and Southern European countries (Aureli et al., 2016).

This disparity is attributed to insufficient government support and a lack of investments in innovation and training by Hungarian SMEs (Brodny & Tutak, 2022). While investments in innovation and training are key elements in digital transformation approaches, their under-provision constrains impacts the competitiveness of Hungarian SMEs (Dobák et al., 2012; Ferincz, 2012; Hortoványi & Szabó, 2012; Szern, 2010). In terms of innovation and skills-related activities - key elements of this study - the limitations in Hungary relative to the EU average are marked. The difference is considerable in terms of in-house innovations or introducing organisational innovations, with roughly half the participation rate of EU-27 counterparts (note: Croatia was not in EU in 2010).

Figure 9.1 Innovative Activities EU-27 vs Hungary 2010 (European Commission, 2014)



Overall the digital transformation of Hungarian SMEs has been gradual, with significant gaps compared to other EU countries. Current research indicates that Hungary still lags behind in digital infrastructure and the integration of digital technologies (Mészáros, 2024). Key barriers remain: financial constraints, lack of awareness and skills gap (Endrődi-Kovács & Stukovszky, 2022; Kadarova et al., 2023). At the ecosystem/country level, DT readiness is uneven in Central Europe. Comparative work finds Austria ahead of Hungary in digital maturity and Industry 4.0 uptake, with different managerial emphases (market-position improvement vs. profit focus), which shape adoption choices and capability gaps (Katona et al., 2023).

Overall, broad digitalisation of Hungarian SMEs remains low but shows selective improvement in 2025; cloud adoption and data analytics are outpacing other advanced technologies (e.g., cloud usage ~37% from ~21% a year prior; data analytics ~53% vs. EU average ~33%) (European Commission, 2025). However, only 3.7% of Hungarian enterprises use any AI-based solution, well below the EU average of 8%. SME engagement with e-commerce is higher than the EU average (21.8% vs. 19.1%), but overall digital intensity still lags (Mihályi & Molnár, 2025; Péntek et al., 2025).

Recent representative data (n=600 SMEs, Feb 2024) indicate stagnation in Hungarian SME digitalisation: the main Hungarian-specific Digiméter index remains 40/100 (unchanged since 2020–2022), masking widening gaps between sub-domains (Smartcommerce Consulting, 2024). Digital Finance improved (65), driven by near-universal online banking (88%), growing mobile-bank app use (61%), and rising e-invoicing (67%). In contrast, Sales & Marketing deteriorated to

14: 70% of SMEs do no online sales, only 13% run a webshop, and 20% offer merely a quote-request form. Digital Presence slipped despite 72% having a website (down from 79% in 2022); only 34% maintain an active Google Business Profile and many check it infrequently. Business Management shows mixed capability: ERP use at 35% (back to 2021), heavy reliance on spreadsheets for monitoring (69%), and declining routine data tracking—limiting AI-readiness. Digital Everyday Life is levelling between physical and cloud servers; home-office options exist in 31% of firms (covering 12% of employees). IT Security is flat (54): VPN use rebounded to 19%, yet 29% of firms don't back up (or don't know). Overall, the pattern suggests islands of maturity in finance alongside structural weaknesses in market-facing and data/AI capabilities, reinforcing the need for ecosystem support and inside-the-firm practices that translate tools into innovative use (Smartcommerce Consulting, 2024). In the framework applied in this study, these country-level frictions (weak online sales, limited data routines, uneven security) are likely to dampen ICT payoffs without organisational support that enables employees to exploit digital affordances (challenge appraisal, innovation culture) during transformation.

Hungarian SMEs face the familiar triad of skills gaps, planning constraints, and uneven uptake; a DASAT-guided approach offers a concrete sequence for right-sizing initiatives to local capabilities—beginning with awareness and inclusion (sector workshops, vendor training, association programmes), then lean road-maps tied to near-term value, pilot-oriented adoption to build in-house know-how, and lightweight continuous-improvement routines to lock in gains and lift digital literacy for the next cycle.

Appendix B3. Tablet Devices Overview

Tablet Device Definition and Scope

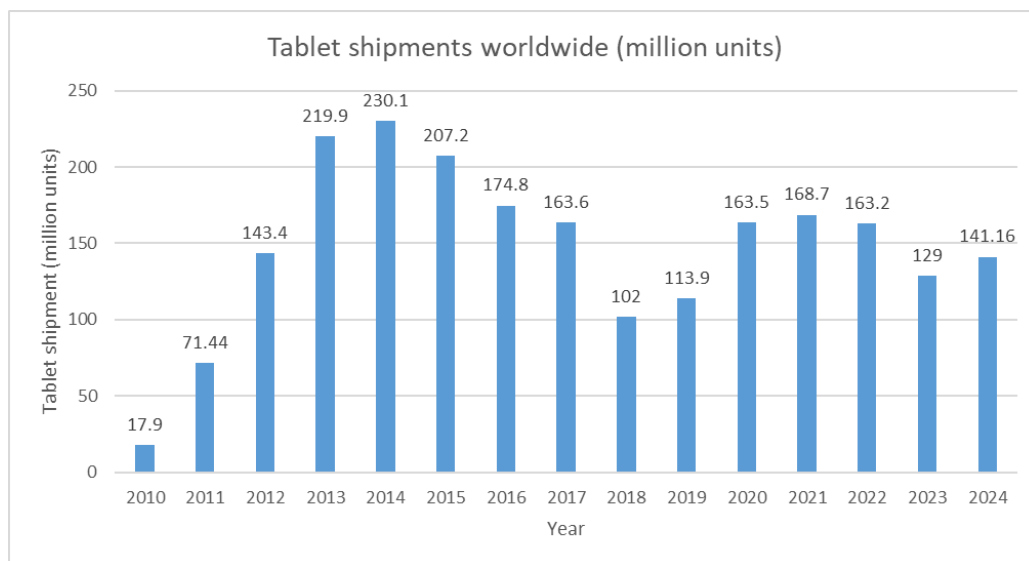
'Mobile information technology' historically spans smartphones, PDAs and pen-enabled tablets, emphasising portability (Sharples & Beale, 2003). With the launch of the iPad in 2010, tablets emerged as a distinct slate-form factor: colour touch displays, instant-on, and wireless connectivity (Wi-Fi/cellular), operated primarily by direct touch or pen input (Alvarez et al., 2011). To avoid ambiguity with large-screen phones, this study adopts a 7-inch lower screen-size bound for tablets (Hur et al., 2014; Lee et al., 2017). Conceptually, tablets sit between smartphones (communication-centric, smaller) and laptops/clamshells (keyboard-centric). At the time of the 2015 SME survey used here, detachable 2-in-1s were not yet widespread. Therefore this study treats tablets as a coherent artefact category for analysis despite emerging 2-in-1s in premium segments.

Tablets are often positioned as convergent, general-purpose devices—bundling media consumption, web, lightweight productivity and app ecosystems—yet debates persist about hype, comparative price–performance and task–technology fit (Alvarez et al., 2011; Courtois et al., 2014; Ferrer et al., 2011; Henderson & Yeow, 2012; Ifenthaler & Schweinbenz, 2013; Quade & Leimstoll, 2017; Sena & Sena, 2013).

Tablet Devices in Numbers

When the first survey window opened (2015), mobile ICT led device sales globally; aggregate ICT shipments reached ~2.4 billion units in 2014 (+3.2% YoY), within which tablets accounted for ~230 million and smartphones ~1.83 billion units (Gartner, 2014, 2015). Estimated tablet users climbed from ~0.86 billion (2014) to ~1 billion (2015), stabilising around 1.2–1.5 billion users in the 2020s (IDC, 2025). After a pandemic-era lift, shipments slowed from mid-2021 as saturation set in; 2023 ended at ~129 million units (–10% YoY), with a modest uptick signalled in 2024 amid ongoing device convergence (IDC, 2025). Vendor and OS leadership consolidated around Apple, Samsung, Huawei, Lenovo and Amazon; platforms remain predominantly iOS/iPadOS and Android, with Windows tablets a small minority (IDC, 2025). Overall, tablets are “squeezed” by large smartphones from below and ultra-light convertibles from above; nonetheless, the category persists due to distinct mobility-plus-screen affordances and maturing enterprise management (Lee et al., 2017).

Figure 9.2 Worldwide Tablet Shipments 2010-2024 (million units) (IDC, 2025b)



These dynamics matter analytically. First, they confirm that in 2015 tablets were still in a diffusion/assimilation phase in enterprises—useful for studying post-adoption continuance before

novelty fully decays (Park & Burford, 2013; Quade & Leimstoll, 2017). Second, the stable user base through the 2020s supports continued organisational relevance even as shipments fluctuate. Finally, convergence pressures foreground task–fit and workflow integration as the differentiators are really value-focused: the raw number count of the devices is less relevant.

SMEs and Tablet Devices

For SMEs, tablets offer a low-friction, low-cost pathway to digitise point-of-work activities and customer touchpoints. Typical patterns include: mobile POS and payments; field service/inspection with photo, geotag and signature capture; on-site access to inventory/ERP/CRM; floor-level dashboards; and lightweight content creation/annotation. Reported benefits cluster around speed, accuracy, flexibility and timeliness, provided deployment is integrated with processes rather than layered on top (Quade & Leimstoll, 2017). Enterprise manageability, app distribution, and accessory ecosystems (rugged cases, barcode sleds, pens, stands) make scaled deployment feasible even in resource-constrained firms, while cloud back-ends generalise many use cases beyond device specifics (Gupta et al., 2013; Quade & Leimstoll, 2017).

Evidence from managerial and frontline contexts illustrates how tablets mediate decision-making and coordination: managers increasingly use tablets for document handling and communication tied to support systems; clinical/field evaluations show that multi-device data availability improves workflow integration and decision speed/accuracy; early-mover SMEs using mobile tools report service improvements and competitiveness gains (Liu et al., 2021; Saleem & Weiler, 2018; Vanhove et al., 2015; Xiao et al., 2017). At the same time, BYOD expands access but introduces governance and security risks that require policy, training, and technical controls (Ogie, 2016; Sadiku et al., 2020) .

The most directly relevant SME-focused quantitative study finds that the perceived value of smartphones/tablets is driven far more by workflow integration and information use than by the number of devices (n=900 Swiss SMEs) (Quade & Leimstoll, 2017). Process-specific apps were less common than document/message access, reflecting the costs of deep process change; nonetheless, integration quality—rather than device count—explains perceived value (exploratory SEM, $R^2 \approx 0.35$). This aligns with the Hungarian SME context, where finance/skills gaps and uneven digitisation (Endrődi-Kovács & Stukovszky, 2022; Kadarova et al., 2023) imply that employee-level mechanisms (skills, attitudes, innovative behaviours) and organisational support (involvement, innovation climate) condition the pay-off from general-purpose devices (Agrawal et al., 2023; Kovács & Nemeslaki, 2024).

Unlike desktops or single-purpose line-of-business systems, tablets combine mobility, instant-on, touch interaction and rich app ecosystems. These affordances make tablets boundary objects that travel with employees (shop floor, field sales, point of service), enabling emergent, user-driven adaptations at the moment of work. Literature connecting mobile/digital tools to employee innovative behaviour remains comparatively sparse when the artefact is a general-purpose device in SMEs (with Quade & Leimstoll, 2017 a key outlier), creating a clear empirical gap. In this thesis, tablets therefore provide a logically constrained yet richly variable device class through which to observe IT-enabled Innovative Behaviour (ITIB) and continuance in mandated SME settings. These affordances and integration dependencies motivate the post-adoption lens in Section 2.5 and the hypotheses in Section 2.6.

Appendix C Innovativeness and Related Streams

Innovation (outcome). Realised novelty at the organisational level—new or significantly improved products, services, processes, or administrative methods. Emphasises measurable change and value creation (Crossan & Apaydin, 2010).

Innovative behaviour (IB) (individual actions). Discretionary, extra-role actions by employees that generate, champion, and implement beneficial novelty (idea generation → championing → application) (de Jong & den Hartog, 2010; Kleysen & Street, 2001).

Innovativeness (propensity). A relatively stable tendency to try novel ideas or technologies. In the IT domain, this is often measured as Personal Innovativeness in IT (PIIT)—a domain-specific trait capturing readiness to experiment with new IT under uncertainty (Agarwal & Prasad, 1998).

IT-enabled Innovative Behaviour (ITIB). The subset of IB enacted with digital tools, where employees experiment with, repurpose, and extend IT features to achieve novel or improved work outcomes (de Jong & den Hartog, 2010; Trivellas & Santouridis, 2013).

Distinctions at a glance

- Level: Innovation = firm outcomes; IB/ITIB = individual actions; Innovativeness/PIIT = individual propensity.
- Time: Innovativeness predisposes; IB/ITIB enact; Innovation materialises after accumulation/selection.
- Measurement: Innovativeness via trait scales; IB/ITIB via behaviour scales; Innovation via performance/outputs.

Table 9.6 Overview of Innovation and Innovativeness

	Organisational level	Individual level
Product: Innovation	Result or outcome at a firm level - new services, new products etc., usually at one given time point.	Result of an individual in coming up with new ideas, developing and / or introducing a new product or process.
Behaviour: Innovative Behaviour	Actions of the firm as a whole to generate, produce or apply a novelty.	Individual actions directed at generation, production or application of a novelty, idea or approach.

	Organisational level	Individual level
Trait: Innovativeness	Capability of a firm to be open to new ideas, explore and exploit new niche markets, product portfolios etc., also referred to as continued strategic level of innovativeness.	Enduring characteristic feature of an individual, trait-like behaviour toward new things / objects etc.

For parsimony and proximity to outcomes, ITIB is modelled as a higher-order behavioural index, with PIIT retained as a complementary trait antecedent. Note: Many studies model IB as a single higher-order construct. Here, a parsimonious, ideation-focused operationalisation is used to capture the stage most immediately stimulated by ICT use. This aligns with evidence that ideation is pivotal for downstream innovation performance and is strongly correlated with later IB stages.

Table 9.7 ITIB Streams

Stream	Primary unit	Core emphasis	Typical measures	Fit to post-adoption tablet use	Representative sources
Exploration in IT (EIT)	Individual	Searching/experimenting to learn IT possibilities; breadth of feature trial	Self-reports of exploration frequency, feature trial breadth	Useful for early stages; less outcome-proximal than ITIB	de Jong & den Hartog (2010) (exploration facet), related exploration scales
Technology Innovativeness in IT (TIIT)	Individual (trait-like)	Novelty orientation toward IT in general	Trait-style items on willingness to try new IT	Captures predisposition; needs behavioural link to predict outcomes	Hirschman lineage; domain-specific variants

Stream	Primary unit	Core emphasis	Typical measures	Fit to post-adoption tablet use	Representative sources
IT-enabled Innovative Behaviour (ITIB)	Individual behaviour	Generating, championing, applying ideas <i>using IT</i> ; repurposing/combining features; routinising improvements	IB scales adapted to IT tasks; task-specific IT adaptation items	Most proximal to value in mandated post-adoption use; links naturally to continuance	Kleysen & Street (2001); de Jong & den Hartog (2010); Trivellas & Santouridis (2013)

Notes. In this study, ITIB is operationalised as ideation rather than as a full three-stage innovative-behaviour construct.

Literature Review: Operationalise Innovativeness

Purpose. To map how employee-level innovativeness/innovation constructs are operationalised around IT use and to position ITIB versus trait measures (e.g., PIIT).

Scope and sources. Records were identified across major bibliographic databases (e.g., Web of Science, Scopus, IEEE Xplore, ABI/INFORM). Search strings combined terms for behaviour and IT (e.g., “innovative behaviour” OR “idea generation” OR “employee innovation”) AND (“IT” OR “IS” OR “digital” OR “technology”) AND (“post-adoption” OR “use” OR “continuance” OR “appropriation”). Time window emphasised the modern mobile/cloud era while retaining foundational works (anchor papers from 1990s–2010s). Duplicates and non-organisational settings were excluded. The final working set comprised ~84 studies.

Coding. Studies were coded on: (i) construct family (EIT, TIIT, IB/ITIB), (ii) unit/level (individual vs team), (iii) phase (initial vs post-adoption), (iv) outcome proximity (behavioural vs performance), (v) presence of UTAUT/TAM beliefs, (vi) context (SME vs large firm; mandated vs voluntary). Intersections (e.g., IB with UTAUT beliefs) were flagged.

Limitations. Not a formal PRISMA review; emphasis is on conceptual mapping relevant to post-adoption tablet use in SMEs. Regional bias is possible due to database coverage and English-language publications.

Conclusion. Evidence clusters around three streams (EIT, TIIT, ITIB). For continuance models, ITIB offers the most direct behavioural conduit to realised value, while PIIT captures stable differences in exploration propensity.

Table 9.8 Overview of Use Innovativeness Streams of Research

Stream & Definition	Source	Structural Model Key Elements	Ind. Phases
Explore IT A user's willingness and purpose to explore a new technology and find potential uses. Operationalised with 3-item construct.	(Nambisan et al., 1999)	IT Steering Committee + IT Planning Team +	pre-adoption adoption
	(Magni et al., 2010)	PIIT ns Cognitive Absorption + Image Enhancement + Performance Expectancy +	post-adoption
	(Saeed & Abdinnour-Helm, 2008)	Perceived Usefulness+ System Integration+ Information Quality+	post-adoption
	(Kim & Gupta, 2014)	User Empowerment+ Integrative Use+	post-adoption
	(Thatcher et al., 2011)	PIIT ns Computer Self-Efficacy+ Social Norms+ Perceived Usefulness+ Perceived Ease of Use+	post-adoption
Trying to Innovate with IT A user's goal of finding novel uses of information technology. Operationalised with 2-item construct.	(Bagozzi et al., 1992)	Attitude to Success of Learning+ Attitude to Failure of Learning+ Attitude to Process of Learning+ +Intention to Use	pre-adoption adoption
	(Ahuja & Thatcher, 2005)	Autonomy + Overload +	post-adoption
	(Wang et al., 2013)	Satisfaction+ Perceived Usefulness+ Moderator: PIIT and IT Self-Efficacy	post-adoption
IT-enabled Innovative Behaviour The extent to which the use of IT helps users create and try out new ideas.	(Torkzadeh & Doll, 1999; Torkzadeh et al., 2005)	NA	pre-adoption adoption post-adoption
	(Deng et al., 2008)	Decision Support + + Performance Expectancy	post-adoption

Operationalised with 3-item construct.	(Doll & Xiaodong, 2010)	Empowerment+ Problem Solving/Decision Support+	post-adoption
	(Doll & Deng, 2011)	Decision Support Usage / Performance Expectancy + Software Capability+ Work Planning Usage + Autonomy + Length of Use +	post-adoption
	(Tarafdar et al., 2010)	End User Satisfaction + Technostress Creators -	post-adoption
	(Trivellas & Santouridis, 2013)	Open Systems+ Human Relations+ Internal Process+ Rational Model+	post-adoption

Table 9.9 Use Innovativeness Constructs and Items

Construct & Source	Items
Intention to Explore (Magni et al., 2010; Nambisan et al., 1999)	IE1. I intend to explore how (ICT) can be used for other tasks. IE2. I intend to explore other ways that (ICT) may enhance my effectiveness. IE3. I intend to spend time and effort in exploring (ICT) for potential applications.
Exploratory Usage (Saeed & Abdinnour-Helm, 2008)	EU1. I explore how I can use (ICT) to manage my tasks. EU2. I explore new uses of (ICT) to manage my tasks. EU3. I explore how (ICT) can better support my needs.
Emergent Use (Kim & Gupta, 2014)	EMG1. I explore how (ICT) can better support my work. EMG2. I often find new uses of (ICT) to support my work. EMG3. I often use (ICT) in novel ways to perform my tasks.
Intention to Explore (Thatcher et al., 2011)	ITE1. I intend to spend considerable time exploring uses of (ICT). ITE2. I intend to explore (ICT) for enhancing the effectiveness at work. ITE3. I intend to use (ICT) in novel ways.
Intention to Try (Bagozzi et al., 1992; Bagozzi & Warshaw, 1990)	IntTry1. I presently intend to try learning to use (ICT) effectively.
Trying to Innovate with IT (Ahuja & Thatcher, 2005)	TryIT1. I try to find new uses of (ICT). TryIT2. I try to use (ICT) in novel ways.
Innovate with IT (Wang et al., 2013)	IwIT1: I have found new uses of this (ICT) to enhance my productivity. IwIT2: I have used this (ICT) in novel ways to help my work.
IT-enabled Innovative Behaviour (Torkzadeh & Doll, 1999; Torkzadeh et al., 2005)	ITIB1: This (ICT) helps me create new ideas. ITIB2: This (ICT) helps me come up with new ideas. ITIB3: This (ICT) helps me try out innovative ideas.

Innovation (outcome). Realised novelty at the organisational level—new or significantly improved products, services, processes, or administrative methods. Emphasises measurable change and value creation (Crossan & Apaydin, 2010).

Innovative behaviour (IB) (individual actions). Discretionary, extra-role actions by employees that generate, champion, and implement beneficial novelty (idea generation → championing → application) (de Jong & den Hartog, 2010; Kleysen & Street, 2001).

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Appendix D Framework Model Comparison

Organisational Models

In ICT adoption context, an organisational level framework is the Technology, Organisation and Environment (TOE) approach (Tornatzky & Fleischer, 1990). Tornatzky and Fleisher (1990) identify three major aspects impacting the decision making related to technology adoption. These aspects are described as follows: a) technological context incorporates both the relevant and available internal and external technologies; b) organisational context reflects on the specific characteristics of the organisation, including size, structure or leadership style; and c) environmental context is comprised of the external variables impacting the firm, including industry characteristics, nature of competition or regulations (Oliveira & Martins, 2011; Tornatzky & Fleischer, 1990). TOE includes the environmental context, and provides additional explanatory power at firm level (Hsu et al., 2006). The TOE framework was successfully applied to IT adoption in SMEs regarding e-business (Kuang-Wei & Yan, 2010), cloud computing (Alshamaila et al., 2013), knowledge management (Lin, 2014), business-to-business e-commerce (Lip-Sam & Hock-Eam, 2011) or Enterprise Resource Planning system usage (Ruivo et al., 2014).

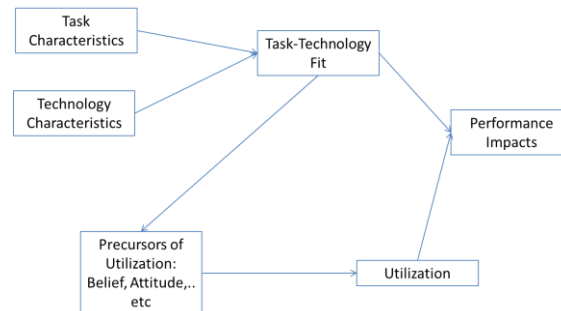
Institutional theory (InT) emphasises the fact that organisational decisions may not be explained as purely efficiency-driven rational decisions, since social, cultural and interacting institutions may impact the adoption decision (Oliveira & Martins, 2011). Institution in this context is defined as “any standing social entity that exerts influence and regulation over other social entities” (King et al., 1994 p 148). Similarly to the TOE framework, the institutional theory is considering the organisational level, rather than moving to the micro level of an employee. Owing to the nature of the model and generic definition of institution, most studies discuss adoption of ICT without reflecting on the size of the organisation in case of web technologies (Chatterjee et al., 2002), using knowledge platforms (Purvis et al., 2001) or evaluating financial electronic data interchange (Teo et al., 2003). In case of SMEs, InT was successfully applied for the Knowledge Transfer Partnership programme in the United Kingdom (Choudrie & Culkin, 2013).

A comprehensive model has been formulated for measuring IT satisfaction as Small Business User IT Satisfaction (SBUSIT) approach (Palvia, 1996). This model combines several IT-characteristic items (e.g. Software Adequacy, Hardware Adequacy etc.) with system introduction items (e.g. Vendor Support, Training and Education etc.) to gain an overall evaluation score.

Task Technology Fit Model

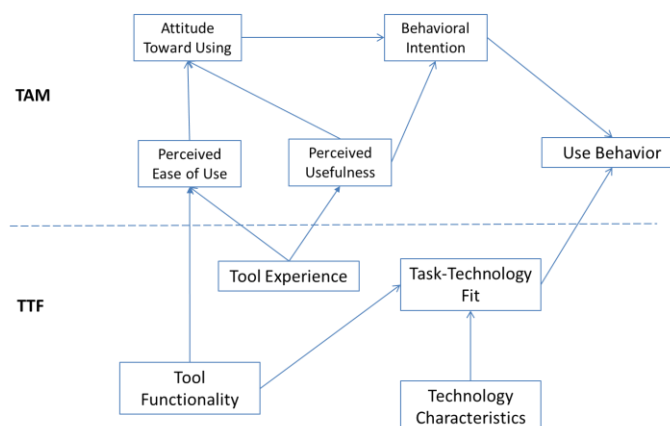
This particular model is a more specific approach in comparison to the original TAM: rather than discussing the technology in general, it looks at the specific fit of technology to a task.

Figure 9.3 Task Technology Fit Model (Goodhue & Thompson, 1995)



It should be noted, that TAM2 also incorporated Job Relevance, which is a close surrogate for Task Characteristics and Task-Technology Fit (Venkatesh & Davis, 2000). Nevertheless, this model highlights that requirement of employing an IT solution that specifically fits the desired task. A complex combination of TAM and TTF has been suggested, as displayed below (Dishaw & Strong, 1999).

Figure 9.4 TAM and TTF Combined Model (Dishaw & Strong, 1999)

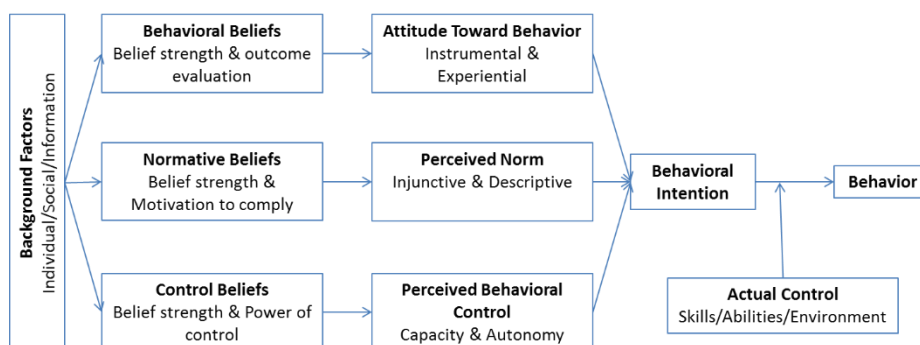


A number of papers applied a combination of TAM and TTF, including adoption of e-learning systems (Lin & Wang, 2012b; Ma et al., 2013), virtual reality and learning effectiveness (Zhang et al., 2017), adoption of Massive Open Online Courses (Wu & Chen, 2017), or knowledge management adoption (Ren-Zong & Gwo-Guang, 2011) or utilisation of online learning systems (Yu & Yu, 2010). These examples highlight both the advantage and disadvantage of the model: a very specific task has to be defined to measure task-technology fit.

Reasoned-Action Approach and Related Models

Reasoned-Action Approach is an integrative approach of behaviour predicting models (Theory of Reasoned Action - TRA, Theory of Planned Behaviour - TPB) (Fishbein & Ajzen, 2010). A fundamental assumption of these models is that individuals process information rationally and underlying reasons determine motivation to perform a behaviour (Ajzen, 1991; Fishbein & Ajzen, 1980, 2010).

Figure 9.5 Reasoned-Action Approach



Key elements of this model include observable behaviours and intentions. Intentions are considered as the individual's perceived likelihood estimate of performing a given behaviour. Direct determinants of individuals' behavioural intention are attitude toward performing the behaviour, subjective norm associated with the behaviour and perceived control in situations without complete volitional control over a behaviour.

The attitude – a latent disposition to respond favourably or unfavourably to a psychological object – toward the behaviour may be experiential (affective evaluation of the behaviour) or instrumental (anticipated consequences). Perceived norm – perceived social pressure – may be based on injunctive norm (whether most people approve or disapprove of the behaviour) or descriptive norm (whether most people would perform the behaviour). Finally, perceived behavioural control represents people's perceptions of their ability to perform a given behaviour.

