Table 1.3: Findings from SLR 2

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
1	Rajanayagam H., Poologanathan K., Gatheeshgar P., Varelis G.E., Sherlock P., Nagaratnam B., Hackney P.	A-State-Of-The-Art review on modular building connections	A Review	R	Connection Classification, experimental and numerical analysis methods	high rise MiC	Modular building connections *Assemblage (M & C)*	UK
2	Zhang W., Kang K., Zhong R.Y.	A cost evaluation model for IoT-enabled prefabricated construction supply chain management	Quantitative analysis	Quant	System dynamics (A combination of system techniques and analysis) Quite related to ML analysis but does more of relation than prediction	IoT and government data repository evaluation with respect to SCM	Prefabricated construction cost for supply chain management *Pre-Construction Prelims, SCL/M (M &C)*	Hong Kong
3	Wang S., Sinha R.	Life cycle assessment of different prefabricated rates for building construction	Case study, real life project study	CS	Sensitivity analysis	High rise MiC	Energy consumption *Design Issues, Manufacturing (DI, M&C), (material Extraction, In-plant processing and On-site work*	Sweden
4	Ofori-Kuragu J.K., Osei-Kyei R.	Mainstreaming pre-manufactured offsite processes in construction – are we nearly there?	Exploratory Literature review and cases studied	MM	Content Analysis, narrative approach, case study; validated with 30 industry reports.	Pre-manufactured offsite processes in construction	OSC influencing factors *Pre-Construction Prelims, Decision*	Hong Kong and UK
5	Lu W., Lee W.M.W., Xue F., Xu J.	Revisiting the effects of prefabrication on construction waste minimization: A quantitative study using bigger data	Quantitative analysis of 114 sizable Highrise density area.	Quant	Basic statistical Analyses (correlation analysis, t-test, and such), followed by cross-sectional comparison	114 sizable, high rise buildings from High density area in Hong Kong	Waste minimization management *M & C, Post-construction*	Hong Kong
6	Zhou J.X., Shen G.Q., Yoon S.H., Jin X.	Customization of on-site assembly services by integrating the internet of things and BIM technologies in modular integrated construction	Mixed method research	MM	Interviews, case study	A trial project in Hong Kong	Data management and exchange, insufficient data *Assemblage (M & C)*	Hong Kong
7	Bendi D., Rana M.Q., Arif M., Goulding J.S., Sawhney A.	An off-site construction readiness maturity model for the Indian construction sector	Qualitative research approach interpretivism philosophy	Qual	Interviews (15 semi-structured interviews and 5 validation interviews) Content analysis, discourse analysis and actor verification	Indian construction industry and OSC	Organizational readiness for transition *Pre-Construction and Prelims*	India

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
8	Yang Y., Pan W.	Automated guided vehicles in modular integrated construction: potentials and future directions	Qualitative research approach (Lit Review, Site Visits and Interviews)	Qual	Scenario Approach (6 iterations)	Automated Guided Vehicles (AVG)	Logistics (Automated Guided Vehicles) *Assemblage (M & C)*	Hong Kong
9	Wuni I.Y., Shen G.Q., Antwi-Afari M.F.	Exploring the design risk factors for modular integrated construction projects	mixed method research (Lit Review, Validation through expert review/interview; survey questionnaire)	MM	Basic statistical analysis (Cronbach alpha test, Pearson, correlation analysis, Mann-Whitney U-test, Shapiro-Wilk test)	No focused project.	Design risks *Pre-Construction and Prelims*	Global View
10	Jin X., Ekanayake E.M.A.C., Shen G.Q.P.	Critical policy drivers for Modular integrated Construction projects in Hong Kong	SLR to identify factors Quantitative approach, positivism (deductive research approach)	Quant	Basic Statistical Analysis for significance (criticality) analysis, exploratory factor analysis,	No focused project.	policy driving force (PDFs) Policies *Pre-Construction and Prelims*	Hong Kong
11	Balogun T.B., Awonuga O.O., Abowen-Dake R.	Investigating digital technological competencies amongst Black Asian minority ethnic construction students in the UK	positivism philosophy Purposive sampling Quantitative approach using questionnaire	Quant	Basic statistics using Shapiro-Wilk test and mean values	Black Asian Minority Ethnic (BAME) Construction Undergraduates Graduate Students (CUGS)	skill shortage *Pre-Construction and Prelims (Strategy and Design Issues)*	UK
12	Wuni I.Y., Shen G.Q.	Exploring the critical production risk factors for modular integrated construction projects	Literature review of academic and expert articles, questionnaire survey, exploratory study using quantitative analysis	Quant	Basic Statistical analysis (Cronbach alpha test, mean value for factor severity)	No project	production risk factors *Manufacturing (M & C)*	Global View
13	Saad S., Alaloul W.S., Ammad S., Qureshi A.H.	A qualitative conceptual framework to tackle skill shortages in offsite construction industry: a scientometric approach	Literature Review	R	Scientometric analysis	No project developed a qualitative conceptual framework	skill shortage *Pre-Construction and Prelims (Strategy, Design Issues, M & C)*	Global View
14	Zhang Z., Pan W., Pan M.	Critical considerations on tower crane layout planning for high-rise modular integrated construction	Multi-method (mixed method)	MM	Interviews and Case Study	High rise MiC	tower crane layout planning *SCL/M (M &C)*	Hong Kong

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
15	Lin T., Lyu S., Yang R.J., Tivendale L.	Offsite construction in the Australian low-rise residential buildings' application levels and procurement options	Mixed method research (Survey questionnaire with 35 professionals and semi-structured interviews with 20 interviewees)	MM	Thematic analysis basic stats using mean value	Low rise prefab buildings	low rise OSC buildings *Pre-Construction Prelims, SCL/M (M &C)*	Australia
16	Ginigaddara B., Perera S., Feng Y., Rahnamayiezekavat P.	An evaluation of offsite construction skill profiles	Qualitative research	Qual	Round table discussion, word cloud, ranking data	OSC and trad constructions	OSC skill requirement *Pre-Construction and Prelims (Strategy, Design Issues, M & C)*	Australia
17	Malla P., Xiong F., Cai G., Xu Y., Larbi A.S., Chen W.	Numerical study on the behaviour of vertical bolted joints for precast concrete wall-based low-rise buildings	Experimentation (Numeric)	Exp	Finite element analysis, contact analysis, parametric study, developed a simplified model for predicting shear capacity of bolted joints	Experimental precast concretes	bolted joints *Assemblage (M & C)*	
18	Gbadamosi A.-Q., Oyedele L., Mahamadu A.-M., Kusimo H., Bilal M., Davila Delgado J.M., Muhammed-Yakubu N.	Big data for Design Options Repository: Towards a DFMA approach for offsite construction	Exploratory Study using case study	ExpSt	Case study, expert sampling method,	Block of Offices	BIM repository for OSC *Design Issues, Post Construction Evaluation*	UK
19	Wang Z., Pan W.	A hybrid coupled wall system with replaceable steel coupling beams for high-rise modular buildings	Experimentation (Case study)	Exp	Non-finite Element Analysis	Modular high rise building	Seismic effect on modular high rise building *Operation (M & C)*	Hong Kong
20	Ismail Z.-A.	Lesson learned in maintaining the precast concrete buildings	Exploratory study using case study	ExpSt	Case study	Residential and non-residential PC buildings (8)	Maintenance management (building lifecycle) *Post Construction and Evaluation*	Malaysia
21	Bras A