These theories have been used extensively in a wide range of areas, including information technology research. To list a few examples, successful applications include electronic commerce (Pavlou & Fygenson, 2006), environmental management in SMEs (Sánchez-Medina et al., 2014) or educational technology usage by teachers (Jung et al., 2010).

Meta-analytic reviews highlight the applicability of the model to a variety of situations, but also comment on its limitations because of its generic nature (Armitage & Conner, 2001; Durlabhji & Fusilier, 2005; Jokonya, 2017). Another typical argument relates to the problems of models effectively only being tested in a confirmatory environment, thus rejection is never actually tested

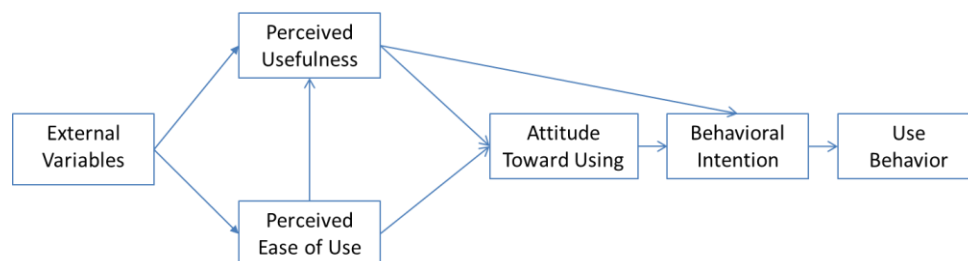
(i.e. it is not falsifiable) (Ogden, 2003). This is a generic question for social cognition models, and the answer is that if all factors fail in the prediction, the model would be disconfirmed for the specific context (Ajzen & Fishbein, 2004).

Technology Acceptance and Related Models

In terms of IT adoption and usage, the most commonly cited framework in the literature (Chang et al., 2010) is the Technology Acceptance Model (TAM) (Davis, 1989). TAM was developed to predict individual adoption and use of new information technologies. The model is generally considered the “most robust, parsimonious, and influential in explaining IT/IS behaviour” (Lu et al., 2003 p 207).

A key hypothesis of TAM is that use behaviour is driven by behavioural intention, which in turn is determined by attitude towards the system. These items are directly affected by two variables: Perceived Usefulness and Perceived Ease of Use. Perceived Usefulness (PU) is defined as “the degree to which a person believes that using a particular system would enhance his or her job performance”, while Perceived Ease of Use (PEOU) is defined as “the degree to which a person believes that using a particular system would be free of effort” (Davis, 1989 p.320). Finally, Attitude is defined “as an individual's positive or negative feelings (evaluative affect) about performing the target behaviour” (Davis, 1989 p.320).

Figure 9.6 Technology Acceptance Model (Davis, 1989)



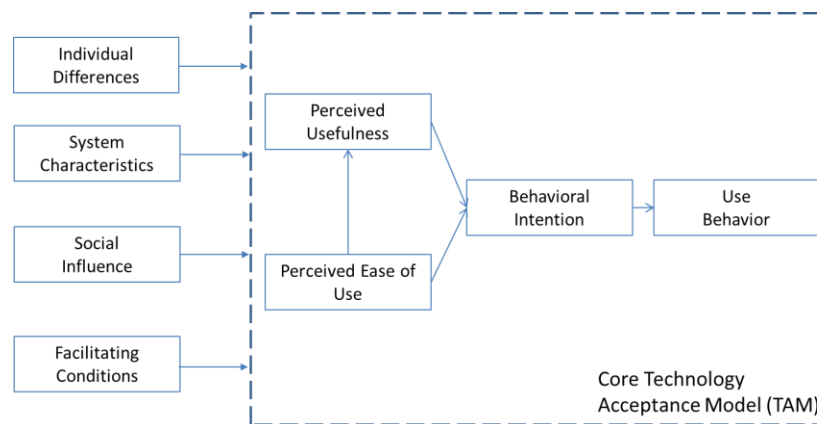
Davis admittedly took ideas from the Theory of Planned Behaviour, however, the model is a clearly more specific, as beliefs are split into Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), targeting information technology usage. Two papers were published in 1989, which subsequently formed the basis of one of the most successful adoption theories (Davis, 1989; Davis et al., 1989). An early modification of the model included the exclusion of the Attitude construct, as PE and PEOU had a direct influence on behavioural intention (Davis et al., 1989).

As several meta-analysis papers show, TAM has been validated and used extensively and successfully in the IT/IS community in a large number of scenarios (Chuttur, 2009; King & He,

2006; Lee et al., 2003; Ma & Liu, 2004; Marangunić & Granić, 2015; Schepers & Wetzels, 2007; Yousafzai et al., 2007a, 2007b).

In chronological terms, the TAM was tested, validated and replicated in several studies until the late 90s, then the model extension and elaboration approach took the focus (Lee et al., 2003). As a consequence, TAM has been refined and updated several times: additional antecedents and individual determinants were connected to the original model. Throughout the development of TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008) the core of TAM remained unchanged.

Figure 9.7 TAM-based Models (Venkatesh & Bala, 2008)

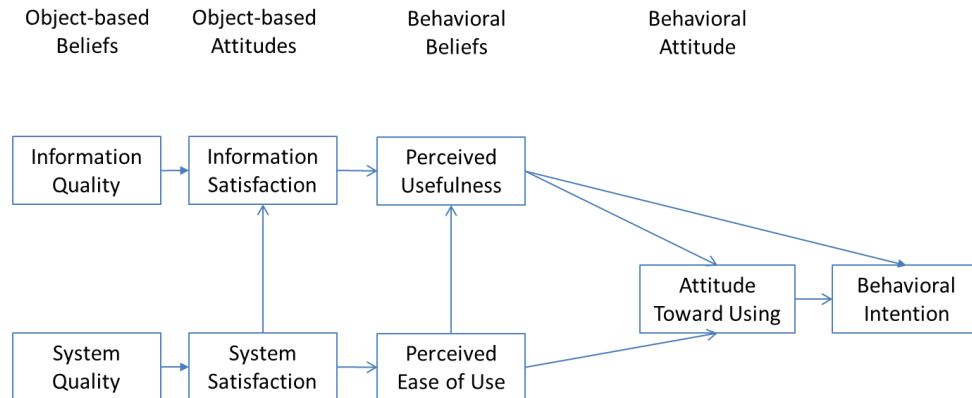


TAM-based models add – or remove – specific elements within the major categories of individual differences, system characteristics, social influence and facilitating conditions (Venkatesh & Bala, 2008). Individual difference variables include traits and/or states of individuals (e.g. personal innovativeness used in this study). Individuals develop their perceptions based on salient system characteristics. Social influence covers various social processes and approaches. Finally, facilitating conditions represent organisational support (Venkatesh & Bala, 2008).

Summarizing the typical approaches, researchers regularly extend the core model with a) contextual factors, b) external predictors, c) factors from other models and d) usage measures (Marangunić & Granić, 2015).

Wixom and Todd (2005) recommended an integration of TAM with User Satisfaction research (DeLone & McLean, 2003; Petter et al., 2008). Their model advocates the combination of object-based and behavioural beliefs and attitudes, considering that a) object-based attitudes are weak predictors, but provide a more elaborate picture of IT; and b) behavioural beliefs are good predictors, but less appropriate for capturing details.

Figure 9.8 Integrated TAM-User Satisfaction Model



TAM has also been used in SME context: a few examples include electronic commerce application surveying SME leaders (Grandon & Pearson, 2004), digital media usage (Camilleri, 2019), acceptance of knowledge management (Siregar et al., 2017) or ICT adoption of young entrepreneurs (Zaremozhzabieh et al., 2016). In addition, an entrepreneur-specific version was developed (ETAM), although key TAM constructs have proven to be valid within the participating entrepreneur group (Ndubisi & Richardson, 2002). E-business is a repeatedly studied element in SME context (Vasin et al., 2007). Some authors comment on the limited number of applications in SMEs, but the model was confirmed in this environment as well (Nguyen, 2009). One particular issue relating to adoption of IT in organisations is the mandatory vs voluntary use debate. In contrast to the large number of studies in voluntary situations, very few studies considered mandatory use (Yousafzai et al., 2007a, 2007b), although organisations primarily proceed with mandatory ICT use (Lee et al., 2003).

Arguably, in IS/IT research, one of the most influential and widely used model at individual level is the technology acceptance model (TAM) (Benbasat & Barki, 2007; Chuttur, 2009; Yousafzai et al., 2007a, 2007b). Despite the extensive usage of TAM, there are a number of critical comments (Bagozzi, 2007; Benbasat & Barki, 2007; Chuttur, 2009; Marangunić & Granić, 2015; Turner et al., 2010). Some of the comments relate to the actual application of the model: its parsimonious nature makes it easy to use for researchers, yet limits the actual meaningful advice for practitioners that can be extracted from the model (Legris et al., 2003; Lu et al., 2003; Marangunić & Granić, 2015). Overall the agreement has been that parsimony is both an advantage and disadvantage for the model (Venkatesh & Davis, 2000). Due to the extensive use of the model and the complication of actually measuring usage patterns, most researchers limit the model to the behavioural intention, which again raises questions of actual usage versus intention (Turner et al., 2010). Other criticisms include methodological issues related to the testing of the model

(falsifiability), and discussions on antecedents and stability of existing relationships (e.g. the role of attitude) (Chuttur, 2009; Marangunić & Granić, 2015).

SiSIT Model

The six-stage IT (SiSIT) model of Cooper and Zmud (1990) considers the IT implementation as an organisational effort, aimed at diffusing appropriate information technology within a user community, or enterprise (Cooper & Zmud, 1990). The model is displayed below, leading from its opening stage of Initiation to the last stage of Infusion.

Table 9.10 Six-Stage IT Implementation Model (Cooper & Zmud, 1990 p 124-125)

Stage	Description: Process	Description: Product
Stage 1: Initiation	An inventory of organisational problems and/ or opportunities and IT solutions are undertaken. Pressure to change evolves from either organisational need (pull), technological innovation (push), or both.	A match is found between an IT solution and its application in the organisation.
Stage 2: Adoption	Rational and political negotiations to get organisational backing for implementation of the IT application.	A decision is reached to invest resources necessary to accommodate the implementation effort.
Stage 3: Adaptation	The IT application is developed, installed, and maintained. Organisational procedures are revised and developed. Organisational members are trained both in the new procedures and in the IT application.	The IT application is available for use in the organisation.
Stage 4: Acceptance	Organisational members are induced to commit to IT application usage.	The IT application is employed in organisational work.
Stage 5: Routinization	Usage of the IT application is encouraged as a normal activity.	The organisation's governance systems are adjusted to account for the IT application; the IT application is no longer perceived as 'out of the ordinary'.
Stage 6: Infusion	Increased organisational effectiveness is obtained by using the IT application in a more comprehensive and integrated manner to support higher level aspects of organisational work.	The IT application is used within the organisation to its fullest potential

Appendix E Ethics Process and Clearance

Table 9.11 Ethics Summary

Phase	Key activities	Dates	Ethics reference
Pilot A (students, CEU)	CEU student survey (instrument shakedown); progression viva informed refocus to SMEs	Ethics submitted 15 Jul 2012; approved 1 Sept 2012; fielding 1– 31 Jan 2013	CEU approval No. 1/2012/13
Context change to SMEs	Progression viva; decision to refocus to SMEs	7 Oct 2013	—
Pilot B (SMEs)	SME pilot launch; instrument tuning	CEU ethics submitted 1 Jun 2014; approved 15 Jun 2014; pilot begins 1 Jul 2014	CEU approval No. 2/2013/14
Main survey (SMEs)	Primary fieldwork window with reminders; data lock and cleaning	1 Jul–28 Nov 2014 (primary window); (secondary window / late entries to 31 Mar 2015)	CEU approval No. 2/2013/14 UH approval: ‘Social Sciences Arts and Humanities ECDA Minute 134’.
Interviews (qualitative follow-up)	Semi-structured interviews with SME employees/managers; purposive sampling from survey cases; transcription & initial coding	Conducted 9 Jun–1 Oct 2021	UH ECDA approval BUS/PGT/UH/04934 (valid during interview window)

Survey Clearance

Ethical Clearance UH Protocol Number:

'Social Sciences Arts and Humanities ECDA Minute 134'.

Interview Clearance

Protocol number: BUS/PGT/UH/04934

Title of study: Examining the adoption, use and diffusion of tablet devices: A study of small and medium enterprises in Hungary

Your application for ethics approval has been accepted and approved with the following conditions by the ECDA for your School and includes work undertaken for this study by the named additional workers below:

no additional workers named

Validity:

This approval is valid:

From: 09/06/2021

To: 01/10/2021

Appendix F Philosophies and Paradigm Reviews

Appendix F1. Methodology Development Options

For the methodology development, three particular approaches are considered, including the epistemology-focused Research Methodology Framework (Crotty, 1998), the paradigm-based view and related Methods Map (Guba & Lincoln, 1994, 2005; O’Gorman & MacIntosh, 2015), and the Research Methodology Onion (Saunders et al., 2019).

All these approaches aim to clarify three dimensions – or three key questions – in relation to the given research, as (a) the ontological question, (b) the epistemological question and (c) the methodological question (Guba & Lincoln, 1994). This defines the researcher’s belief in the form and nature of reality, the relationship between the researcher and knowledge, and how the researcher aims to find out what can be known, respectively.

Focusing on ontology, the root of the word (‘Ontos’) may be considered as referring to ‘being’ or ‘reality’: ontology deals with the study of reality (O’Gorman & MacIntosh, 2015). Epistemology is also defined as the theory of knowledge and describes a pathway to valid knowledge (Hirschheim, 1992). Another conceptualisation refers to epistemology as “a broad and high-level outline of the reasoning process by which a school of thought performs its empirical and logical work” (Mingers & Willcocks, 2004 p 6).

One particular approach to defining research methodology is presented by Crotty (1998) in his seminal book (*The Foundations of Social Research*). Interestingly, Crotty removes ontology, arguing that it would emerge together with epistemology, informing the theoretical perspective, “for each theoretical perspective embodies a certain way of understanding what is (ontology) as well as a certain way of what it means to know (epistemology)” (Crotty, 1998 p 10). The priority of ontology versus epistemology is a much-argued element (Smith, 2006). Even within specific philosophies, some start with an ontological view, rather than an epistemological foundation (e.g. critical realism (Bhaskar, 1978)).

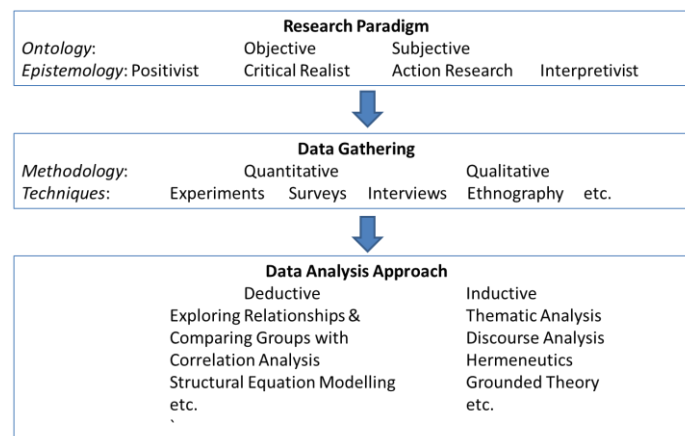
The development of a research methodology would entail defining the relationship between columns by drawing arrows from left to right. For example, linking Objectivism to Positivism, and then to Survey research and Questionnaires would formulate a methodological plan.

Table 9.12 Research Methodology Frameworks (adapted from Crotty, 1998)

Epistemology	Theoretical perspective	Methodology	Methods
Objectivism Constructivism Subjectivism	Positivism Interpretivism Critical Inquiry etc.	Experimental research Survey research Ethnography Grounded theory Action research etc.	Sampling Statistical analysis Questionnaire Observation Interview Content analysis etc.

A slightly different paradigm-based view is outlined by O’Gorman and MacIntosh (2015), advocating a particular set of steps called Methods Map. In this approach, the first step concerns the objective versus subjective ontology. An objective ontology considers the independent existence of reality from the observer; as to “establish and explain universal principles and facts through robust, replicable methods” (O’Gorman & MacIntosh, 2015 p 57). A subjective ontology considers facts as dependent (subject to) the attitudes, behaviours and beliefs of both the observer and observed. At the same time, objectivism does not imply the rejection of subjectivity: an objective ontology may incorporate a study of people’s attitudes or beliefs, as long as the objectivity remains (Gray, 2014). Once the ontological stance is defined, the Methods Map leads to epistemological considerations, which in turn will enable progress in the data gathering and analysis approaches.

Figure 9.9 Methods Map (adapted from O’Gorman & MacIntosh, 2015)



Finally, another approach – with perhaps a more pragmatic phrasing – asserts that the selection of the actual methodology requires reviewing the research questions and objectives, the breadth and width of existing knowledge on the subject and resources available (Saunders et al., 2019). A guiding overall framework in the form of an onion was developed by Saunders, Levin and Thornill (2019), presented on Figure 3.1. This approach seeks to move from the outer bands to the inner circles, narrowing down various research choices as progressing through the layers of the onion.

Appendix F2. Philosophies and Paradigms

Positivism and post-positivism

The word ‘positivism’ is frequently attributed to Auguste Comte (1798-1857), but he should be considered more in terms of popularising the phrase, rather than introducing it (Crotty, 1998). Positivism generally considers that the existence of the world is external to the researcher. Its core argument emphasises that this external world can be measured directly (and independently) of the researcher, through observation. Nevertheless, as with every philosophical school, the meaning of ‘positivism’ has changed considerably from Comte, through the influence of the Vienna Circle and logical positivism, finally arriving at the contemporary interpretation. It was a leading paradigm from the 1930s to the 1960s, and throughout its history, it has retained a strong link to empirical science (Crotty, 1998). Thus, adopting positivism usually implies the approach of a natural scientist (Saunders et al., 2019). Hirschheim (1992) identifies 5 key pillars for positivism:

- Unity of the scientific method: knowledge acquisition (hypothesis-thesis) is all-encompassing, relevant and valid for any domains of study;
- Search for human causal relationships: cause and effect can be studied, and findings appropriately generalised to predict patterns or behaviour;
- Belief in empiricism: valid data is experienced from the senses;
- Science (and its process) is value-free: the researcher plays a neutral role in knowledge acquisition;
- The foundation of science is based on logic and mathematics, which provide a universal language.

The positivist paradigm is frequently evaluated by applying four criteria in research: internal validity, external validity, reliability and objectivity (Burns, 2000).

- Internal validity reflects on the independent variable(s) used in the study: it evaluates the dependence of the results on the studied variables within the given research framework.

- External validity refers to the degree of generalisation based on the study.
- Reliability evaluates the stability and consistency of research instruments.
- Finally, objectivity is a broader term, reflecting on eliminating any bias and subjective considerations.

With a rigorous approach, positivism has produced a large pool of research invaluable for understanding the adoption and use of ICT (Orlikowski & Baroudi, 1991). Indeed, while the actual ratio of different paradigmatic approaches depends on the reviewed research sources, generally positivism dominates the research in information systems (Goles & Hirschheim, 2000). At the same time, IT is used by humans, and as such, requires a socio-technical view, which raises the question of distinguishing between natural and social phenomena.

As a critique, the typical answer of a positivist researcher may represent “an unreflexive use of methods (e.g., experiments, hypothesis testing, quantification) assumed to be successful in the natural sciences and readily transferable to the domain of the social sciences” (Knights, 1992 p 514). These issues led to the post-positivist approach, which relaxes the perfectly knowable reality and introduces a level of uncertainty with what can be known (Shanks & Parr, 2003). It has to be emphasised that the argumentation against positivism has a lot more to do with the (sometimes excessive) status assigned to scientific knowledge, rather than to the actual articulation of scientific results (Crotty, 1998). Initially, positivism followed a naïve realist ontology by claiming a full apprehension of reality. In connection with an objectivist epistemology, it focused on quantitative methods and verifiable hypotheses (Crotty, 1998; Guba & Lincoln, 1994). Guba and Lincoln (1994) suggest that post-positivism incorporates some specific changes, including the ontology (adopting a critical realist approach) and epistemology (modified dualist/objectivist). Post-positivism is strongly connected to Popper’s principle of demarcation, raising the issue of falsifiability for models and theories (Popper, 1992). As a consequence, it questions some of the tenets of the Technology Acceptance Model as well (Silva, 2007).

Interpretivism

Interpretivism argues that the reductionist approach of positivism, while successful in some areas, inherently has limitations due to its nature of not recognising differences between the social and natural phenomena. Interpretivism considers reality as a human construction: thus, by definition, even the researcher’s views are subjective and depend on his/her filtering lenses (Kroeze, 2011; Walsham, 2009). The interpretivist approach looks for “culturally derived and historically situated interpretations of the social life-world” (Crotty, 1998 p 67). Consequently, interpretive research generally focuses more heavily on the details, and its final goal is to find deep insights into social

situations, rather than defining general laws or rules (De Villiers, 2005; Walsham, 2009). The introduction of the interpretivist stance is frequently connected to Max Weber (1864-1920) (Crotty, 1998). The interpretivist stance assumes multiple realities, created by individuals (ontology), believes in fluid and provisional knowledge (epistemology), and concludes that empirical approaches provide limited answers and require further insights and probing to understand the 'how' and 'why' questions from the individual point of view (Kroeze, 2011). The interpretivist stance provides both advantages (deeper insights) and disadvantages (difficult generalisation) in comparison to the positivist approach.

Realism

Realism takes the position that objects have an existence independent of the human mind (Sayer, 2000). There are several streams and approaches using realism as a key starting point. As an example, scientific realism is closer to post-positivism (McKelvey, 1999), while critical realism is taking a stand closer to interpretivism (Saunders et al., 2019). Some researchers advocate critical realism as a way to overcome theory-practice inconsistencies present in both positivist and interpretivist approaches (Smith, 2006; Volkoff & Strong, 2013). Critical realism has its roots in Roy Bhaskar's work (1978) and may be summarised based on Mingers, Mutch and Willcocks's application to information systems research (2013) as follows:

- critical realism advocates the worldview of an "existing, causally efficacious world independent of our knowledge" (Mingers et al., 2013 p 795);
- critical realism also recognises that "our access to this world is in fact limited and always mediated by our perceptual and theoretical lenses" (Mingers et al., 2013 p 795); and
- critical realism accepts that the different types of knowledge will require different research methodologies to understand them.

Regarding the methodology, the critical realist keeps an open mind and may use both quantitative and qualitative methods (McEvoy & Richards, 2006). At the same time, the role of quantitative methods is rather descriptive than inferential, as causal mechanisms cannot be explained by generalisations and correlations between variables. In contrast, qualitative methods describe the phenomenon in more detail and help in constructing propositions.

The scientific methodology of critical realism is focused on taking some unexplained phenomenon and proposing hypothetical mechanisms, which, if they existed, would generate the phenomenon in question (Mingers et al., 2013). This mechanism has to be envisaged across a three-fold ontological differentiation of domains of the real (mechanisms, events and experiences); the

actual (events which truly occur); and the empirical (what we truly observe or experience) (Bhaskar, 1978). Consequently, our empirical observation would require an explanation in the real (based on what is experienced in the empirical), and this process is called retroduction by Bhaskar (1978).

Critical realism thus adopts a realist ontology and accepts that our access may be limited and coloured by our perceptual and theoretical lenses, but at the same time rejects that all viewpoints must be equally valid (judgemental relativity) (Bhaskar, 1978; Mingers et al., 2013).

Table 9.13 Paradigms at a Glance

Dimension	Positivism / Post-positivism	Interpretivism / Constructivism	Critical / Transformative	Pragmatism
Core aim	Explanation, prediction, law-like generalisations	Understanding meaning, context, lived experience	Critique, emancipation, change	Problem-solving; actionable knowledge
Ontology	Single reality; knowable (imperfectly under post-positivism)	Multiple, socially constructed realities	Reality shaped by power/ideology; historical	Reality is what works for the inquiry at hand; plural and provisional
Epistemology	Objective/modified-objective; researcher as neutral tester	Subjective/co-constructed; researcher as instrument	Reflexive, standpoint-aware; researcher as change agent	Knowledge as warranted and useful; strand-specific logics allowed under one frame
Axiology	Value-neutral ideals; minimise bias	Values are inherent and made explicit	Values/power central; aim at justice	Values acknowledged; “fitness-for-purpose” governs choices

Dimension	Positivism / Post-positivism	Interpretivism / Constructivism	Critical / Transformative	Pragmatism
Causality	Regularities, (quasi)-causal models	Contextual, idiographic explanations	Causality linked to structures and power	Causality judged by utility (prediction + credible mechanism)
Theory role	Test theory; deduction	Build/substantiate theory; induction	Critique/transfor m theory	Use/extend theory pragmatically; abduction links strands
Reasoning	Primarily deductive (post- positivism allows retroduction)	Inductive/iterative	Dialectical/critical	Abductive + deductive + inductive as needed
Typical designs	Experiments, surveys, measurement models	Ethnography, case study, phenomenology	Participatory action research, critical case studies	Mixed methods; design chosen for the problem (e.g., explanatory- sequential)
Data & methods	Standardised instruments; statistics (CB- SEM/PLS- SEM)	Interviews, observations, documents	Dialogic, participatory methods	Any method that advances the question (here: PLS- SEM + interviews)
Quality criteria	Reliability; internal/constr uct validity; external validity; predictive	Credibility, transferability, dependability, confirmability	Catalytic/authenti c validity; reflexivity; transformative outcomes	Purpose-contingent: QUAN (measurement/predi ction); QUAL (credibility, audit trail); integration

Dimension	Positivism / Post-positivism	Interpretivism / Constructivism	Critical / Transformative	Pragmatism
	accuracy (post-positivist adds fallibilism)			quality (coherent meta-inferences, handling divergence)
Generalisation	Statistical; population- based	Analytical/transfer ability	Transformative/c ritical relevance	Fit-for-use (statistical where warranted; analytic otherwise)
Researcher role	Detached observer	Co-interpreter	Reflexive advocate/partner	Adaptive designer integrating strands
Mixed methods stance	Leading quantitative role	Leading qualitative role	Possible if it advances emancipation	Natural home of mixed methods; pluralism justified by usefulness

Appendix F3. Mixed Methods Paradigmatic Stances

A key question remains the selection of an appropriate philosophical stance supporting mixed methods research (Almpanis, 2016; Giddings & Grant, 2006; Guba & Lincoln, 2005; McChesney & Aldridge, 2019; Sale et al., 2002). A number of different paradigmatic stances have been applied by researchers and a short overview of the most common approaches follows (McChesney & Aldridge, 2019; O’Gorman & MacIntosh, 2015; Saunders et al., 2019).

The a-paradigmatic stance

Some researchers elect to forego a paradigmatic stance, emphasizing that while paradigms are important, they should not be used to constrain or limit the inquiry process (Shannon-Baker, 2016). This approach practically ignores the paradigm debate, but also results in a study that may have serious logical inconsistencies and problems (McChesney & Aldridge, 2019).

The dual-paradigm or dialectical stance

Another approach is to simplify the usage of quantitative and qualitative approaches by combining – or at least, applying – different paradigmatic stances at different phases of the research (e.g. positivist and interpretivist) (McChesney & Aldridge, 2019). This is a much debated approach, where one key arguments against is rooted in the incompatibility or incommensurability problem of distinct paradigms (Guba & Lincoln, 1994, 2005). Johnson (2017) has proposed the name 'dialectical pluralism' to describe a meta-paradigm, that accepts multiple perspectives within one research, attempting to resolve the incommensurability problem. Another inherent risk in such an approach is the possibility of separating components along paradigmatic grounds, resulting in two parallel, but distinct studies on the same topic within one research study (McChesney & Aldridge, 2019).

The holistic or single-paradigm stance

It is also possible to attempt a reconciliation of quantitative and qualitative methods within a single overarching paradigm. This approach certainly allows a resolution of the paradigmatic issues noted above, any a numbers of papers highlight the usage of particular methodologies within any given paradigm (Crotty, 1998; McChesney & Aldridge, 2019). However, many of these single paradigm studies have been conducted from a positivist viewpoint, while interpretivist approaches are rare (McChesney & Aldridge, 2019). While this resolution may seem very effective, the positivist approach in qualitative research may limit the evaluation of the results (McChesney & Aldridge, 2019).

Appendix G Pilot Data

Appendix G1. Lawshe Content Validation Table

Table 9.14 CVR calculation

Item	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10		CVR
PIIT1	x		x	x	x	x	x	x	x	x		0.8
PIIT2	x	x	x	x	x	x	x	x	x	x		1
PIIT3	x	x	x	x	x	x	x	x	x	x		1
PIIT4	x		x	x	x	x	x	x	x	x		0.8
PE1	x	x	x	x	x	x	x	x	x	x		1
PE2	x	x	x	x	x	x	x	x	x	x		1
PE3	x	x	x	x	x	x	x	x	x	x		1
PE4	x	x	x	x	x	x	x	x	x	x		1
EE1	x	x	x	x	x	x	x	x	x	x		1
EE2	x	x	x	x	x	x	x	x	x	x		1
EE3	x	x	x	x	x	x	x	x	x	x		1
EE4	x	x	x	x	x	x	x	x	x	x		1
ATT1	x	x	x	x	x	x	x	x	x	x		1
ATT2	x	x	x	x	x	x	x	x	x	x		1
ATT3	x	x	x	x	x	x	x	x	x	x		1
CI1	x	x	x	x	x	x	x	x	x	x		1
CI2	x	x	x	x	x	x	x	x	x	x		1
CI3	x	x	x	x	x	x	x	x	x	x		1
ITIB1	x	x	x	x	x	x	x	x	x	x		1
ITIB2	x	x	x	x	x	x	x	x	x	x		1
ITIB3	x	x	x	x	x	x	x	x	x	x		1
IS1	x		x	x	x	x	x	x	x	x		0.8
IS2	x	x	x	x	x	x	x	x	x	x		1
IS3	x	x	x	x	x	x	x	x	x	x		1
IS4	x	x	x	x	x	x	x	x	x	x		1
IS5	x	x	x	x	x	x	x	x	x	x		1
IF1	x	x	x	x	x	x	x	x	x	x		1
IF2	x	x	x	x	x	x	x	x	x	x		1
IF3	x	x	x	x	x	x	x	x	x	x		1
IF4	x	x	x	x	x	x	x	x	x	x		1
Functionality	x	x	x			x		x				0
Gender	x	x	x	x	x	x		x	x	x		0.8
Age	x	x	x		x	x	x	x	x	x		0.8
Mgt Level	x	x	x	x	x	x		x	x	x		0.8
Experience		x	x		x	x		x	x	x		0.4
SME Sector		x	x		x			x	x	x		0.2

Item	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10		CVR
SME Location	x		x	x	x	x		x	x	x		0.6
SME Size		x	x		x	x		x	x	x		0.4
Education	x		x	x		x		x		x		0.2
Work Area	x		x		x			x	x	x		0.2
CVR(Critical) for a panel size (N) of 10 is 0.8.								AVG CVR				0.845

Appendix G2. Pilot Statistical Data

Table 9.15 Pilot full descriptive statistics

Stat	Nbr. of obs.	Min	Max	Median	Mean	Standard deviation (n-1)	Skewness (Fisher)	Kurtosis (Fisher)
PIIT1	148	1.000	5.000	4.000	3.426	1.037	-0.484	-0.433
PIIT3	148	1.000	5.000	4.000	3.514	1.020	-0.466	-0.295
PIIT2	148	1.000	5.000	3.000	3.061	1.144	-0.093	-1.021
PIIT4	148	1.000	5.000	4.000	3.750	1.055	-0.856	0.234
PE1	148	1.000	5.000	4.000	3.662	1.073	-0.665	-0.152
PE2	148	1.000	5.000	4.000	3.595	0.989	-0.567	-0.113
PE3	148	1.000	5.000	4.000	3.527	0.965	-0.308	-0.325
PE4	148	1.000	5.000	4.000	3.419	1.113	-0.379	-0.592
EE1	148	1.000	5.000	3.500	3.426	1.082	-0.328	-0.513
EE2	148	1.000	5.000	4.000	3.838	0.926	-0.608	0.102
EE3	148	1.000	5.000	4.000	3.669	0.936	-0.603	0.147
EE4	148	1.000	5.000	4.000	3.520	1.000	-0.574	0.020
CI1	148	1.000	5.000	4.000	3.608	0.938	-0.745	0.325
CI2	148	1.000	5.000	4.000	3.649	0.910	-0.780	0.407
CI3	148	1.000	5.000	4.000	3.561	0.935	-0.635	-0.253
ITIB1	148	1.000	5.000	4.000	3.676	0.740	-1.034	2.355
ITIB2	148	1.000	5.000	4.000	3.520	0.812	-0.530	0.365
ITIB3	148	1.000	5.000	4.000	3.473	0.778	-1.053	1.339
ATT1	148	1.000	5.000	4.000	3.777	0.698	-1.488	3.494
ATT2	148	2.000	5.000	4.000	3.736	0.950	-0.268	-0.838
ATT3	148	1.000	5.000	4.000	3.878	0.903	-0.881	0.710
IF1	148	1.000	5.000	3.000	3.324	0.920	-0.426	-0.073
IF2	148	1.000	5.000	3.000	3.446	0.851	-0.265	-0.025
IF3	148	1.000	5.000	4.000	3.791	1.051	-0.745	0.050
IF4	148	1.000	5.000	4.000	3.811	0.992	-0.627	-0.053
IS1	148	1.000	5.000	4.000	3.473	0.892	-1.026	1.032
IS2	148	1.000	5.000	3.000	3.135	0.822	-0.182	0.525
IS3	148	1.000	5.000	4.000	3.682	0.738	-0.137	0.351
IS4	148	1.000	5.000	3.000	3.378	0.741	-0.537	0.446
IS5	148	1.000	5.000	3.000	2.986	0.990	-0.058	-0.585

Table 9.16 Pilot Kaiser-Meyer-Olkin measure

PIIT1	0.631
PIIT2	0.561
PIIT3	0.681
PIIT4	0.683
PE1	0.840
PE2	0.746
PE3	0.830
PE4	0.869
EE1	0.795
EE2	0.724
EE3	0.746
EE4	0.843
CI1	0.732
CI2	0.795
CI3	0.800
ITIB1	0.817
ITIB2	0.822
ITIB3	0.871
ATT1	0.691
ATT2	0.839
ATT3	0.805
IF1	0.775
IF2	0.665
IF3	0.796
IF4	0.775
IS1	0.765
IS2	0.720
IS3	0.507
IS4	0.701
IS5	0.830
KMO	0.767

Table 9.17 Pilot Bartlett's sphericity test

Chi-square (Observed value)	1914.549
Chi-square (Critical value)	484.626
DF	435
p-value (Two-tailed)	<0.0001
alpha	0.05

Table 9.18 Pilot VIF

	Tolerance	VIF
PIIT1	0.414	2.414
PIIT2	0.490	2.039
PIIT3	0.479	2.087
PIIT4	0.678	1.474
PE1	0.359	2.782
PE2	0.268	3.736
PE3	0.325	3.076
PE4	0.418	2.393
EE1	0.572	1.749
EE2	0.380	2.632
EE3	0.421	2.376
EE4	0.399	2.505
CI1	0.470	2.126
CI2	0.404	2.474
CI3	0.520	1.925
ITIB1	0.421	2.375
ITIB2	0.505	1.981
ITIB3	0.528	1.894
ATT1	0.465	2.151
ATT2	0.448	2.233
ATT3	0.479	2.087
IF1	0.455	2.196
IF2	0.422	2.372
IF3	0.549	1.823
IF4	0.523	1.912
IS1	0.475	2.104
IS2	0.342	2.926
IS3	0.505	1.979
IS4	0.586	1.706
IS5	0.628	1.593

Table 9.19 Pilot factor analysis results

	D1	D2	D3	D4	D5	D6
PIIT1	0.017	0.882	-0.110	-0.005	0.068	0.020
PIIT3	-0.109	0.667	0.302	-0.167	0.003	0.103
PIIT2	0.101	0.574	-0.196	0.294	-0.102	-0.240
PIIT4	0.073	0.452	0.155	-0.152	0.075	0.020
PE1	0.640	-0.032	0.037	-0.033	0.116	0.120
PE2	0.994	0.006	0.069	-0.234	-0.035	-0.076

	D1	D2	D3	D4	D5	D6
PE3	0.842	0.016	0.016	-0.027	-0.110	0.085
PE4	0.695	0.065	-0.068	0.134	0.074	-0.019
EE1	0.256	-0.062	0.006	0.118	0.372	-0.138
EE2	-0.090	0.052	-0.048	-0.056	0.963	-0.021
EE3	-0.028	0.159	-0.046	-0.046	0.738	0.175
EE4	0.154	-0.190	0.014	0.153	0.578	-0.067
CI1	-0.191	-0.011	0.225	0.611	0.097	-0.033
CI2	-0.014	-0.015	0.307	0.687	0.009	-0.062
CI3	0.001	-0.110	0.040	0.595	-0.068	0.223
ITIB1	0.010	0.105	0.715	0.160	0.014	-0.055
ITIB2	0.099	0.121	0.609	0.126	-0.097	0.022
ITIB3	0.001	-0.094	0.678	0.092	-0.026	-0.003
ATT1	0.007	0.049	-0.219	0.484	-0.057	0.508
ATT2	0.240	0.009	0.106	0.236	0.055	0.343
ATT3	0.041	-0.013	0.023	0.073	0.039	0.734

Values in bold correspond for each variable to the factor for which the squared cosine is the largest

Table 9.20 Pilot PCA results

	D1	D2
IF1	0.016	0.537
IF2	0.018	0.456
IF3	0.042	0.582
IF4	0.004	0.549
IS1	0.334	0.060
IS2	0.641	0.015
IS3	0.600	0.078
IS4	0.461	0.001
IS5	0.361	0.033

Values in bold correspond for each variable to the factor for which the squared cosine is the largest

Appendix H Pilot and Final Survey

Appendix H1. Pilot Survey

This is the pilot survey after the Expert Reviews, the survey is updated based on recommendations.

----- BEGIN SURVEY-----

Dear Sir/Madam,

We would like to seek your assistance in completing this survey, which is part of a research project being conducted at University of Hertfordshire's Business School by Tibor Vörös, Research Student and Professor Jyoti Choudrie, Professor of Information Systems.

The aim of this research is to identify and understand the adoption, use and diffusion of tablet devices in the SME sector of Hungary. Collecting information about differences in individual perception of mobile technology usage will help in developing strategies to spread information communication technologies in organisations and understand factors affecting continued use better.

In this survey, mobile technology represents tablet devices with a screen size over 7 inches. Tablet devices are characterized by touch-based input and convenience of usage - they can be used without a keyboard almost instantaneously. Some examples of these devices include Samsung Galaxy Note 10.1, Microsoft Surface Tablet or Lenovo Yoga tablets. In order to participate in this survey, you should have been using a tablet in your organisation for at least 3 months.

Procedures

You will be shown a set of questions listed over 5 short pages: completion should take no more than 15 minutes. Please answer all questions.

Confidentiality

Please note that your contributions to this survey are confidential. All responses are anonymous. The results will only be reported in an aggregate format, without any individual identifying information. The data collected will be stored in a Qualtrics secure database. Participation in this research study is completely voluntary.

I have read and understood the above consent form and desire of my own free will to participate in this study.

☐ Yes

☐ No

I have a tablet and use it in my workplace at least for 3 months.

☐ Yes

☐ No [skip to end]

Demographics

Note: these questions are optional, you may skip them if you prefer so.

Please select your age group.

☐ 18-20 (1)

☐ 21-30 (2)

☐ 31-40 (3)

☐ 41-50 (4)

- ☐ 51-60 (5)
- ☐ 61-70 (6)
- ☐ 71 or older (7)

Please select your gender.

- ☐ Male (1)
- ☐ Female (2)

At what management level of the organisation do you work?

- ☐ Employee (1)
- ☐ Junior Manager (2)
- ☐ Mid-level Manager (3)
- ☐ Senior Manager (4)

Please rate your agreement or disagreement with the following short statements. Please use the scale provided.

☐ Strongly Disagree ☐ Disagree ☐ Neither Agree nor Disagree ☐ Agree ☐ Strongly Agree

1. If I heard about a new information technology, I would look for ways to experiment with it.
2. Among my peers, I am usually the first to explore new information technologies.
3. I like to experiment with new information technologies.
4. In general, I am hesitant to try out new information technologies.
5. This tablet device helps me to identify innovative ways of doing my job.
6. This tablet device helps me to come up with new ideas relating to my job.
7. This tablet device helps me to try out innovative ideas.
8. Using this tablet device enables me to complete my work more quickly.
9. Using this tablet devices increases my productivity.
10. Using this tablet device enhances my effectiveness in my work
11. Using this tablet device enhances my performance in my work.
12. I find it easy to use this tablet device in my work.
13. Learning to use this tablet device in my work is easy for me.
14. It is easy for me to become skilful at using this tablet device in my work.
15. Learning to operate this tablet device is easy for me.
16. I intend to continue using this tablet device in my work.
17. If asked, I would recommend the continued use of this tablet device for my work.
18. As a user, I would continue using this tablet device in my work.
19. Using tablet devices in my work is a good idea.
20. Overall, I have a positive attitude toward using tablets in my job.
21. Using a tablet helps me perform my work more effectively.
22. In our organisation, we have a very open communications environment.
23. In our organisation, employees and managers are supportive of each other.
24. In our organisation, employees at all levels are rewarded for learning new skills.
25. In our organisation, experimental mind-sets and risk taking is encouraged.
26. In our organisation, new ideas are easy to be implemented.

27. In our organisation, employees are encouraged to try out new information technologies.
28. In our organisation, employees are rewarded for using new information technologies.
29. In our organisation, employees are consulted before introduction of new information technology.
30. In our organisation, employees are involved in information technology change and implementation.

----- **END SURVEY**-----

Appendix H2. Final Survey

This is the final survey instrument after the expert reviews and pilot-based revisions.

----- **BEGIN SURVEY**-----

Dear Sir/Madam,

We would like to seek your assistance in completing this survey, which is part of a research project being conducted at University of Hertfordshire's Business School by Tibor Vörös, Research Student and Professor Jyoti Choudrie, Professor of Information Systems.

The aim of this research is to identify and understand the adoption, use and diffusion of tablet devices in the SME sector of Hungary. Collecting information about differences in individual perception of mobile technology usage will help in developing strategies to spread information communication technologies in organisations and understand factors affecting continued use better.

In this survey, mobile technology represents tablet devices with a screen size over 7 inches. Tablet devices are characterized by touch-based input and convenience of usage - they can be used without a keyboard almost instantaneously. Some examples of these devices include Samsung Galaxy Note 10.1, Microsoft Surface Tablet or Lenovo Yoga tablets. In order to participate in this survey, you should have been using a tablet in your organisation for at least 3 months.

Procedures

You will be shown a set of questions listed over 5 short pages: completion should take no more than 15 minutes. Please answer all questions.

Confidentiality

Please note that your contributions to this survey are confidential. All responses are anonymous. The results will only be reported in an aggregate format, without any individual identifying information. The data collected will be stored in a Qualtrics secure database. Participation in this research study is completely voluntary.

I have read and understood the above consent form and desire of my own free will to participate in this study.

☐ Yes

☐ No

I have a tablet and use it in my workplace at least for 3 months.

☐ Yes

☐ No [skip to end]

Demographics

Note: these questions are optional, you may skip them if you prefer so.

Please select your age group.

☐ 18-20 (1)

- ☐ 21-30 (2)
- ☐ 31-40 (3)
- ☐ 41-50 (4)
- ☐ 51-60 (5)
- ☐ 61-70 (6)
- ☐ 71 or older (7)

Please select your gender.

- ☐ Male (1)
- ☐ Female (2)

At what management level of the organisation do you work?

- ☐ Employee (1)
- ☐ Junior Manager (2)
- ☐ Mid-level Manager (3)
- ☐ Senior Manager (4)

Please rate your agreement or disagreement with the following short statements. Please use the scale provided.

☐ Strongly Disagree ☐ Disagree ☐ Neither Agree nor Disagree ☐ Agree ☐ Strongly Agree

1. If I heard about a new information technology, I would look for ways to experiment with it.
2. Among my peers, I am usually the first to explore new information technologies.
3. I like to experiment with new information technologies.
4. In general, I am eager to try out new information technologies.
5. This tablet device helps me to identify innovative ways of doing my job.
6. This tablet device helps me to come up with new ideas relating to my job.
7. This tablet device helps me to try out innovative ideas.
8. Using this tablet device enables me to complete my work more quickly.
9. Using this tablet devices increases my productivity.
10. Using this tablet device enhances my effectiveness in my work
11. Using this tablet device enhances my performance in my work.
12. I find the tablet device easy to interact with.
13. Learning to use this tablet device in my work is easy for me.
14. It is easy for me to become skilful at using this tablet device in my work.
15. Learning to operate this tablet device is easy for me.
16. I intend to continue using this tablet device in my work.
17. If asked, I would recommend the continued use of this tablet device for my work.
18. As a user, I would continue using this tablet device in my work.
19. Using tablet devices in my work is a good idea.
20. Overall, I have a positive attitude toward using tablets in my job.
21. Using the tablet device would be beneficial to my job.
22. In our organisation, we have a very open communications environment.
23. In our organisation, employees and managers are supportive of each other.

24. In our organisation, employees at all levels are rewarded for learning new skills.
25. In our organisation, experimental mind-sets and risk taking is encouraged.
26. In our organisation, new ideas are easy to be implemented.
27. In our organisation, employees are encouraged to try out new information technologies.
28. In our organisation, employees are rewarded for using new information technologies.
29. In our organisation, employees are consulted before introduction of new information technology.
30. In our organisation, employees are involved in information technology change and implementation.

----- **END SURVEY**-----

Appendix H3. Survey Invitation Letter

Letter of Invitation to the Innovativeness & Tablet Use Survey

Should the enterprise participate –

This survey is evaluating innovativeness and tablet use – we are looking for SMEs using tablet devices in their processes. If there is a provision of tablet devices to the majority of employees in your enterprise, please read on.

Introduction -

Organizations are becoming increasingly dependent on information communication technologies (ICT) along their entire value chain: both their intra- and interorganizational work systems rely on IT-enabled functionalities and processes. While particularly in large organizations specific departments (Research and Development, Innovation Labs, etc.) are dedicated to innovation, small and medium enterprises need all members of the organization to play an increasing role in finding the best recombination of technology and processes due to limited resources.

The use of tablet devices in organizations is spreading: measuring information technology-related innovativeness and tablet use in organizations is a multifaceted endeavor, incorporating measures specific to the user, to the innovation (tablet device) and organization (organizational climate towards innovation). This complex approach, however, may provide valuable knowledge on the more advanced use of modern technology in enterprises; it also provides a snapshot of current innovation practices in organizations. In an attempt to try to disentangle this complicated interrelationship and gain a more thorough understanding, a researcher of the University of Hertfordshire and the Central European University Business School is conducting a survey. The aim of the survey is to gather data from various organizations (concentrating on local SMEs), in a variety of industries to identify and understand the adoption, use and diffusion of tablet devices in the SME sector of Hungary.

The survey investigates individual innovativeness, tablet use intentions and organizational climate elements. This information is often valuable to managers, as it may provide insights into the organization itself. As the research measures continued tablet use, a minimum 3 months completed use is required to stabilise use pattern of tablets.

Things you should know about participating in the survey -

The survey is an online web-based survey, accessible via any browser (Internet Explorer, Firefox etc.). The survey consists of approximately 40 questions across 5 webpages, and should take approx. 15 minutes to complete.

Participation is voluntary, and all the responses are completely anonym. Enterprise names and contact information are only used to contact the enterprise – as the data is collected, all surveys are anonymized (i.e. the name of the company is replaced with a random identifier e.g. SME123). The name of the organization will not appear in any publication of results and the identity of enterprises taking part will not be disclosed. Research papers and academic reports may only contain references to the random SME identifiers, or to the aggregate information based on sectors, industries or other group categories. No information from this survey will ever be sold or leveraged for financial gains.

All the data and related information provided will be handled in a strictly confidential manner and used only for research and educational purposes. The dataset will be stored in a secure database, using an high grade survey system (Qualtrics), with protected access only available to the researcher.

Benefits –

Because the survey has innovation-related questions, it also primes participants towards innovative ideas. It may also provide an interesting discourse in the organization.

If you would like to participate –

Please send an email to / contact the Hungarian Researcher (see contact details below) and you will be provided with a survey link. Survey emails can be sent with a survey link from the Qualtrics email centre, but it may be sent from a local IT Department if necessary.

Thank you for your cooperation,

Tibor Vörös

Senior Lecturer of IT Management

Email : vorost@ceubusiness.org

Tel : +36 1 887 5017

CEU Business School

Frankel leó ut 30-34

Budapest

Hungary

H-1023

If you have further questions regarding this study, please contact the researchers: Mr Tibor Voros (vorost@ceubusiness.org) or Professor Jyoti Choudrie (j.choudrie@herts.ac.uk). Address in Hungary: CEU Business School, Frankel Leó utca 30-34, Budapest 1023. Address in UK: University of Hertfordshire, Business School, De Havilland campus, Hatfield, Herts. AL10 9EU.

Appendix H4. Sample Data Protection Letter

This is an English sample of Data Protection letters sent to HRs in the responding SMEs.

DATA PROTECTION AND CONFIDENTIALITY AGREEMENT

THE CEU BUSINESS SCHOOL (FRANKEL LEÖ UT 30-34, BUDAPEST, HUNGARY H-1023) is conducting a research project concerning management practices and strategy development via online surveys.

All the information provided is completely anonym, individual information (i.e. name) is not required during the survey process.

Company identifiers (company names) are only used during the data collection (survey) phase. Once the data collection phase has completed, all surveys are anonymized (i.e. the name of the company is replaced by a random identifier e.g. Org128).

The CEU Business School will not provide information to anyone that could disclose the identity of firms taking part. Research papers and academic reviews may only contain references to aggregate information based on sectors, industries and other group categories.

All the data and related information provided will be handled in a strictly confidential manner and used only for research and educational purposes.

Thank you for your cooperation.



Research Leader

Senior Lecturer of IT Management and Quantitative Studies

Tel : +36 1 887 5017

Fax 36 1 887 5005

CEU Business School

Frankel Leo ut 30-34

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Hungary

H-1023

Appendix H5. Sample Acceptance Letter

Dear Tibor,

I am glad to inform you that *** has agreed to join the survey by opening the survey access to its employees.

Thank you for your patience. The contact persons name and survey modification request will be send to Tibor by end of this week.

Thank you and have a nice evening.

IT Services Business Solutions Outsourcing

Appendix I Final Survey Statistics

Appendix I1. Multicollinearity Statistics

Table 9.21 Multicollinearity statistics

Statistic	R ²	Tolerance	VIF
PIIT1	0.577	0.423	2.365
PIIT2	0.573	0.427	2.341
PIIT3	0.509	0.491	2.036
PIIT4	0.447	0.553	1.807
PE1	0.705	0.295	3.395
PE2	0.773	0.227	4.396
PE3	0.694	0.306	3.272
PE4	0.780	0.220	4.544
EE1	0.532	0.468	2.134
EE2	0.520	0.480	2.083
EE3	0.480	0.520	1.924
EE4	0.617	0.383	2.610
ATT1	0.615	0.385	2.598
ATT2	0.580	0.420	2.383
ATT3	0.602	0.398	2.514
CI1	0.693	0.307	3.253
CI2	0.738	0.262	3.821
CI3	0.505	0.495	2.021
ITIB1	0.663	0.337	2.963
ITIB2	0.627	0.373	2.679
ITIB3	0.683	0.317	3.158
IF1	0.480	0.520	1.923
IF2	0.542	0.458	2.183
IF4	0.509	0.491	2.037
IS1	0.439	0.561	1.783
IS3	0.560	0.440	2.272
IS4	0.533	0.467	2.141
IS5	0.419	0.581	1.721
IS2	0.543	0.457	2.188
IF3	0.485	0.515	1.941

Appendix I2. Final Survey Descriptive Statistics

Table 9.22 Final survey descriptive statistics

Statistic	Nbr. of observations	Minimum	Maximum	Median	Mean	Standard deviation (n-1)	Skewness (Fisher)	Kurtosis (Fisher)
PIIT1	1040	1.000	5.000	3.000	3.318	0.998	-0.193	-0.777
PIIT2	1040	1.000	5.000	3.000	2.951	1.043	0.154	-0.703
PIIT3	1040	1.000	5.000	4.000	3.708	0.942	-0.622	-0.145
PIIT4	1040	1.000	5.000	4.000	3.518	0.933	-0.467	-0.309
PE1	1040	1.000	5.000	4.000	3.606	0.981	-0.475	-0.116
PE2	1040	1.000	5.000	4.000	3.533	0.999	-0.395	-0.240
PE3	1040	1.000	5.000	4.000	3.572	0.964	-0.493	-0.019
PE4	1040	1.000	5.000	4.000	3.571	0.974	-0.442	-0.124
EE1	1040	1.000	5.000	4.000	3.575	1.035	-0.507	-0.336
EE2	1040	1.000	5.000	4.000	3.878	0.942	-0.634	0.031
EE3	1040	1.000	5.000	4.000	3.490	0.951	-0.450	0.111
EE4	1040	1.000	5.000	4.000	3.646	0.948	-0.553	0.101
ATT1	1040	1.000	5.000	4.000	3.794	0.903	-0.431	-0.050
ATT2	1040	1.000	5.000	3.000	3.308	1.079	-0.331	-0.479
ATT3	1040	1.000	5.000	3.000	3.424	1.097	-0.073	-0.900
CI1	1040	1.000	5.000	3.000	3.111	0.964	-0.287	-0.652
CI2	1040	1.000	5.000	3.000	3.156	0.953	-0.335	-0.585
CI3	1040	1.000	5.000	3.000	2.879	0.910	-0.043	-0.667
ITIB1	1040	1.000	5.000	3.000	3.047	0.981	-0.088	-0.794
ITIB2	1040	1.000	5.000	3.000	3.179	0.912	-0.185	-0.382
ITIB3	1040	1.000	5.000	3.000	3.006	0.954	0.035	-0.658
IF1	1040	1.000	5.000	3.000	3.091	0.966	-0.209	-0.565
IF2	1040	1.000	5.000	3.000	2.728	1.001	0.029	-0.607
IF3	1040	1.000	5.000	3.000	3.043	1.012	-0.271	-0.697
IF4	1040	1.000	5.000	3.000	3.089	0.963	-0.277	-0.658
IS1	1040	1.000	5.000	4.000	3.639	1.014	-0.716	-0.111
IS2	1040	1.000	5.000	4.000	3.671	0.985	-0.692	-0.047
IS3	1040	1.000	5.000	3.000	2.871	1.035	0.051	-0.705
IS4	1040	1.000	5.000	3.000	3.016	0.980	-0.168	-0.620
IS5	1040	1.000	5.000	3.000	2.902	0.954	0.010	-0.523

Appendix I3. SME Descriptive Data

Table 9.23 SME Response Data

Organization	Used	No of responses	SME size	Location	Sector	Response rate	Use rate
SME01	30	45	89	Rural	Manufacturing	51%	67%
SME02	35	61	125	Capital	ICT	49%	57%
SME03	18	64	145	Capital	Services	44%	28%
SME04	41	74	121	City	Services	61%	55%
SME05	23	32	125	Capital	Services	26%	72%
SME06	28	42	157	City	Manufacturing	27%	67%
SME07	43	83	104	City	Manufacturing	80%	52%
SME08	17	27	36	Capital	Services	75%	63%
SME09	89	162	210	City	ICT	77%	55%
SME10	17	23	57	Capital	Services	40%	74%
SME11	50	61	89	Capital	Services	69%	82%
SME12	29	35	71	Capital	Services	49%	83%
SME13	61	97	189	Capital	ICT	51%	63%
SME14	11	13	78	Capital	ICT	17%	85%
SME15	36	86	186	City	Services	46%	42%
SME16	216	221	240	Capital	ICT	92%	98%
SME17	15	32	76	Capital	Services	42%	47%
SME18	43	63	162	Rural	Manufacturing	39%	68%
SME19	189	201	221	Capital	ICT	91%	94%
SME20	23	42	64	Capital	ICT	66%	55%
SME21	26	87	164	Rural	Services	53%	30%
Total	1040	1551	2709			57%	67%

Appendix I4. Factor Analysis Tests

Table 9.24 KMO final model

Kaiser-Meyer-Olkin measure of sampling adequacy:	
PIIT1	0.788
PIIT2	0.797
PIIT3	0.838
PIIT4	0.853

Kaiser-Meyer-Olkin measure of sampling adequacy:	
PE1	0.956
PE2	0.905
PE3	0.950
PE4	0.899
EE1	0.895
EE2	0.824
EE3	0.893
EE4	0.918
ATT1	0.934
ATT2	0.957
ATT3	0.949
CI1	0.914
CI2	0.915
CI3	0.967
ITIB1	0.928
ITIB2	0.895
ITIB3	0.885
KMO	0.913

Table 9.25 Bartlett's test final model

Bartlett's sphericity test:	
Chi-square (Observed value)	14656.152
Chi-square (Critical value)	244.808
DF	210
p-value (Two-tailed)	<0.0001
alpha	0.05

Table 9.26 PCA final model

Squared cosines of the variables IF and IS after Promax rotation:		
	D1	D2
IF1	0.081	0.448
IF2	0.129	0.406
IF4	0.063	0.736
IS1	0.685	0.086
IS3	0.461	0.061
IS4	0.599	0.020
IS5	0.430	0.030

Squared cosines of the variables IF and IS after Promax rotation:

Values in bold correspond for each variable to the factor for which the squared cosine is the largest.

Appendix I5. Baseline Model Data

Table 9.27 Baseline model data

Baseline Model Path Coeffs	Beta	T statistics	P values	2.50%	97.50%
ATT -> CI	0.424	13.626	0.000	0.364	0.487
ATT -> ITIB	0.355	12.974	0.000	0.302	0.409
EE -> ATT	0.223	8.818	0.000	0.173	0.271
EE -> PE	0.401	14.351	0.000	0.345	0.455
IF -> ITIB	0.212	5.374	0.000	0.135	0.288
IS -> IF	0.721	39.830	0.000	0.682	0.755
IS -> ITIB	0.110	2.741	0.006	0.032	0.189
IS -> PE	0.264	9.244	0.000	0.206	0.317
ITIB -> CI	0.363	13.531	0.000	0.310	0.413
PE -> ATT	0.601	26.043	0.000	0.553	0.644
PE -> CI	0.135	4.140	0.000	0.072	0.199
PIIT -> CI	-0.086	3.809	0.000	-0.129	-0.042
PIIT -> ITIB	0.171	6.289	0.000	0.115	0.223

Baseline Model Specific Indirect Effects	Beta	T statistics	P values	2.50%	97.50%
EE -> ATT -> CI	0.095	7.311	0.000	0.071	0.122
PIIT -> ITIB -> CI	0.062	5.512	0.000	0.040	0.085
EE -> PE -> ATT -> ITIB -> CI	0.031	7.042	0.000	0.023	0.041
EE -> PE -> ATT -> ITIB	0.086	8.134	0.000	0.067	0.108
IS -> IF -> ITIB	0.153	5.259	0.000	0.097	0.210
EE -> ATT -> ITIB	0.079	7.345	0.000	0.059	0.101
PE -> ATT -> CI	0.255	12.352	0.000	0.216	0.298
IS -> PE -> ATT -> ITIB	0.056	7.175	0.000	0.042	0.072
PE -> ATT -> ITIB -> CI	0.077	8.314	0.000	0.060	0.096
EE -> PE -> ATT -> CI	0.102	9.450	0.000	0.082	0.124
PE -> ATT -> ITIB	0.213	10.858	0.000	0.175	0.253
IS -> PE -> ATT -> CI	0.067	7.071	0.000	0.049	0.087
IS -> IF -> ITIB -> CI	0.055	4.889	0.000	0.034	0.079
EE -> ATT -> ITIB -> CI	0.029	6.151	0.000	0.020	0.039
IS -> PE -> ATT -> ITIB -> CI	0.020	6.178	0.000	0.015	0.027
ATT -> ITIB -> CI	0.129	8.927	0.000	0.101	0.158
EE -> PE -> ATT	0.241	12.320	0.000	0.203	0.279

Baseline Model Path Coeffs	Beta	T statistics	P values	2.50%	97.50%
EE -> PE -> CI	0.054	3.817	0.000	0.028	0.084
IS -> PE -> ATT	0.158	8.393	0.000	0.121	0.194
IF -> ITIB -> CI	0.077	4.990	0.000	0.048	0.109
IS -> PE -> CI	0.036	3.825	0.000	0.019	0.055
IS -> ITIB -> CI	0.040	2.701	0.007	0.012	0.070

Baseline Model Total Effects	Beta	T statistics	P values	2.50%	97.50%
ATT -> CI	0.553	17.957	0.000	0.493	0.614
ATT -> ITIB	0.355	12.974	0.000	0.302	0.409
EE -> ATT	0.464	18.426	0.000	0.412	0.511
EE -> CI	0.311	16.232	0.000	0.273	0.348
EE -> ITIB	0.165	9.983	0.000	0.134	0.199
EE -> PE	0.401	14.351	0.000	0.345	0.455
IF -> CI	0.077	4.990	0.000	0.048	0.109
IF -> ITIB	0.212	5.374	0.000	0.135	0.288
IS -> ATT	0.158	8.393	0.000	0.121	0.194
IS -> CI	0.219	11.168	0.000	0.178	0.254
IS -> IF	0.721	39.830	0.000	0.682	0.755
IS -> ITIB	0.319	10.422	0.000	0.252	0.374
IS -> PE	0.264	9.244	0.000	0.206	0.317
ITIB -> CI	0.363	13.531	0.000	0.310	0.413
PE -> ATT	0.601	26.043	0.000	0.553	0.644
PE -> CI	0.468	18.142	0.000	0.417	0.517
PE -> ITIB	0.213	10.858	0.000	0.175	0.253
PIIT -> CI	-0.024	0.980	0.327	-0.071	0.024
PIIT -> ITIB	0.171	6.289	0.000	0.115	0.223

Table 9.28 Baseline model outer loadings

Baseline Model Outer Loadings	Loading	T statistics	P values
ATT1 <- ATT	0.884	109.720	0.000
ATT2 <- ATT	0.851	88.631	0.000
ATT3 <- ATT	0.885	120.590	0.000
CI1 <- CI	0.907	120.529	0.000
CI2 <- CI	0.930	175.236	0.000
CI3 <- CI	0.835	56.874	0.000
EE1 <- EE	0.836	50.566	0.000

Baseline Model Outer Loadings	Loading	T statistics	P values
EE2 <- EE	0.788	39.977	0.000
EE3 <- EE	0.787	46.273	0.000
EE4 <- EE	0.887	119.983	0.000
ITIB1 <- ITIB	0.908	131.445	0.000
ITIB2 <- ITIB	0.888	92.253	0.000
ITIB3 <- ITIB	0.916	147.500	0.000
PE1 <- PE	0.901	121.512	0.000
PE2 <- PE	0.917	113.541	0.000
PE3 <- PE	0.888	103.265	0.000
PE4 <- PE	0.917	130.922	0.000
PIIT1 <- PIIT	0.859	63.600	0.000
PIIT2 <- PIIT	0.861	62.115	0.000
PIIT3 <- PIIT	0.825	47.374	0.000
PIIT4 <- PIIT	0.812	45.056	0.000

Table 9.29 Baseline model outer weights

Baseline Model Outer Weights	Loading	T statistics	P values
IF1 -> IF	0.414	9.768	0.000
IF2 -> IF	0.534	12.236	0.000
IF4 -> IF	0.270	7.323	0.000
IS1 -> IS	0.146	3.506	0.000
IS3 -> IS	0.480	10.323	0.000
IS4 -> IS	0.291	5.927	0.000
IS5 -> IS	0.341	8.011	0.000

Appendix I6. Fully Augmented Model Data

Table 9.30 Augmented model data

Fully Augmented Model Path Coeffs	Sample	T statistics	P values	2.50%	97.50%
ATT -> CI	0.421	13.153	0.000	0.360	0.488
ATT -> ITIB	0.156	4.078	0.000	0.080	0.231
EE -> ATT	0.224	8.833	0.000	0.174	0.272
EE -> CI	0.014	0.564	0.573	-0.035	0.066
EE -> ITIB	-0.002	0.047	0.962	-0.069	0.066
EE -> PE	0.460	16.501	0.000	0.403	0.511

Fully Augmented Model Path Coeffs	Sample	T statistics	P values	2.50%	97.50%
IF -> CI	0.022	0.746	0.455	-0.036	0.078
IF -> ITIB	0.197	5.209	0.000	0.122	0.270
IS -> CI	-0.055	1.785	0.074	-0.114	0.006
IS -> IF	0.721	40.044	0.000	0.682	0.754
IS -> ITIB	0.075	1.910	0.056	-0.003	0.149
ITIB -> CI	0.370	13.691	0.000	0.315	0.421
PE -> ATT	0.600	25.928	0.000	0.552	0.644
PE -> CI	0.139	4.194	0.000	0.073	0.203
PE -> ITIB	0.306	7.640	0.000	0.224	0.381
PIIT -> CI	-0.084	3.746	0.000	-0.128	-0.040
PIIT -> ITIB	0.174	6.649	0.000	0.121	0.224

Fully Augmented Model Specific Indirect Effects	Sample	T statistics	P values	2.50%	97.50%
EE -> PE -> ITIB	0.141	6.558	0.000	0.099	0.184
IS -> IF -> CI	0.016	0.744	0.457	-0.026	0.057
PE -> ITIB -> CI	0.113	6.726	0.000	0.082	0.148
EE -> ATT -> CI	0.094	7.315	0.000	0.072	0.122
PIIT -> ITIB -> CI	0.064	5.819	0.000	0.044	0.087
EE -> PE -> ATT -> ITIB -> CI	0.016	3.772	0.000	0.008	0.025
EE -> PE -> ATT -> ITIB	0.043	3.936	0.000	0.023	0.066
IS -> IF -> ITIB	0.142	5.117	0.000	0.088	0.198
EE -> ATT -> ITIB	0.035	3.646	0.000	0.018	0.056
PE -> ATT -> CI	0.253	11.911	0.000	0.214	0.297
PE -> ATT -> ITIB -> CI	0.035	3.866	0.000	0.018	0.053
EE -> PE -> ATT -> CI	0.116	9.810	0.000	0.095	0.141
PE -> ATT -> ITIB	0.094	4.071	0.000	0.049	0.140
EE -> PE -> ITIB -> CI	0.052	6.024	0.000	0.036	0.070
IS -> IF -> ITIB -> CI	0.053	4.831	0.000	0.033	0.075
EE -> ATT -> ITIB -> CI	0.013	3.456	0.001	0.006	0.021
ATT -> ITIB -> CI	0.058	3.853	0.000	0.029	0.089
EE -> PE -> ATT	0.276	13.515	0.000	0.237	0.317
EE -> PE -> CI	0.064	3.933	0.000	0.033	0.096
EE -> ITIB -> CI	-0.001	0.047	0.963	-0.025	0.025
IF -> ITIB -> CI	0.073	4.918	0.000	0.045	0.103
IS -> ITIB -> CI	0.028	1.892	0.059	-0.001	0.056

Fully Augmented Model Total Effects	Sample	T statistics	P values	2.50%	97.50%

Fully Augmented Model Path Coeffs	Sample	T statistics	P values	2.50%	97.50%
ATT -> CI	0.479	13.856	0.000	0.413	0.546
ATT -> ITIB	0.156	4.078	0.000	0.08	0.231
EE -> ATT	0.499	20.086	0.000	0.447	0.545
EE -> CI	0.369	12.877	0.000	0.31	0.422
EE -> ITIB	0.217	6.978	0.000	0.155	0.277
EE -> PE	0.460	16.501	0.000	0.403	0.511
IF -> CI	0.095	2.812	0.005	0.027	0.16
IF -> ITIB	0.197	5.209	0.000	0.122	0.27
IS -> CI	0.041	1.597	0.110	-0.011	0.091
IS -> IF	0.721	40.044	0.000	0.682	0.754
IS -> ITIB	0.217	7.087	0.000	0.152	0.273
ITIB -> CI	0.370	13.691	0.000	0.315	0.421
PE -> ATT	0.600	25.928	0.000	0.552	0.644
PE -> CI	0.539	19.615	0.000	0.485	0.594
PE -> ITIB	0.400	12.529	0.000	0.334	0.459
PIIT -> CI	-0.020	0.835	0.404	-0.067	0.028
PIIT -> ITIB	0.174	6.649	0.000	0.121	0.224

Appendix I7. Final Model Data

Table 9.31 R^2 of Latent Variables Final Model

Construct	R^2	Adjusted R^2	Comment
Attitude	0.533	0.532	Moderate
Continuance Intention	0.600	0.599	Moderate
Involvement Facilitation	0.522	0.522	Moderate
IT-enabled Innovative Behaviour	0.354	0.351	Moderate
Performance Expectancy	0.276	0.275	Moderate

Table 9.32 f^2 Final Model

f-square for pathways	f2	T statistics	P values	2.50%	97.50%	Sig	Effect size
Attitude -> Continuance Intention	0.221	5.898	0.000	0.155	0.301	sig	medium

f-square for pathways	f2	T statistics	P values	2.50%	97.50%	Sig	Effect size
Attitude -> IT-enabled Innovative Behaviour	0.019	2.062	0.039	0.006	0.042	sig	none/borderline
Effort Expectancy -> Attitude	0.084	4.153	0.000	0.049	0.129	sig	small
Effort Expectancy -> Performance Expectancy	0.213	6.027	0.000	0.152	0.292	sig	medium
Innovation Support -> Involvement Facilitation	1.093	9.432	0.000	0.890	1.355	sig	large
Innovation Support -> Performance Expectancy	0.091	4.256	0.000	0.054	0.138	sig	medium
Involvement Facilitation -> IT-enabled Innovative Behaviour	0.082	3.949	0.000	0.046	0.128	sig	small
IT-enabled Innovative Behaviour -> Continuance Intention	0.230	6.140	0.000	0.165	0.311	sig	medium
Performance Expectancy -> Attitude	0.610	8.427	0.000	0.485	0.771	sig	large
Performance Expectancy -> Continuance Intention	0.021	2.053	0.040	0.006	0.046	sig	small
Performance Expectancy -> IT-enabled Innovative Behaviour	0.075	3.787	0.000	0.041	0.118	sig	small
Personal Innovativeness in IT -> Continuance Intention	0.017	1.842	0.066	0.004	0.041	non-sig	none/borderline
Personal Innovativeness in IT -> IT-enabled Innovative Behaviour	0.048	3.286	0.001	0.024	0.081	sig	small

Predictive relevance (Q^2)

Note: If the value of Q^2 is more than 0.00, that means there is a predictive accuracy of the path model is acceptable (Hair, 2018).

Table 9.33 Construct Cross Validated Redundancy (Q^2 predict) Final Model

Construct	Q^2 predict	Comment
Attitude	0.284	Predictive relevance
Continuance Intention	0.183	Predictive relevance
Involvement Facilitation	0.516	Predictive relevance
IT-enabled Innovative Behaviour	0.193	Predictive relevance
Performance Expectancy	0.272	Predictive relevance

Table 9.34 Final model data

Final Model Path Coeffs	Beta	T statistics	P values	2.50%	97.50%
ATT -> CI	0.424	13.633	0.000	0.363	0.486
ATT -> ITIB	0.157	4.252	0.000	0.086	0.231
EE -> ATT	0.223	8.827	0.000	0.173	0.272
EE -> PE	0.402	14.360	0.000	0.345	0.455
IF -> ITIB	0.246	8.425	0.000	0.185	0.301
IS -> IF	0.723	40.189	0.000	0.683	0.755
IS -> PE	0.262	9.154	0.000	0.203	0.315
ITIB -> CI	0.363	13.553	0.000	0.310	0.414
PE -> ATT	0.600	25.993	0.000	0.553	0.644
PE -> CI	0.135	4.138	0.000	0.072	0.199
PE -> ITIB	0.315	8.028	0.000	0.235	0.391
PIIT -> CI	-0.086	3.810	0.000	-0.129	-0.042
PIIT -> ITIB	0.176	6.732	0.000	0.124	0.227

Final Model Specific Indirect Effects	Beta	T statistics	P values	2.50%	97.50%
PE -> ITIB -> CI	0.114	6.888	0.000	0.082	0.148
PIIT -> ITIB -> CI	0.064	5.827	0.000	0.044	0.087
EE -> PE -> ATT -> ITIB	0.038	4.101	0.000	0.021	0.057
IS -> IF -> ITIB	0.178	7.998	0.000	0.132	0.220
IS -> PE -> ATT -> ITIB	0.025	3.723	0.000	0.013	0.040
PE -> ATT -> ITIB -> CI	0.034	3.967	0.000	0.018	0.053
EE -> PE -> ATT -> CI	0.102	9.447	0.000	0.083	0.124

Final Model Path Coeffs	Beta	T statistics	P values	2.50%	97.50%
IS -> PE -> ATT -> CI	0.067	7.032	0.000	0.049	0.086
IS -> PE -> ITIB -> CI	0.030	5.585	0.000	0.021	0.042
IS -> IF -> ITIB -> CI	0.065	7.039	0.000	0.047	0.083
EE -> ATT -> ITIB -> CI	0.013	3.505	0.000	0.006	0.021
IS -> PE -> ATT -> ITIB -> CI	0.009	3.507	0.000	0.005	0.015
EE -> PE -> ATT	0.241	12.312	0.000	0.203	0.280
EE -> PE -> CI	0.054	3.816	0.000	0.028	0.084
IS -> PE -> ATT	0.157	8.329	0.000	0.120	0.194
IS -> PE -> CI	0.035	3.819	0.000	0.019	0.055
EE -> PE -> ITIB	0.127	6.675	0.000	0.089	0.164
EE -> ATT -> CI	0.095	7.317	0.000	0.071	0.122
IS -> PE -> ITIB	0.083	6.212	0.000	0.060	0.112
EE -> PE -> ATT -> ITIB -> CI	0.014	3.883	0.000	0.007	0.022
EE -> ATT -> ITIB	0.035	3.744	0.000	0.018	0.056
PE -> ATT -> CI	0.255	12.352	0.000	0.216	0.298
PE -> ATT -> ITIB	0.094	4.242	0.000	0.052	0.140
EE -> PE -> ITIB -> CI	0.046	6.075	0.000	0.032	0.062
ATT -> ITIB -> CI	0.057	3.955	0.000	0.030	0.087
IF -> ITIB -> CI	0.089	7.346	0.000	0.066	0.115

Final Model Total Effects	Beta	T statistics	P values	2.50%	97.50%
ATT -> CI	0.482	0.481	0.034	14.368	0.000
ATT -> ITIB	0.157	0.157	0.037	4.252	0.000
EE -> ATT	0.465	0.465	0.025	18.434	0.000
EE -> CI	0.324	0.324	0.019	16.647	0.000
EE -> ITIB	0.200	0.200	0.018	11.138	0.000
EE -> PE	0.402	0.403	0.028	14.360	0.000
IF -> CI	0.089	0.090	0.012	7.346	0.000
IF -> ITIB	0.246	0.246	0.029	8.425	0.000
IS -> ATT	0.157	0.158	0.019	8.329	0.000
IS -> CI	0.206	0.206	0.018	11.295	0.000
IS -> IF	0.723	0.724	0.018	40.189	0.000
IS -> ITIB	0.285	0.286	0.023	12.243	0.000
IS -> PE	0.262	0.263	0.029	9.154	0.000
ITIB -> CI	0.363	0.363	0.027	13.553	0.000
PE -> ATT	0.600	0.601	0.023	25.993	0.000
PE -> CI	0.538	0.539	0.024	22.430	0.000

Final Model Path Coeffs	Beta	T statistics	P values	2.50%	97.50%
PE -> ITIB	0.409	0.409	0.029	14.234	0.000
PIIT -> CI	-0.022	-0.022	0.024	0.908	0.364
PIIT -> ITIB	0.176	0.177	0.026	6.732	0.000

Appendix I8. Final Model Mediation Data

Table 9.35 Significant indirect effects (final model, bootstrapped, two-tailed)

From	To	Mediator chain	β	t	p	95% CI [LL, UL]
PE	CI	ITIB	0.114	6.888	.000	[0.082, 0.148]
PIIT	CI	ITIB	0.064	5.827	.000	[0.044, 0.087]
PE	CI	ATT → ITIB	0.034	3.967	.000	[0.018, 0.053]
EE	CI	PE → ATT	0.102	9.447	.000	[0.083, 0.124]
IS	CI	PE → ATT	0.067	7.032	.000	[0.049, 0.086]
IS	CI	PE → ITIB	0.030	5.585	.000	[0.021, 0.042]
IS	CI	IF → ITIB	0.065	7.039	.000	[0.047, 0.083]
EE	CI	ATT → ITIB	0.013	3.505	.000	[0.006, 0.021]
IS	CI	PE → ATT → ITIB	0.009	3.507	.000	[0.005, 0.015]
EE	CI	PE	0.054	3.816	.000	[0.028, 0.084]
EE	CI	ATT	0.095	7.317	.000	[0.071, 0.122]
EE	ITIB	PE	0.127	6.675	.000	[0.089, 0.164]
PE	ITIB	ATT	0.093	4.061	.000	[0.049, 0.139]
EE	ITIB	ATT	0.035	3.639	.000	[0.018, 0.056]
IS	ITIB	IF	0.178	7.998	.000	[0.132, 0.220]
IS	ITIB	PE → ATT	0.025	3.723	.000	[0.013, 0.040]
EE	ATT	PE	0.241	12.312	.000	[0.203, 0.280]

From	To	Mediator chain	β	t	p	95% CI [LL, UL]
IS	ATT	PE	0.157	8.329	.000	[0.120, 0.194]

Appendix J Final Survey Multigroup Analysis Data

Appendix J1. MGA Model Data

Table 9.36 MGA model path coefficients

MGA Model Path Coeffs	Beta	T statistics	P values	2.50%	97.50%
ATT -> CI	0.424	13.694	0.000	0.363	0.484
ATT -> ITIB	0.158	4.337	0.000	0.086	0.230
EE -> ATT	0.223	8.688	0.000	0.172	0.272
EE -> PE	0.407	14.936	0.000	0.352	0.460
IF -> ITIB	0.245	8.445	0.000	0.187	0.302
IS -> IF	0.720	40.493	0.000	0.681	0.751
IS -> PE	0.250	8.815	0.000	0.192	0.304
ITIB -> CI	0.363	13.624	0.000	0.310	0.414
PE -> ATT	0.600	25.754	0.000	0.553	0.644
PE -> CI	0.135	4.102	0.000	0.071	0.199
PE -> ITIB	0.315	8.091	0.000	0.241	0.393
PIIT -> CI	-0.086	3.746	0.000	-0.129	-0.040
PIIT -> ITIB	0.176	6.700	0.000	0.125	0.227

Table 9.37 MGA model R²

MGA model R²	R2	adj R2
ATT	0.533	0.532
CI	0.600	0.599
IF	0.519	0.518
ITIB	0.354	0.351
PE	0.271	0.269

Appendix J2. MGA Management Level

Decision rule for compositional difference: compositional invariance holds when (i) the original c is $\geq$ the 5% quantile of the permutation distribution and (ii) the permutation p-value $> .05$ (i.e., c not significantly different from 1).

Decision rule for group difference: PLS-MGA (bootstrap): significant group difference if 2-tailed $p < .05$ or $> .95$. Permutation MGA: $p < .05$ indicates significant difference.

Note: In the table headings, due to page size constraint, Dec refers to decision, 5% quant refers to 5% quantile. N.s. means non-significant, Sig refers to significant. PLS-MGA p (2-tailed) is shortened as PLS-MGA p , where necessary.

Pairwise comparison (see all necessary tables below)

Benjamini–Hochberg FDR ($q = .05$), PLS-MGA 2-tailed p 's, by pair and family (paths / R^2 / f^2). In this short summary, BH significance is highlighted by **.

- Paths ($m=13$): ATT → ITIB: $p = .019 \rightarrow q = .247$ (ns)
- R^2 ($m=5$): none (all $p \geq .11$)
- f^2 ($m=13$): ATT → ITIB: $p = .030 \rightarrow q = .390$ (ns)

Sensitivity (pooled across pairs): n/a (single pair only).

Table 9.38 Management levels for group analysis

Category	n	% of total (N=1,040)
Employee	717	68.9%
Manager (Junior+Mid+Senior)	274	26.3%
Blank	49	4.7%
Total	1,040	100%

Table 9.39 Compositional invariance (Employee vs Manager) initial results

Construct	c (original)	5% quantile	p ($H_0: c = 1$)	Decision
ATT	1.000	1.000	0.127	Invariant
CI	1.000	1.000	0.192	Invariant
EE	1.000	0.997	0.774	Invariant
IF	0.993	0.981	0.338	Invariant
IS	0.966	0.971	0.027	Not inv
ITIB	1.000	1.000	0.304	Invariant

Construct	c (original)	5% quantile	p (H0: c = 1)	Decision
PE	1.000	1.000	0.870	Invariant
PIIT	0.997	0.991	0.307	Invariant

Table 9.40 Compositional invariance (Employee vs Manager) updated results

Construct	c (original)	5% quantile	p (H0: c=1)	Decision
ATT	1.000	1.000	0.127	Invariant
CI	1.000	1.000	0.192	Invariant
EE	1.000	0.997	0.773	Invariant
IF	0.997	0.981	0.607	Invariant
IS	0.989	0.977	0.237	Invariant
ITIB	1.000	1.000	0.302	Invariant
PE	1.000	1.000	0.819	Invariant
PIIT	0.997	0.991	0.307	Invariant

Table 9.41 Equality of means (Employee vs Manager)

Construct	ΔMean (E-M)	2.5%	97.5%	Permutation p	Decision
ATT	0.046	-0.139	0.139	0.528	Equal
CI	0.031	-0.146	0.144	0.671	Equal
EE	-0.045	-0.136	0.141	0.522	Equal
IF	-0.012	-0.135	0.140	0.870	Equal
IS	-0.027	-0.140	0.146	0.709	Equal
ITIB	-0.097	-0.139	0.137	0.177	Equal
PE	-0.034	-0.144	0.142	0.642	Equal
PIIT	-0.069	-0.140	0.141	0.338	Equal

Table 9.42 Equality of variances (Employee vs Manager)

Construct	Δ var (E-M)	2.5%	97.5%	Permutation p	Decision
ATT	-0.062	-0.168	0.180	0.487	Equal
CI	0.037	-0.170	0.182	0.692	Equal
EE	0.209	-0.199	0.215	0.049	Not equal
IF	-0.080	-0.179	0.193	0.399	Equal
IS	0.042	-0.183	0.185	0.656	Equal
ITIB	-0.159	-0.181	0.189	0.088	Equal
PE	-0.037	-0.194	0.216	0.701	Equal
PIIT	0.093	-0.165	0.184	0.308	Equal

Table 9.43 Path coefficients (Employee vs Manager)

Path	β Employee	β Manager	Δ (E-M)	PLS-MGA p (2-tailed)	Permutation p	Decision
ATT → ITIB	0.084	0.276	-0.191	0.019	0.025	Sig
ATT → CI	0.436	0.370	0.066	0.333	0.368	n.s.
EE → ATT	0.230	0.184	0.045	0.407	0.438	n.s.
EE → PE	0.385	0.466	-0.082	0.172	0.191	n.s.
IF → ITIB	0.268	0.194	0.074	0.251	0.266	n.s.
IS → IF	0.713	0.722	-0.008	0.817	0.853	n.s.
IS → PE	0.261	0.201	0.060	0.355	0.341	n.s.
ITIB → CI	0.341	0.390	-0.048	0.433	0.436	n.s.
PE → ATT	0.596	0.642	-0.047	0.368	0.383	n.s.
PE → CI	0.137	0.176	-0.039	0.601	0.615	n.s.
PE → ITIB	0.349	0.278	0.071	0.429	0.456	n.s.

Path	β Employee	β Manager	Δ (E-M)	PLS-MGA p (2-tailed)	Permutation p	Decision
PIIT $\rightarrow$ CI	-0.091	-0.101	0.009	0.855	0.858	n.s.
PIIT $\rightarrow$ ITIB	0.148	0.202	-0.054	0.371	0.371	n.s.

Table 9.44 R^2 differences (Employee vs Manager)

Construct	ΔR^2 (E-M)	PLS-MGA p (2-tailed)	Decision
ATT	-0.040	0.488	n.s.
CI	-0.055	0.163	n.s.
IF	-0.012	0.829	n.s.
ITIB	-0.094	0.115	n.s.
PE	-0.040	0.508	n.s.

Table 9.45 f^2 differences (Employee vs Manager)

Path	Δf^2 (E-M)	PLS-MGA p (2-tailed)	Decision
ATT $\rightarrow$ ITIB	-0.054	0.030	Sig
ATT $\rightarrow$ CI	0.069	0.356	n.s.
EE $\rightarrow$ ATT	0.032	0.404	n.s.
EE $\rightarrow$ PE	-0.105	0.230	n.s.
IF $\rightarrow$ ITIB	0.037	0.374	n.s.
IS $\rightarrow$ IF	-0.051	0.890	n.s.
IS $\rightarrow$ PE	0.033	0.399	n.s.
ITIB $\rightarrow$ CI	-0.052	0.586	n.s.
PE $\rightarrow$ ATT	-0.100	0.614	n.s.
PE $\rightarrow$ CI	-0.015	0.656	n.s.
PE $\rightarrow$ ITIB	0.032	0.434	n.s.
PIIT $\rightarrow$ CI	-0.007	0.883	n.s.

Path	Δf^2 (E-M)	PLS-MGA p (2-tailed)	Decision
PIIT → ITIB	-0.037	0.338	n.s.

Appendix J3. MGA Gender

Decision rule for compositional difference: compositional invariance holds when (i) the original c is $\geq$ the 5% quantile of the permutation distribution and (ii) the permutation p-value $> .05$ (i.e., c not significantly different from 1).

Decision rule for group difference: PLS-MGA (bootstrap): significant group difference if 2-tailed $p < .05$ or $> .95$. Permutation MGA: $p < .05$ indicates significant difference.

Note: In the table headings, due to page size constraint, Dec refers to decision, 5% quant refers to 5% quantile. N.s. means non-significant, Sig refers to significant. To shorten the tables, PLS-MGA p (2-tailed) is referenced as PLS-MGA p, where necessary.

Pairwise comparison (see all necessary tables below)

Benjamini–Hochberg FDR ($q = .05$), PLS-MGA 2-tailed p's, by pair and family (paths / R^2 / f^2). In this short summary, BH significance is highlighted by **.

- Paths ($m=13$): IS → IF: $p = .024 \rightarrow q = .312$ (ns)
- R^2 ($m=5$): IF: $p = .023 \rightarrow q = .115$ (ns)
- f^2 ($m=13$): IS → IF: $p = .025 \rightarrow q = .325$ (ns)

Sensitivity (pooled across pairs): n/a (single pair).

Table 9.46 Gender records for MGA

Group	n	% of valid (N = 1,023)
Female	323	31.6%
Male	700	68.4%
Blank	17	—

Table 9.47 Compositional invariance, means and variances (Male vs Female)

Const	c	5% quant	p	Dec	Δ Mean (M-F)	p	Dec	Δ Var (M-F)	p	Dec
ATT	1.000	1.000	0.236	Inv	0.198	0.003	Means differ	-0.023	0.790	Equal

Const	c	5% quant	p	Dec	Δ Mean (M-F)	p	Dec	Δ Var (M-F)	p	Dec
CI	1.000	1.000	0.666	Inv	0.020	0.763	Equal	-0.168	0.047	Variances differ
EE	1.000	0.998	0.996	Inv	0.337	0.000	Means differ	-0.128	0.205	Equal
IF	0.996	0.982	0.467	Inv	-0.074	0.272	Equal	-0.209	0.024	Variances differ
IS	0.997	0.980	0.641	Inv	-0.077	0.258	Equal	-0.276	0.002	Variances differ
ITIB	1.000	1.000	0.141	Inv	-0.054	0.410	Equal	-0.134	0.120	Equal
PE	1.000	1.000	0.603	Inv	0.143	0.037	Means differ	-0.122	0.209	Equal
PIIT	0.992	0.992	0.060	Inv	-0.449	0.000	Means differ	-0.053	0.532	Equal

Table 9.48 Path coefficients (Male vs Female)

Path	β_M	β_F	$\Delta(M-F)$	PLS-MGA p (2-tailed)	Permutation p	Decision
ATT → CI	0.432	0.396	0.036	0.610	0.598	n.s.
ATT → ITIB	0.187	0.098	0.089	0.262	0.268	n.s.
EE → ATT	0.227	0.188	0.038	0.523	0.485	n.s.
EE → PE	0.407	0.393	0.014	0.816	0.795	n.s.
IF → ITIB	0.253	0.196	0.057	0.367	0.379	n.s.
IS → IF	0.749	0.658	0.091	0.024	0.015	Sig
IS → PE	0.255	0.249	0.007	0.920	0.920	n.s.
ITIB → CI	0.346	0.379	-0.032	0.536	0.572	n.s.
PE → ATT	0.595	0.628	-0.032	0.517	0.532	n.s.
PE → CI	0.144	0.147	-0.003	0.962	0.968	n.s.
PE → ITIB	0.290	0.393	-0.103	0.203	0.235	n.s.

Path	β_M	β_F	$\Delta(M-F)$	PLS-MGA p (2-tailed)	Permutation p	Decision
PIIT $\rightarrow$ CI	-0.096	-0.094	-0.002	0.985	0.972	n.s.
PIIT $\rightarrow$ ITIB	0.188	0.154	0.035	0.560	0.543	n.s.

Table 9.49 R^2 differences (Male vs Female)

Construct	ΔR^2 (M-F)	PLS-MGA p (2-tailed)	Decision
ATT	0.001	0.993	n.s.
CI	0.015	0.727	n.s.
IF	0.129	0.023	Sig
ITIB	0.026	0.653	n.s.
PE	0.033	0.547	n.s.

Table 9.50 f^2 differences (Male vs Female)

Path	Δf^2 (M-F)	PLS-MGA p (2-tailed)	Decision
ATT $\rightarrow$ ITIB	0.042	0.576	n.s.
ATT $\rightarrow$ CI	0.020	0.212	n.s.
EE $\rightarrow$ ATT	0.024	0.539	n.s.
EE $\rightarrow$ PE	0.018	0.791	n.s.
IF $\rightarrow$ ITIB	0.036	0.343	n.s.
IS $\rightarrow$ IF	0.517	0.025	Sig
IS $\rightarrow$ PE	0.005	0.865	n.s.
ITIB $\rightarrow$ CI	-0.034	0.662	n.s.
PE $\rightarrow$ ATT	-0.091	0.604	n.s.
PE $\rightarrow$ CI	0.001	0.880	n.s.
PE $\rightarrow$ ITIB	-0.048	0.289	n.s.
PIIT $\rightarrow$ CI	0.001	0.857	n.s.

Path	Δf^2 (M-F)	PLS-MGA p (2-tailed)	Decision
PIIT → ITIB	0.021	0.470	n.s.

Appendix J4. MGA Age

Decision rule for compositional difference: compositional invariance holds when (i) the original c is $\geq$ the 5% quantile of the permutation distribution and (ii) the permutation p-value $> .05$ (i.e., c not significantly different from 1).

Decision rule for group difference: PLS-MGA (bootstrap): significant group difference if 2-tailed $p < .05$ or $> .95$. Permutation MGA: $p < .05$ indicates significant difference.

Note: In the table headings, due to page size constraint, Dec refers to decision, 5% quant refers to 5% quantile. N.s. means non-significant, Sig refers to significant. To shorten the tables, PLS-MGA p (2-tailed) is referenced as PLS-MGA p, where necessary.

Pairwise comparison (see all necessary tables below)

Benjamini–Hochberg FDR ($q = .05$), PLS-MGA 2-tailed p's, by pair and family (paths / R^2 / f^2). In this short summary, BH significance is highlighted by **.

18_30 vs 31_40:

- Paths ($m=13$): PE→CI ($p<.022$, $q=.286$) n.s.
- R^2 ($m=5$): none
- f^2 ($m=13$):
 - ATT→ITIB ($p=.048$, $q=.312$) n.s.
 - PIIT→CI ($p=.031$, $q=.403$) n.s.

18_30 vs 41_80:

- Paths ($m=13$): none
- R^2 ($m=5$): none
- f^2 ($m=13$): none

31_40 vs 41_80:

- Paths ($m=13$): none
- R^2 ($m=5$): none
- f^2 ($m=13$): none

Sensitivity (pooled across the three pairs):

- Paths (m = 39): none
- R^2 (m=15): none
- f^2 (m = 39): none

Table 9.51 Age records for MGA

Group	n	%
Age_18_30	379	36%
Age_31_40	415	40%
Age_41_80	215	21%
Blank	31	3%
Total	1040	100%

18-30 vs 31-40

Table 9.52 Compositional invariance, means and variances (18-30 vs 31-40)

Const	c	5% quant	p	Dec	Δ Mean (18-31)	p	Dec	Δ Var (18-31)	p	Dec
ATT	1.000	1.000	0.303	Inv	0.013	0.846	Equal	0.099	0.268	Equal
CI	1.000	1.000	0.132	Inv	0.094	0.183	Equal	0.049	0.567	Equal
EE	1.000	0.997	0.875	Inv	-0.120	0.091	Equal	0.020	0.845	Equal
IF	0.999	0.982	0.815	Inv	0.156	0.027	Means differ	- 0.075	0.420	Equal
IS	0.998	0.980	0.730	Inv	0.243	0.001	Means differ	- 0.140	0.132	Equal
ITIB	1.000	1.000	0.722	Inv	0.167	0.017	Means differ	0.051	0.579	Equal
PE	1.000	1.000	0.465	Inv	-0.017	0.815	Equal	0.062	0.527	Equal
PIIT	0.995	0.990	0.233	Inv	0.237	0.000	Means differ	0.011	0.896	Equal

Table 9.53 Path coefficients (18-30 vs 31-40)

Path	β 18-30	β 31-40	Δ (Ca-Ci)	PLS-MGA p	Perm	Dec
ATT → CI	0.397	0.464	-0.068	0.312	0.329	n.s.
ATT → ITIB	0.066	0.222	-0.156	0.054	0.058	n.s.

Path	β 18-30	β 31-40	$\Delta(\text{Ca}-\text{Ci})$	PLS-MGA p	Perm	Dec
EE $\rightarrow$ ATT	0.221	0.272	-0.050	0.362	0.362	n.s.
EE $\rightarrow$ PE	0.351	0.449	-0.099	0.112	0.111	n.s.
IF $\rightarrow$ ITIB	0.267	0.266	0.001	0.978	0.984	n.s.
IS $\rightarrow$ IF	0.709	0.718	-0.009	0.836	0.829	n.s.
IS $\rightarrow$ PE	0.245	0.266	-0.020	0.761	0.753	n.s.
ITIB $\rightarrow$ CI	0.316	0.415	-0.099	0.094	0.107	n.s.
PE $\rightarrow$ ATT	0.609	0.573	0.036	0.506	0.511	n.s.
PE $\rightarrow$ CI	0.209	0.042	0.168	0.022	0.024	Sig
PE $\rightarrow$ ITIB	0.342	0.319	0.024	0.767	0.775	n.s.
PIIT $\rightarrow$ CI	-0.078	-0.090	0.012	0.811	0.825	n.s.
PIIT $\rightarrow$ ITIB	0.164	0.144	0.020	0.741	0.742	n.s.

Table 9.54 R^2 differences (18-30 vs 31-40)

Construct	ΔR^2 (18-31)	PLS-MGA p	Decision
ATT	-0.027	0.633	n.s.
CI	-0.052	0.210	n.s.
IF	-0.012	0.837	n.s.
ITIB	-0.097	0.091	n.s.
PE	-0.092	0.106	n.s.

Table 9.55 f^2 differences (18-30 vs 31-40)

Path	Δf^2 (18-31)	PLS-MGA p	Decision
ATT $\rightarrow$ CI	-0.091	0.291	n.s.
ATT $\rightarrow$ ITIB	-0.038	0.048	Sig
EE $\rightarrow$ ATT	-0.038	0.441	n.s.

Path	Δf^2 (18-31)	PLS-MGA p	Decision
EE → PE	-0.137	0.077	n.s.
IF → ITIB	-0.022	0.655	n.s.
IS → IF	-0.052	0.846	n.s.
IS → PE	-0.027	0.545	n.s.
ITIB → CI	-0.128	0.132	n.s.
PE → ATT	0.101	0.558	n.s.
PE → CI	0.046	0.031	Sig
PE → ITIB	-0.001	0.976	n.s.
PIIT → CI	-0.007	0.742	n.s.
PIIT → ITIB	0.004	0.911	n.s.

18-30 vs 41-80

Table 9.56 Compositional invariance, means and variances (18-30 vs 41-80)

Const	c	5% quant	p	Dec	Δ Mean (18-41)	p	Dec	Δ Var (18-41)	p	Dec
ATT	0.999	0.999	0.056	Inv	-0.196	0.021	Means differ	0.228	0.040	Variances differ
CI	1.000	0.999	0.363	Inv	-0.234	0.006	Means differ	0.279	0.009	Variances differ
EE	0.998	0.996	0.330	Inv	-0.137	0.105	Equal	0.029	0.816	Equal
IF	0.993	0.967	0.556	Inv	0.069	0.427	Equal	0.058	0.606	Equal
IS	0.994	0.962	0.643	Inv	0.225	0.007	Means differ	0.006	0.961	Equal
ITIB	1.000	0.999	0.460	Inv	-0.107	0.202	Equal	0.182	0.097	Equal
PE	1.000	1.000	0.154	Inv	-0.281	0.001	Means differ	0.216	0.078	Equal
PIIT	0.995	0.988	0.258	Inv	0.226	0.010	Means differ	0.078	0.466	Equal

Table 9.57 Path coefficients (18-30 vs 41-80)

Path	β 18	β 41	Δ (18-41)	PLS-MGA p	Perm	Dec
ATT → CI	0.397	0.365	0.031	0.740	0.724	n.s.

Path	β 18	β 41	$\Delta(18-41)$	PLS-MGA p	Perm	Dec
ATT → ITIB	0.066	0.089	-0.023	0.814	0.815	n.s.
EE → ATT	0.221	0.208	0.014	0.852	0.838	n.s.
EE → PE	0.351	0.432	-0.081	0.294	0.310	n.s.
IF → ITIB	0.267	0.234	0.034	0.685	0.688	n.s.
IS → IF	0.709	0.711	-0.002	0.934	0.971	n.s.
IS → PE	0.245	0.251	-0.006	0.942	0.947	n.s.
ITIB → CI	0.316	0.331	-0.015	0.836	0.847	n.s.
PE → ATT	0.609	0.576	0.033	0.624	0.631	n.s.
PE → CI	0.209	0.215	-0.006	0.951	0.949	n.s.
PE → ITIB	0.342	0.323	0.020	0.854	0.852	n.s.
PIIT → CI	-0.078	-0.131	0.052	0.464	0.434	n.s.
PIIT → ITIB	0.164	0.221	-0.058	0.430	0.434	n.s.

Table 9.58 R^2 differences (18-30 vs 41-80)

Construct	ΔR^2 (18-41)	PLS-MGA p	Decision
ATT	0.040	0.554	n.s.
CI	0.041	0.445	n.s.
IF	-0.003	0.948	n.s.
ITIB	0.024	0.736	n.s.
PE	-0.069	0.362	n.s.

Table 9.59 f^2 differences (18-30 vs 41-80)

Path	Δf^2 (18-41)	PLS-MGA p	Decision
ATT → CI	0.032	0.699	n.s.
ATT → ITIB	-0.003	0.979	n.s.

Path	Δ^2 (18-41)	PLS-MGA p	Decision
EE → ATT	0.022	0.633	n.s.
EE → PE	-0.105	0.298	n.s.
IF → ITIB	0.015	0.763	n.s.
IS → IF	-0.011	0.994	n.s.
IS → PE	-0.013	0.878	n.s.
ITIB → CI	-0.003	0.996	n.s.
PE → ATT	0.157	0.403	n.s.
PE → CI	-0.002	0.963	n.s.
PE → ITIB	0.006	0.864	n.s.
PIIT → CI	-0.021	0.641	n.s.
PIIT → ITIB	-0.031	0.516	n.s.

31-40 vs 41-80

Table 9.60 Compositional invariance, means and variances (31-40 vs 41-80)

Const	c	5% quant	p	Dec	Δ Mean (31-41)	p	Dec	Δ Var (31-41)	p	Dec
ATT	1.000	0.999	0.385	Inv	-0.216	0.009	Means differ	0.129	0.225	Equal
CI	1.000	1.000	0.999	Inv	-0.334	0.000	Means differ	0.230	0.029	Variances differ
EE	0.999	0.998	0.384	Inv	-0.018	0.828	Equal	0.007	0.960	Equal
IF	0.987	0.972	0.251	Inv	-0.085	0.304	Equal	0.143	0.210	Equal
IS	0.989	0.972	0.310	Inv	-0.033	0.697	Equal	0.137	0.206	Equal
ITIB	1.000	1.000	0.237	Inv	-0.280	0.001	Means differ	0.132	0.229	Equal
PE	1.000	1.000	0.420	Inv	-0.269	0.001	Means differ	0.153	0.213	Equal
PIIT	0.996	0.984	0.448	Inv	-0.017	0.841	Equal	0.082	0.433	Equal

Table 9.61 Path coefficients (31-40 vs 41-80)

Path	β 31	β 41	$\Delta(31-41)$	PLS-MGA p	Perm	Dec
ATT → CI	0.464	0.365	0.099	0.258	0.260	n.s.
ATT → ITIB	0.222	0.089	0.133	0.164	0.166	n.s.
EE → ATT	0.272	0.208	0.064	0.359	0.357	n.s.
EE → PE	0.449	0.432	0.017	0.822	0.793	n.s.
IF → ITIB	0.266	0.234	0.032	0.675	0.657	n.s.
IS → IF	0.718	0.711	0.007	0.937	0.896	n.s.
IS → PE	0.266	0.251	0.014	0.855	0.834	n.s.
ITIB → CI	0.415	0.331	0.084	0.225	0.229	n.s.
PE → ATT	0.573	0.576	-0.004	0.949	0.956	n.s.
PE → CI	0.042	0.215	-0.173	0.054	0.050	n.s.
PE → ITIB	0.319	0.323	-0.004	0.961	0.962	n.s.
PIIT → CI	-0.090	-0.131	0.041	0.566	0.520	n.s.
PIIT → ITIB	0.144	0.221	-0.078	0.283	0.272	n.s.

Table 9.62 R^2 differences (31-40 vs 41-80)

Construct	ΔR^2 (31-41)	PLS-MGA p	Decision
ATT	0.066	0.312	n.s.
CI	0.093	0.074	n.s.
IF	0.010	0.924	n.s.
ITIB	0.121	0.077	n.s.
PE	0.023	0.758	n.s.

Table 9.63 f^2 differences (31-40 vs 41-80)

Path	Δf^2 (31-41)	PLS-MGA p	Decision
ATT → CI	0.123	0.215	n.s.
ATT → ITIB	0.036	0.135	n.s.
EE → ATT	0.060	0.270	n.s.
EE → PE	0.032	0.734	n.s.
IF → ITIB	0.037	0.479	n.s.
IS → IF	0.041	0.876	n.s.
IS → PE	0.014	0.756	n.s.
ITIB → CI	0.125	0.199	n.s.
PE → ATT	0.056	0.715	n.s.
PE → CI	-0.048	0.115	n.s.
PE → ITIB	0.007	0.841	n.s.
PIIT → CI	-0.014	0.809	n.s.
PIIT → ITIB	-0.035	0.460	n.s.

Appendix J5. MGA Location

Decision rule for compositional difference: compositional invariance holds when (i) the original c is $\geq$ the 5% quantile of the permutation distribution and (ii) the permutation p -value $> .05$ (i.e., c not significantly different from 1).

Decision rule for group difference: PLS-MGA (bootstrap): significant group difference if 2-tailed $p < .05$ or $> .95$. Permutation MGA: $p < .05$ indicates significant difference.

Note: In the table headings, due to page size constraint, Dec refers to decision, 5% quant refers to 5% quantile. N.s. means non-significant, Sig refers to significant. To shorten the tables, PLS-MGA p (2-tailed) is referenced as PLS-MGA p , where necessary.

Pairwise comparison (see all necessary tables below)

Benjamini–Hochberg FDR ($q = .05$), PLS-MGA 2-tailed p 's, by pair and family (paths / R^2 / f^2). In this short summary, BH significance is highlighted by **.

Capital vs City:

- Paths (m=13): PIIT→CI (p<.001, q=.013) **; others n.s.
- R² (m=5): none
- f² (m=13): PIIT→CI (p=.001, q=.013) **

Capital vs Rural:

- Paths (m=13):
 - IS → PE: p = .019 → q = .150 (ns)
 - PIIT → CI: p = .023 → q = .149 (ns)
- R² (m=5): none
- f² (m=13): IS → PE: p = .015 → q = .195 (ns)

City vs Rural:

- Paths (m=13): IS → PE: p = .005 → q = .065 (ns)
- R² (m=5): none
- f² (m=13): IS → PE: p = .006 → q = .078 (ns)

Sensitivity (pooled across the three pairs):

- Paths (m = 39): Capital–City: PIIT → CI still survives (q ≈ .039).
- R² (m=15): none.
- f² (m = 39): Capital–City: PIIT → CI still survives (q ≈ .039).

Capital vs City

Table 9.64 Compositional invariance, means and variances (Capital vs City)

Const	c	5% quant	p	Dec	ΔMean (Ca-Ci)	p	Dec	ΔVar (Ca-Ci)	p	Dec
ATT	1.000	1.000	0.716	Inv	-0.176	0.017	Means differ	0.067	0.448	Equal
CI	1.000	1.000	0.627	Inv	-0.157	0.034	Means differ	0.080	0.384	Equal
EE	1.000	0.997	0.680	Inv	-0.145	0.044	Means differ	0.089	0.398	Equal
IF	0.997	0.980	0.675	Inv	0.077	0.307	Equal	0.022	0.809	Equal
IS	0.989	0.976	0.229	Inv	0.013	0.860	Equal	0.047	0.601	Equal

Const	c	5% quant	p	Dec	Δ Mean (Ca-Ci)	p	Dec	Δ Var (Ca-Ci)	p	Dec
ITIB	1.000	1.000	0.364	Inv	-0.043	0.559	Equal	0.145	0.127	Equal
PE	1.000	1.000	0.567	Inv	-0.301	0.000	Means differ	0.229	0.029	Variances differ
PIIT	0.999	0.988	0.746	Inv	0.175	0.016	Means differ	0.048	0.594	Equal

Table 9.65 Path coefficients (Capital vs City)

Path	β Capital	β City	Δ (Ca-Ci)	PLS-MGA p	Perm	Dec
ATT → CI	0.426	0.458	-0.032	0.657	0.664	n.s.
ATT → ITIB	0.166	0.105	0.061	0.477	0.467	n.s.
EE → ATT	0.216	0.263	-0.047	0.402	0.440	n.s.
EE → PE	0.418	0.334	0.084	0.208	0.198	n.s.
IF → ITIB	0.233	0.274	-0.041	0.538	0.556	n.s.
IS → IF	0.695	0.769	-0.074	0.067	0.083	n.s.
IS → PE	0.264	0.331	-0.067	0.291	0.308	n.s.
ITIB → CI	0.356	0.373	-0.016	0.763	0.795	n.s.
PE → ATT	0.588	0.604	-0.016	0.755	0.784	n.s.
PE → CI	0.158	0.052	0.106	0.170	0.166	n.s.
PE → ITIB	0.323	0.345	-0.022	0.790	0.806	n.s.
PIIT → CI	-0.028	-0.211	0.183	0.000*	0.001*	Sig
PIIT → ITIB	0.191	0.132	0.059	0.325	0.344	n.s.

Table 9.66 R^2 differences (Capital vs City)

Construct	ΔR^2 (Ca-Ci)	PLS-MGA p	Decision
ATT	-0.049	0.361	n.s.
CI	0.023	0.591	n.s.

Construct	ΔR^2 (Ca-Ci)	PLS-MGA p	Decision
IF	-0.108	0.068	n.s.
ITIB	0.018	0.762	n.s.
PE	0.024	0.682	n.s.

Table 9.67 f^2 differences (Capital vs City)

Path	Δf^2 (Ca-Ci)	PLS-MGA p	Decision
ATT → CI	-0.014	0.925	n.s.
ATT → ITIB	0.014	0.369	n.s.
EE → ATT	-0.058	0.279	n.s.
EE → PE	0.090	0.228	n.s.
IF → ITIB	-0.023	0.669	n.s.
IS → IF	-0.509	0.091	n.s.
IS → PE	-0.049	0.397	n.s.
ITIB → CI	-0.019	0.840	n.s.
PE → ATT	-0.146	0.406	n.s.
PE → CI	0.028	0.108	n.s.
PE → ITIB	-0.004	0.979	n.s.
PIIT → CI	-0.106	0.001*	Sig
PIIT → ITIB	0.031	0.291	n.s.

Capital vs Rural

Table 9.68 Compositional invariance, means and variances (Capital vs Rural)

Const	c	5% quant	p	Dec	Δ Mean (Ca-Ru)	p	Dec	Δ Var (Ca-Ru)	p	Dec
ATT	1.000	0.999	0.298	Inv	-0.139	0.203	Equal	0.239	0.087	Equal
CI	1.000	0.999	0.615	Inv	-0.353	0.001	Means differ	0.526	0.001	Variances differ
EE	0.998	0.994	0.335	Inv	-0.012	0.916	Equal	0.212	0.192	Equal

Const	c	5% quant	p	Dec	Δ Mean (Ca-Ru)	p	Dec	Δ Var (Ca-Ru)	p	Dec
IF	0.986	0.946	0.441	Inv	0.196	0.067	Equal	0.240	0.104	Equal
IS	0.978	0.940	0.332	Inv	0.185	0.086	Equal	0.219	0.120	Equal
ITIB	1.000	0.999	0.387	Inv	-0.292	0.008	Means differ	0.313	0.027	Variances differ
PE	1.000	1.000	0.939	Inv	-0.124	0.250	Equal	0.010	0.947	Equal
PIIT	0.998	0.907	0.804	Inv	0.104	0.326	Equal	0.258	0.068	Equal

Table 9.69 Path coefficients (Capital vs Rural)

Path	β Ca	β Ru	Δ (Ca-Ru)	PLS-MGA p	Perm	Dec
ATT $\rightarrow$ CI	0.426	0.376	0.050	0.651	0.632	n.s.
ATT $\rightarrow$ ITIB	0.166	0.218	-0.053	0.697	0.689	n.s.
EE $\rightarrow$ ATT	0.216	0.194	0.023	0.737	0.803	n.s.
EE $\rightarrow$ PE	0.418	0.470	-0.052	0.549	0.593	n.s.
IF $\rightarrow$ ITIB	0.233	0.323	-0.090	0.386	0.401	n.s.
IS $\rightarrow$ IF	0.695	0.783	-0.088	0.080	0.186	n.s.
IS $\rightarrow$ PE	0.264	0.025	0.239	0.019*	0.018*	Sig
ITIB $\rightarrow$ CI	0.356	0.273	0.083	0.408	0.397	n.s.
PE $\rightarrow$ ATT	0.588	0.679	-0.091	0.189	0.284	n.s.
PE $\rightarrow$ CI	0.158	0.168	-0.010	0.923	0.934	n.s.
PE $\rightarrow$ ITIB	0.323	0.175	0.148	0.353	0.291	n.s.
PIIT $\rightarrow$ CI	-0.028	-0.197	0.169	0.023*	0.041*	Sig
PIIT $\rightarrow$ ITIB	0.191	0.190	0.001	0.989	0.994	n.s.

Table 9.70 R^2 differences (Capital vs Rural)

Construct	ΔR^2 (Ca-Ru)	PLS-MGA p	Decision
ATT	-0.111	0.193	n.s.
CI	0.116	0.081	n.s.

Construct	ΔR^2 (Ca-Ru)	PLS-MGA p	Decision
IF	-0.130	0.086	n.s.
ITIB	0.068	0.397	n.s.
PE	0.064	0.433	n.s.

Table 9.71 f^2 differences (Capital vs Rural)

Path	Δf^2 (Ca-Ru)	PLS-MGA p	Decision
ATT → CI	0.129	0.145	n.s.
ATT → ITIB	-0.005	0.904	n.s.
EE → ATT	-0.003	0.901	n.s.
EE → PE	-0.037	0.874	n.s.
IF → ITIB	-0.070	0.585	n.s.
IS → IF	-0.651	0.164	n.s.
IS → PE	0.093	0.015*	Sig
ITIB → CI	0.105	0.309	n.s.
PE → ATT	-0.398	0.259	n.s.
PE → CI	0.009	0.637	n.s.
PE → ITIB	0.066	0.166	n.s.
PIIT → CI	-0.070	0.098	n.s.
PIIT → ITIB	0.007	0.765	n.s.

City vs Rural

Table 9.72 Compositional invariance, means and variances (City vs Rural)

Const	c	5% quant	p	Dec	Δ Mean (Ci-Ru)	p	Dec	Δ Var (Ci-Ru)	p	Dec
ATT	1.000	0.998	0.699	Inv	0.046	0.695	Equal	0.173	0.252	Equal
CI	1.000	0.999	0.754	Inv	-0.208	0.091	Equal (ns)	0.446	0.003	Variances differ

Const	c	5% quant	p	Dec	Δ Mean (Ci-Ru)	p	Dec	Δ Var (Ci-Ru)	p	Dec
EE	0.999	0.992	0.768	Inv	0.143	0.226	Equal	0.122	0.513	Equal
IF	0.979	0.952	0.274	Inv	0.113	0.350	Equal	0.212	0.179	Equal
IS	0.982	0.950	0.329	Inv	0.178	0.130	Equal	0.160	0.334	Equal
ITIB	0.999	0.998	0.304	Inv	-0.271	0.023	Means differ	0.167	0.237	Equal
PE	1.000	0.999	0.904	Inv	0.186	0.115	Equal (ns)	-0.220	0.142	Equal
PIIT	0.999	0.981	0.947	Inv	-0.083	0.484	Equal	0.199	0.203	Equal

Table 9.73 Path coefficients (City vs Rural)

Path	β Ci	β Ru	Δ (Ci-Ru)	PLS-MGA p	Perm	Dec
ATT → CI	0.458	0.376	0.082	0.518	0.568	n.s.
ATT → ITIB	0.105	0.218	-0.114	0.463	0.471	n.s.
EE → ATT	0.263	0.194	0.070	0.357	0.431	n.s.
EE → PE	0.334	0.470	-0.136	0.183	0.205	n.s.
IF → ITIB	0.274	0.323	-0.048	0.659	0.655	n.s.
IS → IF	0.769	0.783	-0.015	0.751	0.796	n.s.
IS → PE	0.331	0.025	0.306	0.005	0.005	Sig
ITIB → CI	0.373	0.273	0.099	0.337	0.284	n.s.
PE → ATT	0.604	0.679	-0.075	0.305	0.343	n.s.
PE → CI	0.052	0.168	-0.116	0.405	0.393	n.s.
PE → ITIB	0.345	0.175	0.170	0.315	0.306	n.s.
PIIT → CI	-0.211	-0.197	-0.014	0.861	0.869	n.s.
PIIT → ITIB	0.132	0.190	-0.058	0.553	0.570	n.s.

Table 9.74 R^2 differences (City vs Rural)

Construct	ΔR^2 (Ci-Ru)	PLS-MGA p	Decision
ATT	-0.062	0.472	n.s.

Construct	ΔR^2 (Ci–Ru)	PLS-MGA p	Decision
CI	0.093	0.204	n.s.
IF	-0.023	0.760	n.s.
ITIB	0.050	0.557	n.s.
PE	0.040	0.640	n.s.

Table 9.75 f^2 differences (City vs Rural)

Path	Δf^2 (Ci–Ru)	PLS-MGA p	Decision
ATT → CI	0.143	0.192	n.s.
ATT → ITIB	-0.019	0.783	n.s.
EE → ATT	0.055	0.422	n.s.
EE → PE	-0.127	0.375	n.s.
IF → ITIB	-0.047	0.768	n.s.
IS → IF	-0.143	0.844	n.s.
IS → PE	0.142	0.006	Sig
ITIB → CI	0.124	0.280	n.s.
PE → ATT	-0.252	0.552	n.s.
PE → CI	-0.019	0.777	n.s.
PE → ITIB	0.070	0.186	n.s.
PIIT → CI	0.035	0.567	n.s.
PIIT → ITIB	-0.024	0.751	n.s.

Appendix J6. MGA Sector

Decision rule for compositional difference: compositional invariance holds when (i) the original c is $\geq$ the 5% quantile of the permutation distribution and (ii) the permutation p-value $> .05$ (i.e., c not significantly different from 1).

Decision rule for group difference: PLS-MGA (bootstrap): significant group difference if 2-tailed $p < .05$ or $> .95$. Permutation MGA: $p < .05$ indicates significant difference.

Note: In the table headings, due to page size constraint, Dec refers to decision, 5% quant refers to 5% quantile. N.s. means non-significant, Sig refers to significant. To shorten the tables, PLS-MGA p (2-tailed) is referenced as PLS-MGA p , where necessary.

Pairwise comparison (see all necessary tables below)

Benjamini–Hochberg FDR ($q = .05$), PLS-MGA 2-tailed p 's, by pair and family (paths / R^2 / f^2). In this short summary, BH significance is highlighted by **.

ICT vs Manufacturing

- Paths ($m=13$): none survive FDR (min raw $p=.090$)
- R^2 ($m=5$): none (CI $p=.019 \rightarrow q=.095$ ns)
- f^2 ($m=13$): non.

ICT vs Services

- Paths ($m=13$):
 - PIIT $\rightarrow$ CI ($p=.001 \rightarrow q=.013$) **
 - IS $\rightarrow$ IF ($p=.008 \rightarrow q=.052$) ns
- R^2 ($m=5$): IF ($p=.008 \rightarrow q=.040$) **
- f^2 ($m=13$):
 - PIIT $\rightarrow$ CI ($p=.001 \rightarrow q=.013$) **
 - IS $\rightarrow$ IF: $p = .009 \rightarrow q = .059$ (ns)

Manufacturing vs Services

- Paths ($m=13$): IS $\rightarrow$ IF: $p = .029 \rightarrow q = .377$ (ns)
- R^2 ($m=5$):
 - CI: $p = .026 \rightarrow q = .130$ (ns)
 - IF: $p = .031 \rightarrow q = .155$ (ns)
- f^2 ($m=13$): PIIT $\rightarrow$ CI: $p = .027 \rightarrow q = .351$ (ns)

Sensitivity (pooled across the three pairs):

- Paths ($m = 39$): ICT–Services: PIIT $\rightarrow$ CI still survives ($q \approx .039$).
- R^2 ($m = 15$): IF $p = .008 \rightarrow q \approx .120$ (ns pooled).
- f^2 ($m = 39$): ICT–Services: PIIT $\rightarrow$ CI still survives ($q \approx .039$).

Table 9.76 Sector data for MGA

Sector	n	%
ICT	624	60.0%
Manufacturing	144	13.8%
Services	272	26.2%

ICT vs Manufacturing

Table 9.77 Compositional invariance, means and variances (ICT vs Manufacturing)

Const	c	5% quant	p	Dec	Δ Mean (I-M)	p	Dec	Δ Var (I-M)	p	Dec
ATT	1.000	0.999	0.977	Inv	-0.238	0.012	Means differ	0.174	0.129	Equal
CI	1.000	0.999	0.320	Inv	-0.327	<.001	Means differ	0.352	0.002	Variances differ
EE	0.998	0.996	0.195	Inv	-0.148	0.112	Equal	0.134	0.329	Equal
IF	0.991	0.970	0.422	Inv	0.206	0.023	Means differ	0.034	0.791	Equal
IS	0.977	0.963	0.163	Inv	0.129	0.151	Equal	-0.067	0.581	Equal
ITIB	1.000	0.999	0.298	Inv	-0.313	0.001	Means differ	0.146	0.217	Equal
PE	1.000	1.000	0.165	Inv	-0.240	0.009	Means differ	0.159	0.241	Equal
PIIT	0.998	0.949	0.846	Inv	0.041	0.658	Equal	0.004	0.975	Equal

Table 9.78 Path coefficients (ICT vs Manufacturing)

Path	β I	β M	Δ (I-M)	PLS-MGA p	Perm	Dec
ATT → CI	0.419	0.576	-0.157	0.132	0.096	n.s.
ATT → ITIB	0.173	0.075	0.098	0.406	0.391	n.s.
EE → ATT	0.209	0.215	-0.006	0.942	0.945	n.s.
EE → PE	0.410	0.363	0.047	0.597	0.587	n.s.
IF → ITIB	0.232	0.351	-0.118	0.134	0.174	n.s.

Path	β I	β M	$\Delta(I-M)$	PLS-MGA p	Perm	Dec
IS $\rightarrow$ IF	0.741	0.759	-0.018	0.691	0.727	n.s.
IS $\rightarrow$ PE	0.298	0.174	0.124	0.189	0.149	n.s.
ITIB $\rightarrow$ CI	0.360	0.288	0.071	0.429	0.382	n.s.
PE $\rightarrow$ ATT	0.600	0.644	-0.044	0.487	0.524	n.s.
PE $\rightarrow$ CI	0.159	-0.049	0.208	0.090	0.036	n.s.
PE $\rightarrow$ ITIB	0.310	0.262	0.048	0.714	0.693	n.s.
PIIT $\rightarrow$ CI	-0.037	-0.076	0.039	0.582	0.566	n.s.
PIIT $\rightarrow$ ITIB	0.176	0.236	-0.060	0.435	0.446	n.s.

Table 9.79 R^2 differences (ICT vs Manufacturing)

Construct	ΔR^2 (I-M)	PLS-MGA p	Decision
ATT	-0.054	0.448	n.s.
CI	0.137	0.019	Sig
IF	-0.027	0.708	n.s.
ITIB	0.035	0.632	n.s.
PE	0.107	0.171	n.s.

Table 9.80 f^2 differences (ICT vs Manufacturing)

Path	Δf^2 (I-M)	PLS-MGA p	Decision
ATT $\rightarrow$ CI	-0.065	0.692	n.s.
ATT $\rightarrow$ ITIB	0.020	0.266	n.s.
EE $\rightarrow$ ATT	-0.019	0.843	n.s.
EE $\rightarrow$ PE	0.083	0.347	n.s.
IF $\rightarrow$ ITIB	-0.095	0.210	n.s.
IS $\rightarrow$ IF	-0.140	0.834	n.s.

Path	Δ^2 (I-M)	PLS-MGA p	Decision
IS → PE	0.089	0.117	n.s.
ITIB → CI	0.105	0.258	n.s.
PE → ATT	-0.225	0.407	n.s.
PE → CI	0.029	0.190	n.s.
PE → ITIB	0.028	0.520	n.s.
PIIT → CI	-0.007	0.961	n.s.
PIIT → ITIB	-0.034	0.613	n.s.

ICT vs Services

Table 9.81 Compositional invariance, means and variances (ICT vs Services)

Const	c	5% quant	p	Dec	Δ Mean (I-S)	p	Dec	Δ Var (I-S)	p	Dec
ATT	1.000	1.000	0.251	Inv	-0.007	0.923	Equal	-0.043	0.643	Equal
CI	1.000	1.000	0.558	Inv	0.009	0.903	Equal	0.076	0.411	Equal
EE	0.999	0.997	0.307	Inv	-0.150	0.039	Means differ	0.174	0.100	Equal
IF	0.982	0.979	0.084	Inv	0.280	<.001	Means differ	0.186	0.066	Equal
IS	0.999	0.977	0.932	Inv	0.342	<.001	Means differ	0.276	0.005	Variances differ
ITIB	1.000	1.000	0.114	Inv	0.017	0.816	Equal	0.131	0.170	Equal
PE	1.000	1.000	0.316	Inv	-0.009	0.903	Equal	0.055	0.597	Equal
PIIT	0.998	0.989	0.624	Inv	0.184	0.011	Means differ	0.033	0.724	Equal

Table 9.82 Path coefficients (ICT vs Services)

Path	β_{ICT}	β_{Services}	Δ (I-S)	PLS-MGA p	Perm p	Decision
ATT → CI	0.419	0.373	0.047	0.514	0.514	n.s.
ATT → ITIB	0.173	0.131	0.041	0.617	0.636	n.s.

Path	β_{ICT}	β_{Services}	Δ (I-S)	PLS-MGA p	Perm p	Decision
EE $\rightarrow$ ATT	0.209	0.275	-0.065	0.252	0.277	n.s.
EE $\rightarrow$ PE	0.410	0.419	-0.009	0.874	0.883	n.s.
IF $\rightarrow$ ITIB	0.232	0.286	-0.053	0.442	0.457	n.s.
IS $\rightarrow$ IF	0.741	0.622	0.119	0.008*	0.005*	Sig
IS $\rightarrow$ PE	0.298	0.185	0.113	0.076	0.079	n.s.
ITIB $\rightarrow$ CI	0.360	0.388	-0.028	0.626	0.647	n.s.
PE $\rightarrow$ ATT	0.600	0.569	0.032	0.580	0.577	n.s.
PE $\rightarrow$ CI	0.159	0.137	0.022	0.761	0.777	n.s.
PE $\rightarrow$ ITIB	0.310	0.348	-0.038	0.653	0.674	n.s.
PIIT $\rightarrow$ CI	-0.037	-0.220	0.183	0.001*	0.001*	Sig
PIIT $\rightarrow$ ITIB	0.176	0.154	0.022	0.723	0.737	n.s.

Table 9.83 R^2 differences (ICT vs Services)

Construct	ΔR^2 (I-S)	PLS-MGA p (2-tailed)	Decision
ATT	-0.017	0.761	n.s.
CI	-0.001	0.985	n.s.
IF	0.162	0.008*	Sig
ITIB	0.030	0.606	n.s.
PE	0.072	0.219	n.s.

Table 9.84 f^2 differences (ICT vs Services)

Path	Δf^2 (I-S)	PLS-MGA p (2-tailed)	Decision
ATT $\rightarrow$ CI	0.046	0.560	n.s.
ATT $\rightarrow$ ITIB	0.011	0.536	n.s.
EE $\rightarrow$ ATT	-0.059	0.256	n.s.

Path	Δf^2 (I-S)	PLS-MGA p (2-tailed)	Decision
EE → PE	0.009	0.887	n.s.
IF → ITIB	-0.045	0.437	n.s.
IS → IF	0.587	0.009*	Sig
IS → PE	0.079	0.061	n.s.
ITIB → CI	-0.062	0.510	n.s.
PE → ATT	0.026	0.842	n.s.
PE → CI	0.007	0.711	n.s.
PE → ITIB	-0.022	0.663	n.s.
PIIT → CI	-0.117	0.001*	Sig
PIIT → ITIB	0.014	0.607	n.s.

Manufacturing vs Services

Table 9.85 Compositional invariance, means and variances (Manufacturing vs Services)

Const	c	5% quant	p	Dec	Δ Mean (M-S)	p	Dec	Δ Var (M-S)	p	Dec
ATT	1.000	0.999	0.418	Inv	0.226	0.032	Means differ	-0.221	0.111	Equal
CI	1.000	0.999	0.180	Inv	0.354	<.001	Means differ	-0.278	0.038	Variances differ
EE	0.996	0.992	0.235	Inv	0.000	1.000	Equal	0.034	0.842	Equal
IF	0.980	0.947	0.332	Inv	0.109	0.297	Equal	0.155	0.229	Equal
IS	0.981	0.941	0.388	Inv	0.202	0.052	Equal	0.329	0.020	Variances differ
ITIB	1.000	0.999	0.647	Inv	0.349	<.001	Means differ	-0.018	0.883	Equal
PE	1.000	1.000	0.564	Inv	0.237	0.021	Means differ	-0.105	0.435	Equal
PIIT	0.999	0.991	0.715	Inv	0.145	0.159	Equal	0.027	0.832	Equal

Table 9.86 Path coefficients (Manufacturing vs Services)

Path	$\beta_{\text{Manufacturing}}$	β_{Services}	$\Delta \text{ (M-S)}$	PLS-MGA p	Perm p	Decision
ATT → CI	0.576	0.373	0.204	0.075	0.073	n.s.
ATT → ITIB	0.075	0.131	-0.057	0.654	0.630	n.s.
EE → ATT	0.215	0.275	-0.060	0.440	0.441	n.s.
EE → PE	0.363	0.419	-0.056	0.565	0.570	n.s.
IF → ITIB	0.351	0.286	0.065	0.463	0.487	n.s.
IS → IF	0.759	0.622	0.137	0.029	0.043	Sig
IS → PE	0.174	0.185	-0.012	0.922	0.905	n.s.
ITIB → CI	0.288	0.388	-0.100	0.294	0.258	n.s.
PE → ATT	0.644	0.569	0.076	0.299	0.324	n.s.
PE → CI	-0.049	0.137	-0.186	0.150	0.114	n.s.
PE → ITIB	0.262	0.348	-0.086	0.531	0.486	n.s.
PIIT → CI	-0.076	-0.220	0.144	0.065	0.067	n.s.
PIIT → ITIB	0.236	0.154	0.081	0.346	0.354	n.s.

Table 9.87 R^2 differences (Manufacturing vs Services)

Construct	$\Delta R^2 \text{ (M-S)}$	PLS-MGA p (2-tailed)	Decision
ATT	0.037	0.632	n.s.
CI	-0.138	0.026	Sig
IF	0.189	0.031	Sig
ITIB	-0.005	0.944	n.s.
PE	-0.036	0.657	n.s.

Table 9.88 f^2 differences (Manufacturing vs Services)

Path	Δf^2 (M-S)	PLS-MGA p (2-tailed)	Decision
ATT → CI	0.110	0.453	n.s.
ATT → ITIB	-0.009	0.507	n.s.
EE → ATT	-0.041	0.544	n.s.
EE → PE	-0.074	0.463	n.s.
IF → ITIB	0.050	0.595	n.s.
IS → IF	0.727	0.064	n.s.
IS → PE	-0.010	0.731	n.s.
ITIB → CI	-0.167	0.143	n.s.
PE → ATT	0.251	0.377	n.s.
PE → CI	-0.022	0.319	n.s.
PE → ITIB	-0.049	0.376	n.s.
PIIT → CI	-0.110	0.027	Sig
PIIT → ITIB	0.048	0.437	n.s.

Appendix J7. MGA Size

Pairwise comparison (see all necessary tables below)

Benjamini–Hochberg FDR ($q = .05$), PLS-MGA 2-tailed p's, by pair and family (paths / R^2 / f^2). In this short summary, BH significance is highlighted by **.

SME16 vs SME19

- Paths ($m=13$):
 - EE → ATT: $p = .005 \rightarrow q = .065$ (ns)
 - PE → ATT: $p = .020 \rightarrow q = .130$ (ns)
- R^2 ($m=5$): none.
- f^2 ($m=13$): EE → ATT: $p = .007 \rightarrow q = .091$ (ns)

SME16 vs SME REST

- Paths (m=13):
 - PIIT → ITIB: $p = .018 \rightarrow q = .234$ (ns)
 - PE → ATT: $p = .026 \rightarrow q = .169$ (ns)
- R^2 (m=5): none.
- f^2 (m=13):
 - PIIT → ITIB: $p = .018 \rightarrow q = .234$ (ns)
 - PE → ATT: $p = .026 \rightarrow q = .169$ (ns)

SME19 vs SME REST

- Paths (m=13): EE → ATT: $p = .030 \rightarrow q = .390$ (ns)
- R^2 (m=5): none.
- f^2 (m=13): EE → ATT: $p = .016 \rightarrow q = .208$ (ns)

Sensitivity (pooled across the three pairs):

- Paths (m = 39): none survive; smallest $p = .005 \rightarrow q \approx .195$.
- R^2 (m=15) / f^2 (m=39): none survive pooled FDR.

Table 9.89 SME size data for MGA

Sector	n	%
SME Rest	635	61.1%
SME16	216	20.8%
SME19	189	18.2%

SME16 vs SME19

Table 9.90 Compositional invariance, means and variances (SME16 vs SME19)

Const	c	5% quant	p	Dec	Δ Mean (16-19)	p	Dec	Δ Var (16-19)	p	Dec
ATT	1.000	0.999	0.542	Inv	-0.191	0.051	Equal	0.027	0.835	Equal
CI	1.000	0.999	0.296	Inv	-0.088	0.379	Equal	-0.115	0.355	Equal
EE	1.000	0.995	0.831	Inv	-0.207	0.036	Means differ	0.227	0.119	Equal
IF	0.989	0.967	0.359	Inv	0.359	0.000	Means differ	0.020	0.891	Equal

Const	c	5% quant	p	Dec	Δ Mean (16-19)	p	Dec	Δ Var (16-19)	p	Dec
IS	0.978	0.960	0.196	Inv	0.069	0.484	Equal	0.021	0.872	Equal
ITIB	1.000	0.999	0.800	Inv	-0.084	0.404	Equal	-0.299	0.023	Variances differ
PE	1.000	1.000	0.445	Inv	-0.158	0.110	Equal	0.046	0.748	Equal
PIIT	0.998	0.907	0.898	Inv	0.008	0.942	Equal	-0.101	0.420	Equal

Table 9.91 Path coefficients (SME16 vs SME19)

Path	β_{16}	β_{19}	Δ (16-19)	PLS-MGA p	Perm p	Decision
ATT → CI	0.464	0.383	0.081	0.380	0.401	n.s.
ATT → ITIB	0.179	0.050	0.128	0.288	0.276	n.s.
EE → ATT	0.318	0.065	0.253	0.005	0.002	Sig
EE → PE	0.350	0.436	-0.086	0.343	0.346	n.s.
IF → ITIB	0.248	0.307	-0.059	0.552	0.571	n.s.
IS → IF	0.783	0.701	0.082	0.102	0.139	n.s.
IS → PE	0.302	0.318	-0.016	0.869	0.869	n.s.
ITIB → CI	0.263	0.404	-0.141	0.101	0.114	n.s.
PE → ATT	0.475	0.666	-0.191	0.020	0.020	Sig
PE → CI	0.184	0.185	-0.001	0.995	0.994	n.s.
PE → ITIB	0.341	0.278	0.062	0.641	0.611	n.s.
PIIT → CI	-0.065	-0.006	-0.059	0.422	0.405	n.s.
PIIT → ITIB	0.045	0.194	-0.150	0.130	0.106	n.s.

Table 9.92 R^2 differences (SME16 vs SME19)

Construct	ΔR^2 (16-19)	PLS-MGA p (2-tailed)	Decision
ATT	-0.036	0.665	n.s.
CI	-0.020	0.759	n.s.

Construct	ΔR^2 (16–19)	PLS-MGA p (2-tailed)	Decision
IF	0.122	0.102	n.s.
ITIB	0.060	0.514	n.s.
PE	-0.078	0.352	n.s.

Table 9.93 f^2 differences (SME16 vs SME19)

Path	Δf^2 (16–19)	PLS-MGA p (2-tailed)	Decision
ATT → CI	0.125	0.355	n.s.
ATT → ITIB	0.030	0.234	n.s.
EE → ATT	0.146	0.007	Sig
EE → PE	-0.122	0.315	n.s.
IF → ITIB	-0.027	0.757	n.s.
IS → IF	0.616	0.124	n.s.
IS → PE	-0.031	0.764	n.s.
ITIB → CI	-0.205	0.079	n.s.
PE → ATT	-0.318	0.113	n.s.
PE → CI	0.004	0.929	n.s.
PE → ITIB	0.056	0.393	n.s.
PIIT → CI	0.010	0.713	n.s.
PIIT → ITIB	-0.052	0.167	n.s.

SME16 vs SMEREST

Table 9.94 Compositional invariance, means and variances (SME16 vs SMEREST)

Const	c	5% quant	p	Dec	Δ Mean (16-R)	p	Dec	Δ Var (16-R)	p	Dec
ATT	1.000	0.999	0.489	Inv	-0.418	0.000	Means differ	-0.022	0.823	Equal
CI	1.000	1.000	0.245	Inv	-0.327	0.000	Means differ	0.030	0.768	Equal

Const	c	5% quant	p	Dec	Δ Mean (16-R)	p	Dec	Δ Var (16-R)	p	Dec
EE	0.999	0.997	0.459	Inv	-0.342	0.000	Means differ	0.260	0.024	Variances differ
IF	0.997	0.977	0.693	Inv	0.216	0.006	Means differ	0.106	0.310	Equal
IS	0.997	0.975	0.670	Inv	0.157	0.044	Means differ	0.078	0.435	Equal
ITIB	1.000	0.999	0.740	Inv	-0.248	0.002	Means differ	-0.132	0.192	Equal
PE	1.000	1.000	0.767	Inv	-0.462	0.000	Means differ	0.042	0.702	Equal
PIIT	0.998	0.987	0.634	Inv	0.151	0.060	Equal	-0.089	0.384	Equal

Table 9.95 Path coefficients (SME16 vs SMEREST)

Path	β_{16}	β_R	Δ (16-R)	PLS-MGA p	Perm p	Decision
ATT → CI	0.464	0.431	0.033	0.657	0.683	n.s.
ATT → ITIB	0.179	0.172	0.007	0.935	0.940	n.s.
EE → ATT	0.318	0.235	0.083	0.168	0.163	n.s.
EE → PE	0.350	0.390	-0.039	0.594	0.593	n.s.
IF → ITIB	0.248	0.237	0.011	0.890	0.884	n.s.
IS → IF	0.783	0.713	0.070	0.078	0.109	n.s.
IS → PE	0.302	0.242	0.060	0.393	0.393	n.s.
ITIB → CI	0.263	0.386	-0.124	0.084	0.083	n.s.
PE → ATT	0.475	0.617	-0.142	0.026	0.017	Sig
PE → CI	0.184	0.095	0.090	0.274	0.286	n.s.
PE → ITIB	0.341	0.303	0.038	0.658	0.684	n.s.
PIIT → CI	-0.065	-0.124	0.058	0.324	0.327	n.s.
PIIT → ITIB	0.045	0.213	-0.169	0.018	0.008	Sig

Table 9.96 R^2 differences (SME16 vs SMEREST)

Construct	ΔR^2 (16-R)	PLS-MGA p (2-tailed)	Decision
ATT	-0.111	0.080	n.s.
CI	0.006	0.890	n.s.
IF	0.104	0.080	n.s.
ITIB	0.024	0.718	n.s.
PE	0.011	0.883	n.s.

Table 9.97 f^2 differences (SME16 vs SMEREST)

Path	Δf^2 (16-R)	PLS-MGA p (2-tailed)	Decision
ATT → CI	0.108	0.380	n.s.
ATT → ITIB	0.010	0.844	n.s.
EE → ATT	0.051	0.410	n.s.
EE → PE	-0.035	0.612	n.s.
IF → ITIB	0.003	0.963	n.s.
IS → IF	0.548	0.107	n.s.
IS → PE	0.043	0.481	n.s.
ITIB → CI	-0.138	0.084	n.s.
PE → ATT	-0.361	0.026	Sig
PE → CI	0.036	0.310	n.s.
PE → ITIB	0.043	0.449	n.s.
PIIT → CI	-0.024	0.319	n.s.
PIIT → ITIB	-0.067	0.018	Sig

SME19 vs SMEREST

Table 9.98 Compositional invariance, means and variances (SME19 vs SMEREST)

Const	c	5% quant	p	Dec	Δ Mean (19-R)	p	Dec	Δ Var (19-R)	p	Dec
ATT	1.000	0.999	0.755	Inv	-0.234	0.004	Means differ	-0.046	0.669	Equal
CI	1.000	0.999	0.934	Inv	-0.232	0.005	Means differ	0.146	0.179	Equal
EE	0.999	0.995	0.612	Inv	-0.130	0.117	Equal	0.037	0.773	Equal
IF	0.996	0.971	0.652	Inv	-0.150	0.070	Equal	0.088	0.423	Equal
IS	0.990	0.966	0.410	Inv	0.080	0.332	Equal	0.062	0.569	Equal
ITIB	1.000	1.000	0.297	Inv	-0.155	0.062	Equal	0.169	0.115	Equal
PE	1.000	1.000	0.342	Inv	-0.312	0.000	Means differ	-0.003	0.983	Equal
PIIT	0.999	0.988	0.797	Inv	0.134	0.106	Equal	-0.003	0.978	Equal

Table 9.99 Path coefficients (SME19 vs SMEREST)

Path	β_{19}	β_R	Δ (19-R)	PLS-MGA p	Perm p	Decision
ATT → CI	0.383	0.431	-0.048	0.522	0.573	n.s.
ATT → ITIB	0.050	0.172	-0.121	0.259	0.243	n.s.
EE → ATT	0.065	0.235	-0.170	0.030	0.014	Sig
EE → PE	0.436	0.390	0.046	0.522	0.538	n.s.
IF → ITIB	0.307	0.237	0.070	0.394	0.377	n.s.
IS → IF	0.701	0.713	-0.012	0.828	0.815	n.s.
IS → PE	0.318	0.242	0.076	0.345	0.324	n.s.
ITIB → CI	0.404	0.386	0.017	0.785	0.802	n.s.
PE → ATT	0.666	0.617	0.049	0.453	0.421	n.s.
PE → CI	0.185	0.095	0.090	0.296	0.340	n.s.
PE → ITIB	0.278	0.303	-0.025	0.848	0.825	n.s.
PIIT → CI	-0.006	-0.124	0.117	0.051	0.056	n.s.

Path	β_{19}	β_R	$\Delta (19-R)$	PLS-MGA p	Perm p	Decision
PIIT $\rightarrow$ ITIB	0.194	0.213	-0.019	0.815	0.791	n.s.

Table 9.100 R^2 differences (SME19 vs SMEREST)

Construct	$\Delta R^2 (19-R)$	PLS-MGA p (2-tailed)	Decision
ATT	-0.074	0.287	n.s.
CI	0.026	0.555	n.s.
IF	-0.017	0.816	n.s.
ITIB	-0.036	0.636	n.s.
PE	0.089	0.180	n.s.

Table 9.101 f^2 differences (SME19 vs SMEREST)

Path	$\Delta f^2 (19-R)$	PLS-MGA p (2-tailed)	Decision
ATT $\rightarrow$ CI	-0.017	0.799	n.s.
ATT $\rightarrow$ ITIB	-0.020	0.197	n.s.
EE $\rightarrow$ ATT	-0.096	0.016	Sig
EE $\rightarrow$ PE	0.086	0.450	n.s.
IF $\rightarrow$ ITIB	0.030	0.737	n.s.
IS $\rightarrow$ IF	-0.068	0.775	n.s.
IS $\rightarrow$ PE	0.074	0.350	n.s.
ITIB $\rightarrow$ CI	0.067	0.609	n.s.
PE $\rightarrow$ ATT	-0.044	0.784	n.s.
PE $\rightarrow$ CI	0.032	0.378	n.s.
PE $\rightarrow$ ITIB	-0.014	0.697	n.s.
PIIT $\rightarrow$ CI	-0.035	0.068	n.s.
PIIT $\rightarrow$ ITIB	-0.015	0.664	n.s.

Appendix J8.MGA Outlier

Table 9.102 Compositional invariance, means and variances (FULL vs OUTLIER)

Const	c	5% quant	p	Dec	Δ Mean (F-O)	p	Dec	Δ Var (F-O)	p	Dec
ATT	1.000	1.000	0.996	Inv	-0.008	0.864	Equal	0.002	0.970	Equal
CI	1.000	1.000	0.996	Inv	-0.006	0.899	Equal	-0.006	0.915	Equal
EE	1.000	0.999	1.000	Inv	-0.003	0.950	Equal	0.001	0.986	Equal
IF	1.000	0.993	0.995	Inv	-0.003	0.948	Equal	-0.002	0.971	Equal
IS	1.000	0.992	0.987	Inv	-0.004	0.922	Equal	-0.001	0.986	Equal
ITIB	1.000	1.000	0.990	Inv	-0.005	0.916	Equal	-0.007	0.902	Equal
PE	1.000	1.000	0.999	Inv	-0.006	0.886	Equal	0.004	0.951	Equal
PIIT	1.000	0.997	1.000	Inv	-0.004	0.938	Equal	-0.002	0.972	Equal

Appendix J9.MGA Wave Analysis for Nonresponse Bias

Table 9.103 Compositional invariance, means and variances (Early vs Late)

Const	c	5% quant	p	Dec	Δ Mean (E-L)	p	Dec	Δ Var (E-L)	p	Dec
ATT	1.000	1.000	0.666	Inv	-0.051	0.412	Equal	0.067	0.390	Equal
CI	1.000	1.000	0.719	Inv	-0.050	0.425	Equal	0.045	0.572	Equal
EE	0.999	0.998	0.314	Inv	-0.004	0.950	Equal	-0.049	0.595	Equal
IF	0.986	0.985	0.055	Inv	-0.001	0.985	Equal	0.205	0.013	Variances differ
IS	0.999	0.983	0.810	Inv	-0.005	0.941	Equal	0.094	0.261	Equal
ITIB	1.000	1.000	0.281	Inv	-0.094	0.127	Equal	0.058	0.462	Equal
PE	1.000	1.000	0.715	Inv	-0.054	0.391	Equal	-0.029	0.743	Equal
PIIT	0.999	0.994	0.733	Inv	0.049	0.432	Equal	0.066	0.402	Equal

Appendix K Interview Documentation

Appendix K1. Interview Firm Selection Criteria

Table 9.104 SME shortlist for interviews

	SME_ID	Sector	Location	Size	Quant Sample	Reasoning
Shortlist - 10 SMEs	SME01	Manufacturing	Rural	50-250	30	Low ATT × High ITIB, but High CI z=0.62. Behaviour/continuance despite lukewarm attitudes.
	SME03	Services	Capital	50-250	18	High ATT × Low ITIB, very low IS/IF; OutlierScore 2.40. No innovation support / involvement facilitation.
	SME04	Services	City	50-250	41	Low IS × Low CI with high OutlierScore 2.77. Classic laggard.
	SME07	Manufacturing	City	50-250	43	High ATT × High ITIB, High IS × High CI. Positive, coherent climate in manufacturing.
	SME08	Services	Capital	10-50	17	Extreme low profile (all z's << 0). Negative deviant: barriers story.
	SME14	ICT	Capital	50-250	11	Extreme high on everything (all z's >> 1; OutlierScore 6.45). Positive deviant.
	SME16	ICT	Capital	50-250	216	High IS, low ITIB, outlier, large n. Support, but little innovation mechanism.
	SME18	Manufacturing	Rural	50-250	43	High ATT, Low IS × High CI OutlierScore 1.63. Rural success drivers.
	SME19	ICT	Capital	50-250	189	Near the center (OutlierScore ~1.03), typical ICT case with big n. Reference/benchmark.
	SME20	ICT	Capital	50-250	23	High IS, low CI, and High ATT × Low ITIB. Innovation not sticking despite support / attitude.
Follow- ups	SME12	Services	Capital	50-250	29	Low IS/CI typical; medium n
	SME21	Services	Rural	50-250	26	Rural laggard

Table 9.105 SME z-scores for shortlist

SME_id	ATT_mean_z	PE_mean_z	EE_mean_z	IS_mean_z	IF_mean_z	ITIB_mean_z	CI_mean_z	n
SME01	-0.524	-0.330	-1.018	-0.032	-0.028	0.542	0.625	30
SME02	0.207	0.052	-0.642	0.620	0.076	0.514	0.890	35
SME03	1.074	0.078	1.728	-1.725	-1.261	-0.070	0.208	18
SME04	0.325	-0.068	1.003	-2.241	-1.385	-0.728	-0.330	41
SME05	-1.102	-1.236	-1.974	0.440	0.040	-0.285	-1.764	23
SME06	-0.430	-0.126	-0.360	0.025	-0.592	-0.173	-0.354	28
SME07	0.873	0.447	0.241	0.937	0.551	1.008	0.635	43
SME08	-1.091	-1.156	-0.941	-1.977	-1.387	-1.461	-1.368	17
SME09	0.444	0.574	-0.439	1.041	1.033	0.092	0.192	89
SME10	0.362	0.270	1.547	0.708	0.567	0.012	0.003	17
SME11	0.428	0.630	-0.022	0.079	-0.558	-0.139	0.071	50
SME12	-0.368	-0.757	0.174	-0.249	0.816	-0.459	-0.320	29
SME13	0.633	0.599	0.217	-0.273	-0.586	-0.656	-0.288	61
SME14	2.642	3.293	1.220	1.493	2.943	3.638	3.237	11
SME15	-0.924	-0.096	-0.386	0.262	-0.071	-0.654	0.180	36
SME16	-1.048	-0.994	-0.995	0.585	0.350	-0.645	-0.748	216
SME17	-1.634	-0.238	0.110	-0.279	-0.407	-0.392	-0.827	15
SME18	0.948	0.802	0.743	-0.755	-0.507	0.356	0.894	43
SME19	-0.502	-0.610	-0.358	0.075	-0.581	-0.427	-0.526	189
SME20	0.626	0.300	1.417	1.271	1.256	-0.503	-0.134	23
SME21	-0.940	-1.435	-1.264	-0.004	-0.268	0.427	-0.277	26

Appendix K2. Interview Protocol

Table 9.106 Interview protocol

SID	Section	Timing	QID	Question	Constructs / Information
A	Opening & ethics	2–3 min	ID0	Thank you for joining. This is confidential and anonymised; you can skip any question and stop anytime. I'm interested in concrete examples of how tablets are (or aren't) used in your work.	
B		2-3 min	ID1	What's your current role and key responsibilities? (Tenure in role/team?)	

	Role & context (warm-up)			– Probe: Typical day; tasks done mostly in the field/office.	context/baseline; task characteristics.
			ID2	Before tablets, how were these tasks done? (Paper, phone, desktop?)	
C	Tablet access & usage profile	4-5 min	ID3	Do you use a tablet for work? If no/rarely: Why not? (Route to barriers.)	facilitating conditions (availability), experience/habit, device/app fit.
			ID4	Is the device company-issued or personal? Do you use more than one device?	
			ID5	What kind of tablet is it (Android / iPadOS / Windows)? Key apps?	
			ID6	How long have you used a tablet in general and in this job? Frequency per day/week?	
D	Critical incidents: concrete task episodes	6–8 min	ID7	Think of the last time the tablet clearly helped with your work. What happened? Probes (CI): Task, app, people involved, time saved/quality improved, what you did differently, follow-up effects.	PE (usefulness), EE (effort), infrastructure, CI (continuance), habit/routinisation.
			ID8	Now a time it created friction or you stopped using it. What happened? – Probes: Connectivity/data sync, login/security, ergonomics, approvals, customer interaction.	
E	Attitudes, expectations, and continuance	3–5 min	ID9	Overall, how do you feel about using a tablet for work? Why?	ATT (attitude), CI (continuance), habit/routinisation.
			ID10	Do you plan to keep using it in the next 6–12 months? Under what conditions would you stop/scale back?	
			ID11	Compared to phone and desktop, when do you choose the tablet vs. not? (Task–device fit, substitution/complementarity)	
F	Innovative behaviour with tablets	5–6 min	ID12	Have you tried out new ways of doing your job with the tablet (workarounds, templates, new app features)? Give an example. Probes: Who initiated? Any micro-automation (shortcuts, forms, scripts), photo/video use, data capture hacks.	ITIB (idea generation/trying new things), social influence/peer learning.
			ID13	Did any of these ideas spread beyond you (team adoption)? How? (Peer diffusion)	
			ID14	What blocks you from experimenting? (Time, policy, skills, risk, lack of feedback)	

G	Organisational support & climate + facilitating conditions	4–6 min	ID15	What kind of support did you have: training, coaching/champions, time to tinker, recognition? (IS) Probes: One concrete moment of visible support from a manager.	IS, IF, facilitating conditions
			ID16	How reliable are the basics: network coverage, data sync, device management, accessories?	
			ID17	Are there rules/governance that help or hinder (security, approvals, app store restrictions)?	
			ID18	Who do you go to when something doesn't work? How fast is it resolved? (Service pathway)	
H	Barriers & boundary conditions	3–4 min	ID19	What makes tablet use hard in your context (sector/site/rural vs. city)?	Location, boundary, future
			ID20	If you don't use a tablet (or seldom), what would have to change for you to start/continue?	
I	Future & comparison over time	2–3 min	ID21	Since the original survey (years ago), what has changed in how tablets fit your work?	Future
			ID22	Looking ahead 12–24 months, what's your wish list for tablet use (apps, processes, training, policy)?	
J	Demographics	1-2 min	ID23	Age band & gender (may decline).	Demographics
			ID24	Tenure at firm; team size; site (Capital/City/Rural).	
K	Wrap-up	1 min	ID25	Anything I should have asked but didn't? May I contact you for a brief follow-up if needed?	

Optional modules

A. High IS – Low ITIB (support without experimentation)

- What time/space exists to try things? Is it *real* or symbolic?
- Are there costs to failure (errors, blame)?
- How are ideas captured and fed back (suggestion systems, stand-ups)?
- What would make experimentation safe and rewarding?

B. High ATT – Low ITIB (positive attitude, little trying)

- You like the tablet—what stops new uses? (App permissions, workflow rigidities, KPIs)
- Do you need peer examples or a playground environment?

C. High ITIB – Low CI (innovation didn't stick)

- Which ideas worked but didn't become routine? Why? (handover gaps, training, version drift)
- What would help standardise successful workarounds (templates, SOP updates, coaching)?

D. Low IS – Low CI (laggard)

- If you had one lever (infra/training/policy), what would move the needle most?
- Any local champion you'd trust to lead changes?

Appendix K3. Gatekeeper Email for Qualitative Follow-up

Subject: Short research interview at [SME Name] — request for one “champion” and one “sceptic” (tablet use study)

Dear [Gatekeeper's name],

I'm following up on our earlier collaboration on the tablet-use study. I'm conducting brief follow-up **interviews (max. 30 minutes)** to understand *what helped or hindered* everyday tablet use and small innovations in your workflows.

To get a balanced view, could you please help identify **two colleagues**:

1. **A “champion”** — someone who has been positive about the tablets (e.g., piloted features, coached others, or adapted processes).
2. **A “sceptic/heavy user with concerns”** — someone with hands-on experience who has been cautious or critical (e.g., raised issues about fit, reliability, or workload).

Inclusion criteria (both):

- Worked at [SME name] during or after the initial rollout period and used the tablets in their role (around 2015).
- Comfortable discussing concrete examples (tasks, apps, situations).
- Available for a 30 minute conversation (MS Teams/Zoom or phone), scheduled at their convenience.

What I'll ask about: specific tasks where tablets helped/hurt, local workarounds or improvements, support/training, connectivity/app fit, and whether initial enthusiasm translated into ongoing use.

Confidentiality & ethics: Participation is voluntary. Interviews are confidential, anonymised in reporting (e.g., “Ops manager, Manufacturing”), and stored securely under university ethics approval. No performance evaluation is implied.

Proposed times:

- Option A: [date/time window]
- Option B: [date/time window]
- Option C: [date/time window]
- (Or suggest alternatives; I’ll adapt.)

If helpful, I can send a one-paragraph info sheet you can forward internally. Thank you very much for your support—this “champion + sceptic” pairing really improves the quality of findings.

Best regards,

Tibor Vörös

Appendix L Gioia Analysis Further Details

Appendix L1. Stage 1: Open Coding and First-Order Concepts

The data analysis started with uploading all the interviews into an MS Excel datafile. Paragraphs were numbered and separate columns were created for identifying the SME and interviewee (code) / paragraph number (e.g., SME08_G01 paragraph 45). 853 rows were created with this method (one row can be a long paragraph). Without metadata and interviewer questions, 564 rows remained. These rows were sorted based on the SME ID and paragraph numbers and read one by one, to start establishing open coding.

The analysis began with open coding of interview transcripts, identifying discrete informant-centric terms, phrases, and narratives that captured participants' lived experiences with tablet use. This stage prioritised fidelity to participant voice, avoiding premature imposition of theoretical categories. Coding was conducted manually using MS Excel to facilitate systematic organisation and retrieval of textual segments (Gioia et al., 2013). MS Excel VBA scripts were used to facilitate quicker work.

Procedure:

1. Each transcript was read in full to gain full understanding.
2. Paragraph-level identifiers (e.g., SME01_D01_34) were used to enable precise traceability.
3. Meaningful units of text (sentences, short paragraphs) were assigned descriptive codes using participants' own language wherever possible (e.g., "on and off use", "company should pay for apps", "drawing live, make tweaks"). Open coding was performed in Hungarian to identify first-order concepts.
4. One row may link to more than one first order code (several columns).
5. Iterative comparison across transcripts identified recurring patterns and variations.
6. First-order concepts were translated to English (concise paraphrases of in vivo statements)
7. Translations were verified through back-translation and colleague review

Outcome: This stage yielded 287 preliminary first-order codes, which were then collapsed to 226 final first-order codes, representing the raw empirical grounding of the data structure.

Appendix L2. Stage 2: Axial Coding and Second-Order Themes

The second stage involved axial coding. In this stage first-order concepts were grouped into higher-level categories reflecting researcher interpretation. This stage asked, "What broader patterns or mechanisms do these participant statements collectively represent?" Guided by the UTAUT-based theoretical framework and emerging patterns in the data, similar first-order concepts were clustered into second-order themes.

Procedure:

- First-order concepts were compared and contrasted to identify conceptual similarities.
- Thematic labels were developed to capture the essence of each cluster, balancing descriptive accuracy with analytical abstraction.
- Constant comparison across interviews ensured themes were grounded in multiple data sources.
- Negative cases (instances that contradicted emerging themes) were actively sought and analysed to refine thematic boundaries.

Outcome: The 226 first-order concepts were systematically organised first into 24 second-order themes and finally collapsed into 14 second-order themes. Representative examples include:

- Technology Evolution and Maturity (from "five years ago hype only", "now can load useful apps", "hardware incredibly powerful")
- Failed Organisational Rollouts (from "project funded no support", "batteries dead, outdated", "novelty wore off")
- Cloud-Accelerated Cloud Transformation (from "COVID forced acceleration", "tablet beautiful terminal", "work happening elsewhere")

Appendix L3. Stage 3: Selective Coding and Aggregate Dimensions

The final stage employed selective coding to organise second-order themes into aggregate dimensions—overarching theoretical constructs that answer the study's research questions and connect to the broader literature. This stage moved from description to theoretical abstraction, asking, "What fundamental processes or structures explain tablet continuance and innovative use in Hungarian SMEs?"

Procedure:

- Second-order themes were examined for higher-level patterns and relationships.

- Themes were grouped based on shared theoretical concerns (e.g., all themes related to organisational enablers/constraints were consolidated under one dimension).
- Each aggregate dimension was defined conceptually, with explicit linkages to the quantitative model constructs (PE, EE, ATT, IS, IF, ITIB, CI).
- The final data structure was reviewed for internal coherence, ensuring that dimensions were mutually exclusive yet collectively exhaustive.

Outcome: The second-order themes were synthesised into 4 aggregate dimensions:

1. Task-Technology Fit and Use Contexts (specific work activities where tablets do or don't fit employee needs)
2. Technology Maturation and Adoption Trajectories (technology changes, patterns and pathways of tablet adoption, use, and abandonment over time)
3. Organisational Context and Support (company-level factors enabling or constraining tablet use and innovation, organisational outcomes)
4. Innovation-Oriented Behaviours and Emergent Use (employee experimentation, peer diffusion, and creative appropriation)

Themes were reviewed iteratively with the supervisory team through refinement cycles (October 2024 - November 2025), resulting in consolidation from 24 initial second-order themes to the final 14 themes across 4 aggregate dimensions. Some of the themes were actually considered sub-themes of an overall theme (e.g. initially two themes within the 4. Innovation-Oriented Behaviours and Emergent Use dimension: Time Scarcity Constraints and Policy Constraints were collapsed into a single theme Constraints on Innovation) and the final structure was developed, described in the next section.

Appendix M Gioia Coding Examples

Theme 1.1 Reading & Light Documentation

"In work, I use it for checking my emails, reviewing slides, content, drafting graphics, note taking."
[SME03_C01_15]

"..First, people discovered them for reading—technical books, API documentation, long articles. It's just a superior reading experience." [SME19_P01_23]

"[...] I did use it for jotting down new ideas and then I could find them years later. Papers notes would get lost.[...] So yeah, the note taking capability is good." [SME01_D01_50]
[SME01_D01_51]

Theme 1.2 Meetings & Collaborative Work

"It's less of a barrier in a meeting than a laptop screen. When you open a laptop, it's like you're building a small wall between you and the other person." [SME12_S01_15]

"It's less intrusive in a meeting than a full laptop. It's a convenient, elegant tool for the right job."
[SME16_K01_33]

"The main advantage is its immediacy and its form factor. It's lightweight, it starts instantly, and the touch interface is very direct for showing things. Taking notes with a stylus feels more organic and less disruptive in a creative meeting than typing on a keyboard. It feels more collaborative than hiding behind a laptop screen." [SME04_M01_40]

Theme 1.3 Role-specific Workflows

"At work we standardised on iPads for field staff and a mix of Android tablets for warehouse and shop-floor tasks." [SME14_B01_7]

Even sceptics praised tablets in specific contexts:

"But many colleagues swear by their iPads, especially the designers who use Procreate and other specific apps." [SME19_P01_36]

"It's so much easier in design and Photoshop to come up with anything creative that you have to literally draw." [SME03_C01_55]

"For instance, when I went in to design with the designer, he was drawing it live and had a model preset with all this stuff. I said, maybe make this tweak. And instead of erasing and going through the whole works, you just take the eraser, touch it and that's it. So for that I really like it."
[SME03_C01_56]

The task-technology fit was very different in a design team, than in a standard office environment:

"Then I got into the design/drawing team and it [the tablet] really got a lot more useful."
[SME03_C01_32]

Theme 1.4: Boundaries for Complex Work

"Sure, if you only go to meetings, maybe [tablets are good]. But to do something more serious, you need a computer. I am not going to design Powerpoints or Sales reports on a tablet."
[SME08_H01_17]

"I was always very sceptical, it looked to me this is just an extra toy, but I have to admit with all the cloud stuff I can see my younger colleagues using it more." [SME19_Q01_21]

"I learned type writing and can use all of my fingers to do that so I am very productive on a laptop.[...] Never felt the need for a tablet, phone and laptop are enough. I think we can agree that for people like us who work and use (MS) Office most of the time, the laptop is still better. So we are probably not the primary market for these." [SME08_G01_22] [SME08_G01_45]

Theme 2.1: Ecosystem and Platform Maturation

"At that time it was quite basic. You just had the same applications like you have on your mobile phone. The only difference was that you would have a bigger screen... Now iPad Pro can use everywhere, take notes easily like notebook." [SME03_E01_12] [SME03_E01_13]

"Five years ago, the dream was bigger than the reality. The ecosystem was still limited. The software often felt like just a blown-up phone app, not a dedicated tablet experience. [...] The gap is closing now. The hardware has become incredibly powerful" [SME16_K01_27]
[SME16_K01_28]

"I see it as a device that is being squeezed from both ends. Phones got so large and capable that for many quick tasks, they are good enough. And from the other end, ultralight laptops and 2-in-1 convertibles became so good that they erased the tablet's main advantage of portability. Once you add a keyboard case to a tablet to do real work, you've basically just built a less functional, more compromised laptop." [SME12_S01_13]

Theme 2.2: COVID-Accelerated Cloud Transformation

"[With cloud] tablet is very useful: it can also support Citrix or other relevant MultiTech stops that you can start from your iPad and work on it" [SME14_I01_10]

"[...] and most important, was the forced acceleration to the cloud during the COVID pandemic. That was the game-changer. [...] Suddenly, the processing power of the local device mattered less. COVID forced acceleration to cloud, game-changer [...]" [SME19_P01_24]
[SME19_P01_26]

"You can still use a software for SQL around the same syntax in the tablet. You can use it. You can also download and use Python. You with the cloud, you should be able to use everything on it." [SME14_I01_21]

"Now, a tablet isn't just a tablet; it's a beautiful, high-resolution terminal into a powerful remote server." [SME19_P01_28]

Theme 2.3: Discontinuous Usage Patterns

"I don't use the tablet much here [...] Sometimes I take it to meetings so I can take notes or make some sketches of how the sales material about the sales campaign will look." [SME08_H01_9]
[SME08_H01_10]

"[using tablets] the camera-as-a-sensor idea—documents, barcodes, QR, even shelf condition photos—became natural. [...] Input-heavy tasks are painful: Long spreadsheets, complex accounting entries—still better on a full keyboard with dual monitors." [SME14_B01_21]
[SME14_B01_33]

"It's a very different use case for each device. My desktop [...] is my workhorse. That is where the real "heavy lifting" happens [...] The tablet sits somewhere in the middle. It's my primary device for meetings, for taking quick notes with the Apple Pencil, and for reading." [SME16_K01_16]

Theme 3.1: Organisational Support Mechanisms

"Training was easy [...] Short, tappable guides with screenshots ("scan here, then tap Save")." [SME14_B01_63]

"We don't really get any help in the company... No one really owns it [the tablet support]." [SME03_C01_20]

"Back then [in 2015], we thought it would replace the computer. We had sessions to share tips & tricks." [SME16_K01_29]

"Company should pay for new apps... If I don't get necessary apps, that's it." [SME03_C01_69]

"If somebody has an idea, prototyping a workflow on a tablet is fast: spin up a form in a low-code tool, connect to a REST API, test with a barcode." [SME14_B01_41]

Theme 3.2: Infrastructure Constraints

"Wi-Fi sometimes drops, the floors are tricky" [SME01_D01_43]

"First, Wi-Fi and coverage in warehouses—dead zones killed productivity. We had to invest in better AP placement" [SME14_B01_74]

"[...] yeah, I probably used it [the tablet] for a year. And then somehow it became obsolete. I solved the problem in different ways, in more convenient ways." [SME01_F01_12]

"Anyway, the ones we bought back then were outdated a long time ago, they've been out of service for a long time, and the batteries are dead, so you can only work for half an hour or an hour or do anything with it." [SME08_G01_27]

Theme 3.3: Failed Organisational Rollouts

"[...] the management at the time decided, as a move to look modern and innovative, to buy iPads for a large number of employees. [...] Initially, it was a prestige item. It was exciting. [...] But the reality was, we received the hardware with little else. [...] There was no real integration, no special training, no dedicated apps for our workflow. [...] It slowly faded away." [SME04_M01_25] [SME04_M01_29] [SME04_M01_31] [SME04_M01_33]

"Yes, I own a personal Android tablet. The company doesn't issue them as standard equipment anymore, though we had a phase with that years ago.[...] The novelty wore off.[...] The disadvantages are numerous from an SME's perspective. [...] First, the total cost of ownership [...] Then there's the issue of security" [SME12_R01_11] [SME12_R01_19] [SME12_R01_24] [SME12_R01_25] [SME12_R01_26]

One of the managers mentioned positive stories as well, but overall summarised the situation with tablets as follows:

"[Tablet results were] Mixed. We ran a survey in 2015 after the first year. The overall impression was that the tablets were used more at home for media—reading, games with family—than at work. [...] the heavy lifting stayed on laptops and desktops. [...] We also had people proposing brilliant ideas [...] But we were under financial pressure [...] That was a lesson: device first, without budget for apps and process change, rarely pays off" [SME07_A01_57]

Theme 3.4: Successful Organisational Rollouts

"We have training for new hires, they get get orientation, but experienced staff get advanced workshops on specialized apps " [SME14_I01_19]

Crucially, workflows were reengineered to match tablet affordances (mobile capture, cloud sync, real-time updates) rather than layered onto unchanged desktop-centric processes. Ongoing support was explicit:

"sales rep can test a digital form [...] In a resource-constrained SME, that matters. We don't have a formal innovation lab; the tablet is a lightweight sandbox." [SME07_A01_43]

Use cases were specifically targeted and evaluated, with long-term planning:

"Use-case first: do they present often? Need mobility without a laptop? Benefit from pen input? [...] We budget for apps, MDM, and training at the same time." [SME07_A01_80]

Theme 4.1: Peer-Driven Innovation Diffusion

"[using tablets] over ten years personally. [in the company] We started experimenting around 2012–2013 because we saw POS-on-iPad success stories.[...] For me it was curiosity—could we do inventory, photo capture, and approvals without laptops? People got excited when I showed them how to do this." [SME14_B01_13]

Sometimes the senior staff was providing ideas:

"Some of the senior staff who picked up tablets quickly started helping others understand the features..." [SME16_K01_17]

One participant recalled it offhandedly in one of the interviews:

"Though sometimes we show fun new apps to each others in the office. Even useful ones, I saw some useful tools my colleague was showing me." [SME01_D01_35]

Theme 4.2: Emergent Innovation Processes

"The sales team members can launch presentations on their tablets instantly, we can show examples, we can show the catalogues, they can browse it, turn the page etc. I'm not saying that everyone needs a tablet, but it can be very useful. For the sales team, it helped a lot." [SME07_J01_9]

Where IT support leaned in, prototyping accelerated:

"If somebody has an idea, prototyping a workflow on a tablet is fast: spin up a form in a low-code tool, connect to a REST API, test with a barcode. Field staff can pilot changes the same day." [SME14_B01_41]

Another participant commented on note taking – again starting with "playing around":

“When I worked more in a consultant role, all my bosses, the partners or senior managers all used tablets because they took notes during the presentations and all the meetings with clients. I was bored one afternoon and started playing around different note-taking apps... found one that syncs perfectly with our project management system. Showed my boss and then we used it for all the notes.” [SME03_C01_59]

Role-specific, customer-facing scenarios were easiest to spread (see Dimension 1):

“Like if you're a sales guy and have to go for a meeting, it's nice to show a presentation right there [on the tablet]. It's easy, as we said, for signing contracts or these things.” [SME01_F01_42]

Playing around with various apps resulted in a solid work impact later:

“Crossword puzzles or odd activities... Just using for listening to music, sketching, games. Fun, and we were happy we got it. I was playing with sketching on my own and it became really useful in the design work.” [SME03_C01_57]

Theme 4.3: Constraints on Innovation

“I don't really have time to experiment, but it [the tablet] really helps in those things I use it for.” [SME03_C01_71]

“Also, the “walled garden” approach of our strict IT, while secure, can stifle quick adoption of new tools.” [SME16_K01_35]

The strict app installation policies were definitely noticed by the participants – and a slow vetting process was not helping either:

“The infrastructure is very strict. I can't just go to the App Store and install a new app I think might be useful. It has to go through a vetting process, which can be slow.” [SME16_K01_22]

One IT expert even commented on such policies:

“Lock-in and approvals: App store policies, MDM profiles—safer but slower to experiment.” [SME14_B01_36]

Drilling deeper into the participants' comment, they elaborated further:

“Yeah—early on we needed certain capabilities that official app stores didn't provide, or we needed them now, not in six months. We sideloaded custom builds to connect scanners, print labels, do batch uploads—quick fixes. It was fun, but honestly risky and hard to scale. As vendors tightened security, we moved to proper enterprise signing, MDM, and store approvals. That killed

some spontaneity but improved reliability, security, and support—no more “mystery builds” floating around.” [SME14_B01_68]

“The portability encourages informal brainstorming. But idea generation is about culture more than devices. We always welcomed bottom-up suggestions; we just didn’t have formal processes or budget set aside to carry many of them through.” [SME07_A01_46]

Additional Examples

Table 9.107 Gioia coding examples (first-level)

First-Order Concept	Representative Quote(s)	Source(s)
Early adopter/innovator	"I was really an early adopter or an innovator in this technology because I started to use an older solution in the beginning. This was a PDA solution. It was 15 years ago..."	SME01_D01_10-11
Five years ago lot of hype / Hype	"Five years ago there was lot of hype, very little action. 2015 wasn't really useful, even multitasking was a problem."	SME04_N01_14
Management supports use	"Management supports that we use it."	SME01_F01_13
Company should pay for apps	"Company should pay for new apps. If I don't get necessary apps, using it on my own for whatever I can."	SME03_C01_69, 21
On and off use	"Sometimes I don't use it for a week, then charge it and use it for a week, on and off really."	SME01_D01_51
Project funded no support	"It was a big project and in this big project we practically got a lot of hardware... Project only brought hardware, no formal support behind the roof."	SME08_G01_8
COVID forced cloud	"COVID forced acceleration to cloud, game-changer. Processing power of the local device mattered less. Tablet became a beautiful, high-resolution terminal to a powerful remote server."	SME19_P01_27-29

First-Order Concept	Representative Quote(s)	Source(s)
Can't go meeting with computer	"Can't go into a meeting with a computer, it separates you from others. Not a good impression. Tablet is good in that sense."	SME03_E01
Pen and iPad for design	"Pen and iPad for design, Photoshop, incredibly useful for drawing. Draw live, make tweaks immediately."	SME03_C01_54-56
Don't have time experiment	"Don't really have time to experiment. Very busy, lots of trainings, little time to try new things. What works, works, no real need to change."	SME03_C01, SME03_E01

Including the full hierarchical table with 224 final first-order concepts was not feasible. The screenshot shows the initial 280 first-order concepts, with 3.1 Media Consumption and Information Access open. These 280 concepts were then collapsed to 224. In the thesis everywhere else the collapsed 224 first-order concepts are used, this is only shown for illustration.

Figure 9.10 Gioia example

	A	B
10	1. Technology Adoption Trajectories	58
11	1.1 Early Adoption Patterns	18
12	1.2 Technology Evolution and Maturity	9
13	1.3 Device Evolution and Replacement	6
14	1.4 Discontinuous Usage Patterns	10
15	1.5 Failed Organisational Rollouts	15
16	2. Organisational Context and Support	34
17	2.1 Training and Peer Support	5
18	2.2 Management Support and Resources	12
19	2.3 Infrastructure Constraints	3
20	2.4 Strict IT Governance	7
21	2.5 Successful Integration Stories	7
22	3. Task-Technology Fit and Use Contexts	72
23	3.1 Media Consumption and Information Access	11
24	Annotate PDFs comfortable chair	1
25	Code reviews tablet documentation	1
26	Emails calendar documents calls travel	1
27	Gadget home YouTube couch no work	1
28	Home news YouTube not productivity	1
29	Not replaced laptop travel waiting	1
30	Preparing review documents comfortable	1
31	Reading docs checking status easier	1
32	Reading docs logs couch coding keyboard	1
33	Reading technical docs articles superior	1
34	Simple tasks house recipes crossword	1
35	3.2 Note-Taking and Documentation	7
36	3.3 Field and Mobile Work Applications	9
37	3.4 Meeting and Collaboration Dynamics	8
38	3.5 Design and Creative Workflows	6
39	3.6 Specialized Niche Applications	8
40	3.7 Cloud-Enabled Transformation	8
41	3.8 Limitations for Complex Work	5
42	3.9 Professional Identity and Tool Preferences	10
43	4. Innovation-Oriented Behaviours and Emergent Use	16
44	4.1 Peer-Driven Innovation Diffusion	5
45	4.2 Opportunistic Problem-Solving	5
46	4.3 Peripheral Exploration and Play	2
47	4.4 Time Scarcity and Routine Lock-In	4
48	Grand Total	280

Appendix N Extended Contributions

Appendix N1. Academia

For academia, this thesis makes five main contributions.

First, it reconceptualises core post-adoption constructs. The mixed-methods findings show that global measures of Performance Expectancy and Continuance Intention are anchored in a dominant task rather than reflecting a portfolio-wide average. Performance Expectancy is better interpreted as Performance Expectancy in the Dominant Task Context (PE-DTC), while Continuance Intention captures ‘context-dependent readiness-to-re-engage’ rather than a stable commitment to continuous use. This dominant-task anchoring, combined with discontinuous usage patterns, supports a cyclical view of continuance—employees move in and out of active use as roles, tasks, and infrastructures evolve.

Second, the thesis offers a new contingent model of Personal Innovativeness in IT. It explains the paradoxical competitive mediation in the PIIT→CI path by demonstrating that PIIT is a “double-edged sword”: a positive catalyst for tablet-enabled innovation under supportive conditions, yet a direct predictor of disengagement when innovators encounter technological or organisational constraints. This reframes PIIT as a context-sensitive trait whose effects depend on task–technology fit and organisational scaffolding, rather than a uniformly positive antecedent of technology use.

Third, the study refines theorisation of innovation support mechanisms in SMEs. It shows that Innovation Support functions primarily as a climate-level signal that influences IT-enabled Innovative Behaviour only when it is operationalised through Involvement Facilitation – concrete enablers such as time, budgets, governance flexibility and peer-learning structures. This IS→IF→ITIB mechanism positions IF as a bridging construct between macro-level climate and micro-level behaviour, and demonstrates that symbolic support affects motivational access, whereas material support underpins usage access.

Fourth, the thesis extends second-level digital divide theory by specifying how skills and usage access operate at the micro level. It links individual beliefs (PE, EE, ATT), trait dispositions (PIIT), and organisational enablers (IS, IF) to the persistence of the divide after devices are deployed. By demonstrating that access to physical devices does not guarantee productive use, the findings reinforce that closing the digital divide requires attending to motivational and material support structures, not merely device provision.

Finally, the thesis contributes methodologically and contextually. The explanatory sequential design, with a seven-year interval between survey and qualitative follow-up, provides a rare perspective on discontinuous usage and ecosystem maturation. The joint displays illustrate how mixed-methods designs can uncover mechanisms—such as dominant-task anchoring and cyclical continuance—that remain invisible in cross-sectional models. Contextually, the focus on tablet post-adoption in Hungarian SMEs offers one of the few in-depth accounts from a transitional economy, enriching the comparative evidence base.

Appendix N2. Industry

For industry, this thesis contributes a framework for turning SME tablet deployments from hardware projects into sustained, innovation-enabling change programmes.

First, it distinguishes clearly between use and innovation: continuance intention captures employees' readiness to re-engage with tablets when task–technology fit is high, whereas IT-enabled Innovative Behaviour captures the value-creating appropriation of tablets in everyday work. This distinction equips managers to move beyond simple adoption metrics (e.g. log-ins, device counts) and monitor whether technology is reconfiguring workflows, solving problems, and generating new ideas.

Second, the thesis provides a practically grounded model of how organisational support mechanisms operate in SMEs. The IS→IF→ITIB pathway demonstrates that Innovation Support (IS) functions primarily as a climate signal: employees only translate this encouragement into innovative usage when it is operationalised through Involvement Facilitation (IF) in the form of time, budgets, governance flexibility and peer-learning structures. For managers, this offers a concrete checklist of levers—protected experimentation time, innovation “sandboxes”, peer demonstration forums, and flexible mobile device management (MDM) policies—that can be used to convert abstract support for innovation into observable changes in technology use.

Third, the study offers industry a nuanced understanding of discontinuous usage and cyclical continuance. Rather than interpreting 'on–off' usage as failure, managers can recognise dormancy as a rational response to changes in task portfolios, infrastructure constraints, or ecosystem maturity. This reframing encourages SMEs to monitor readiness-to-re-engage (e.g. via periodic check-ins, role transitions, and workflow redesign) instead of pushing for artificial daily use. It also identifies innovation-oriented employees as strategic resources: when supported with IF, they act as internal champions and innovation brokers; when constrained, they become sources of frustration and disengagement.

Finally, by embedding these mechanisms within the DASAT cycle (Digital Awareness, Digital Strategy Roadmap, Digital Adoption Implementation, Digital Transformation–Continuous Improvement), the thesis provides SME leaders with a phase-sensitive roadmap for digital transformation. The contribution lies not in listing 'best practices', but in showing when different interventions—role-based deployment, ecosystem-aligned training, lifecycle management, IS–IF audits—are most effective and how they collectively address the second-level digital divide.

Appendix N3. Policymakers

For policymakers, this thesis offers an empirically grounded micro-level lens on the second-level digital divide in transitional economies. Existing EU and Hungarian digital policies have largely addressed material access: the SMEs in this study possessed adequate devices and connectivity. However, the integrated findings show that inequalities now concentrate on skills and usage access—operationalised here through Effort Expectancy, Performance Expectancy, Attitude, Personal Innovativeness in IT, and organisational enablers such as Innovation Support and Involvement Facilitation. This fine-grained conceptualisation enables policymakers to move from generic calls for 'more skills' toward targeted programmes addressing specific bottlenecks: effort barriers (complexity perception), performance barriers (task relevance), motivational barriers (lack of peer validation), and organisational barriers (insufficient time, governance constraints).

A second contribution is to reposition digital policy from a one-off infrastructure push to an iterative, capability-centric agenda. By embedding the second-level digital divide within the DASAT cycle, the thesis demonstrates that skills and usage access must be renewed at each phase: DA awareness campaigns must set realistic, task-specific expectations; DSR roadmap and funding instruments must allocate for operational support, not merely hardware; DAI adoption initiatives must mandate peer-learning and experimentation structures; DTCL transformation policies must institutionalise periodic re-alignment of workflows, devices, and cloud ecosystems. This perspective complements macro-level targets in the EU's Digital Decade Policy Programme 2030—particularly SME digital intensity and skills targets—by demonstrating how DASAT-aligned, capability-centric interventions operationalise these goals in day-to-day SME practice.

Third, the study contributes a policy-relevant understanding of how digitalisation unfolds in resource-constrained, post-transition economies. The Hungarian SMEs examined here exhibit strong infrastructure but uneven managerial capacity and organisational support for innovation. By linking national-level funding streams (e.g. digital renewal initiatives, European Digital Innovation Hubs) to concrete organisational mechanisms—training intensity, governance

flexibility, peer networks, innovation sandboxes—the thesis offers policymakers a diagnostic framework for evaluating whether interventions genuinely enable usage access and employee readiness-to-re-engage, or merely increase device penetration.

Overall, the thesis translates abstract policy goals—digital intensity, skills access, innovation-enabling capabilities—into actionable micro-level levers that support employees' readiness-to-re-engage and IT-enabled innovative behaviour. This micro–macro bridge provides policymakers with a framework for designing, targeting, and evaluating digital policy instruments in transitional and peripheral economies, where infrastructure is adequate but organisational capacity remains uneven.

Appendix O Extended Implications

Appendix O1. Academia

Overview

Building on the contributions outlined above, this thesis invites scholars to reconceptualise post-adoption use as a cyclical, context-contingent process rather than a linear stage model. The findings suggest that core constructs—Performance Expectancy, Continuance Intention, Personal Innovativeness in IT, and organisational support mechanisms—require re-examination in how they are operationalised and measured. The following subsections develop these implications across four areas: reconceptualising UTAUT's core constructs, modelling trait-based variables as contingent rather than uniformly positive, refining organisational support theorisation, and advancing mixed-methods approaches in post-adoption research.

Core Constructs in UTAUT

The dominant-task anchoring mechanism documented in this thesis carries implications for how UTAUT constructs are operationalised. Future studies in organisational contexts should move beyond device-global perceptions and explicitly model task-level heterogeneity—recognising that Performance Expectancy reflects beliefs about a dominant task context rather than an average across all device uses. This suggests a need for measurement instruments that anchor respondents to specific task contexts, capturing the conditional nature of performance beliefs. Researchers should test whether the PE-DTC mechanism generalises to other multi-purpose technologies (smartphones, laptops, AR/VR devices), where similar task heterogeneity is likely.

For Continuance Intention, the findings suggest that current CI measures conflate three conceptually distinct states: stable commitment (persistent, unconditional use), context-dependent readiness-to-re-engage (cyclical use triggered by task–technology alignment), and true abandonment (permanent discontinuation). Future research should develop measures that distinguish these states, enabling more precise theorisation of post-adoption trajectories and avoiding the conflation of dormancy with failure.

Trait-Based Constructs as Contingent Amplifiers

The competitive mediation pattern observed for Personal Innovativeness in IT challenges the prevailing treatment of trait-based constructs as uniformly positive antecedents in technology acceptance models. The findings demonstrate that PIIT operates as a 'double-edged sword': it amplifies positive outcomes when organisational support is present, but accelerates

disengagement when innovators encounter technological or organisational constraints. This suggests that PIIT's effects are contingent on ecosystem maturity and organisational boundary conditions rather than being linearly positive.

Future UTAUT and TAM extensions should model PIIT—and similar individual-difference variables such as absorptive capacity, learning orientation, or need for cognition—as contingent amplifiers rather than direct predictors. Methodologically, this implies testing interaction effects between trait variables and contextual moderators, and specifying the conditions under which traits enhance or undermine technology outcomes. This reconceptualisation has broader implications for how individual differences are theorised in IS research: traits may not be inherently beneficial or detrimental, but rather magnifiers of environmental conditions.

Organisational Support Mechanisms

The IS→IF→ITIB pathway documented in this thesis has implications for how organisational support is theorised in post-adoption research. The findings suggest that Innovation Support (IS), often conceptualised as a direct enabler of innovative behaviour, functions primarily as a climate-level signal that affects outcomes only when operationalised through Involvement Facilitation (IF). This has two implications for future research.

First, studies examining organisational support should distinguish between symbolic support (management rhetoric, espoused values) and material support (time allocation, budgets, governance flexibility, peer-learning structures). The two operate through different mechanisms: symbolic support shapes motivational access, while material support enables usage access. Conflating them in a single construct obscures these distinct pathways.

Second, the serial mediation pattern (IS→IF→ITIB) suggests that future research should model organisational support as operating through bridging constructs rather than directly on outcomes. This has implications for intervention studies: enhancing IS alone may yield limited results; interventions should target IF as the proximal enabler of behaviour change.

Methodological Implications

The explanatory sequential mixed-methods design employed in this thesis—with a seven-year interval between the quantitative survey and qualitative follow-up—offers methodological lessons for post-adoption research. First, the temporal gap enabled the documentation of discontinuous usage patterns and ecosystem maturation effects that would remain invisible in cross-sectional or short-interval longitudinal designs. Researchers studying post-adoption phenomena should

consider designs that span technology lifecycle phases, allowing observation of how perceptions and behaviours evolve as devices and ecosystems mature.

Second, the joint display approach used to integrate quantitative path coefficients with qualitative themes illustrates how mixed-methods designs can uncover causal mechanisms underlying statistical relationships. The qualitative phase revealed dominant-task anchoring and cyclical continuance mechanisms that explained otherwise puzzling quantitative patterns (e.g., PE→CI non-significance). This suggests that mixed-methods integration should move beyond triangulation (convergence/divergence checking) toward mechanism explication—using qualitative data to specify the 'how' and 'why' behind quantitative effects.

Finally, the study demonstrates the value of retrospective qualitative inquiry for post-adoption research. Interviewees' ability to reflect on usage trajectories over multiple years provided insights into abandonment, re-engagement, and workflow evolution that concurrent designs cannot capture. Future research should balance retrospective bias concerns against the unique insights that temporal distance affords.

Appendix O2. Industry

Overview

For industry, the integrated findings provide concrete guidance for SME managers seeking to move from device deployment to sustained, innovation-oriented use. Tablets generate value when aligned with high-fit tasks, embedded in supportive organisational structures (IS and IF), and interpreted through cyclical continuance rather than binary success/failure. The implications below are organised along the DASAT cycle, enabling managers to select phase-appropriate interventions and design coherent, staged digital transformation strategies.

Digital Awareness (DA) Phase

Objective: Build realistic, task-segmented literacy about tablet affordances and limitations.

Recommendations:

- Avoid generic 'tablets improve productivity' messaging; instead, set bounded, task-specific expectations that clarify where tablets add value and where laptops remain necessary, preventing later disillusionment.
- Identify innovation-oriented early adopters (Theme 4.1) during DA and position them as opinion leaders for peer demonstrations.

Digital Strategy Roadmap (DSR) Phase

Objective: Prioritise deployment, resource allocation, and governance policies that maximise task-technology fit.

Recommendations:

- Role-based deployment strategy: Prioritise high-fit roles (field staff, sales, design) over universal rollout (Theme 1.3 Role-specific Workflows).
- Budget for IS→IF operationalisation: Allocate resources simultaneously for hardware, apps, training, peer-learning infrastructure, and device lifecycle management. Failed rollouts (Theme 3.3) resulted from budgeting hardware without operational support.
- Design governance flexibility: Establish tiered MDM policies—strict for general users, relaxed for vetted innovators (Theme 4.3)—to balance security with innovation capacity.

Digital Adoption Implementation (DAI) Phase

Objective: Provide hands-on experience, peer learning, and task-workflow integration that stabilises positive attitudes and updates performance expectations.

Recommendations:

- Task-anchored training: Rather than generic feature walkthroughs, organise training around concrete workflows (Theme 1.3 Role-specific Workflows).
- Institutionalise peer learning: Create regular "show-and-tell" sessions, WhatsApp groups, or lunch-and-learns where early adopters demonstrate discovered uses (Theme 4.1).
- Protect ludic exploration time: Allow employees 1-2 hours/month for "playful" experimentation (Theme 4.2)—non-instrumental tinkering that seeds later pragmatic innovations.
- Monitor task-fit mismatches: Conduct pulse surveys 3 months post-rollout to identify employees in low-fit roles and offer laptop alternatives rather than forcing tablet use (Aggregate Dimension 1).

Digital Transformation-Continuous Improvement (DTCI) Phase

Objective: Sustain use, enable innovation, and institutionalise learning loops that recalibrate technology value over time.

Recommendations:

- Device lifecycle management: Establish 3-year refresh cycles to prevent capability erosion (Theme 3.2).
- Annual IS-IF audits: Measure the IS-IF gap. High IS/Low IF signals expectation-reality misalignment requiring immediate intervention.
- Track discontinuous usage constructively: Reframe dormancy as 'readiness-to-re-engage' rather than failure; monitor role transitions, ecosystem updates, and infrastructure improvements that may trigger re-adoption (Theme 2.3).
- Ecosystem maturation monitoring: As cloud services, app ecosystems, and hardware capabilities evolve, revisit task-technology fit assessments—previously low-fit tasks may become viable (Theme 2.1).

Cross-Phase Recommendations

- Treat tablet adoption as sociotechnical transformation, not hardware procurement (Themes 3.3 vs. 3.4).
- Measure both continuance intention (CI) and innovative behaviour (ITIB): CI alone does not capture value—ITIB drives competitive advantage.
- Recognise PIIT's double-edged sword (Joint Display 2): High-innovativeness employees require protected experimentation space and governance flexibility, or they become disengaged.
- Integrate tablet strategy with broader digital transformation: Tablet adoption should not be siloed; link it to cloud migration, workflow redesign, and cross-device integration strategies.

Appendix O3. Policymakers

Overview

At the policy level, the findings imply that national and EU digital strategies must pivot from a predominantly infrastructure- and access-focused agenda toward sustained investment in three mechanisms: (1) skills access via competency-building and task-specific training, (2) usage access via organisational support for workflow integration and innovation, and (3) capability-centric monitoring and evaluation. This shift requires attention to how SMEs operationalise innovation support structures on the ground—moving beyond top-down mandates to bottom-up enablement.

The Digital Decade paradox in Hungary

These targets present critical junctures for Hungarian SMEs: the nation boasts strong digital infrastructure but lags in advanced technology adoption (cloud, AI, big data) due to skills and usage gaps. Hungary's 2024–2025 Digital Decade Country Report confirms this paradox, noting that whilst infrastructure is 'very good', SME digitalisation 'is still behind EU peers' and advanced technology uptake 'is still lagging' (European Commission, 2025). With EUR 2.489 billion (0.88% of GDP) in national roadmap funding, plus EUR 1.7 billion in Recovery and Resilience funds and EUR 2.6 billion in Cohesion funds, Hungary possesses substantial resources. However, this thesis demonstrates that hardware investment, whilst necessary, does not automatically translate to productive use without concurrent investment in skills access and organisational support mechanisms.

The quantitative and qualitative findings reveal that Hungarian SMEs face two operationally distinct bottlenecks: (1) skills access, operationalised through Effort Expectancy (reducing perceived complexity) and task-specific digital competencies; and (2) usage access, operationalised through task–technology fit assessment, organisational support mechanisms (IS and IF), and governance policies enabling controlled experimentation. Critically, these bottlenecks are not resolved by device deployment alone; they require active management of workflows, organisational structures, and employee autonomy.

Operationalising the IS–IF pathway through EDIH

Hungary's strong performance in digital infrastructure and the Digital Renewal Operational Programme Plus's emphasis on hardware deployment exemplify the infrastructure-centric approach. However, this thesis demonstrates that the European Digital Innovation Hubs (EDIHs) operating in Hungary provide potential infrastructure for a capability-centric shift. These hubs offer test-before-invest services, skills training, and networking at no cost, operationalising the skills access and usage access mechanisms identified here. However, the EDIH model must explicitly operationalise the IS→IF→ITIB pathway. The evidence (Themes 3.3, 4.3) demonstrates that symbolic support (management rhetoric, training workshops) without structural enablers (time, budgets, governance flexibility, peer-learning forums) fails to produce sustainable innovation and can generate employee frustration. To address this gap, Hungarian policy should:

- Extend EDIH services beyond training to post-deployment operational support: EDIHs should provide 6–12-month post-training facilitation packages including innovation audits (IS–IF gap assessment), peer-learning network brokerage, and governance policy review—not merely one-off training workshops.

- Incentivise SME organisational readiness assessments: Include in EDIH funding mechanisms requirements that participating SMEs conduct pre-deployment readiness assessments and establish accountability for operational support continuity.
- Pilot 'innovation sandbox' governance models: Support a subset of EDIHs to pilot flexible MDM and governance policies as replicable models for other SMEs.

Accounting for ecosystem maturation

Furthermore, ecosystem maturation dynamics (Theme 2.1) reveal that policy timelines must account for technology lifecycle effects. Digital capabilities and task–technology fit are not static. Policy should therefore institutionalise two mechanisms: (1) mandatory 3-year hardware refresh cycles (e.g., through EU Cohesion funding conditions), preventing capability obsolescence; and (2) periodic workflow–technology alignment audits (annually or at role-transition points) to identify newly viable applications as ecosystems mature. These mechanisms could be operationalised through EDIH service packages or included in digital renewal grant conditions.

Translating strategy into sustainable transformation

The EU's Digital Decade 2030 framework positions SMEs as 'enablers of the twin transition' through 'tailor-made digitalisation'—a vision this thesis operationalises by specifying the mechanisms required: cognitive alignment (PE), affective engagement (ATT), trait-based activation (PIIT), and organisational enablement (IS/IF), all embedded within task and ecosystem contexts. Hungary's National Digitalization Strategy 2022–2030, structured around four pillars (infrastructure, skills, economy, state), provides the policy architecture. However, translating these pillars into sustainable outcomes requires that policy interventions move beyond addressing immediate resource scarcity toward institutionalising three-to-five-year capability-building cycles with built-in evaluation and re-alignment mechanisms. This long-term, capability-centric lens may help Hungary to close the second-level digital divide and position SMEs as genuine drivers of the digital and green transitions.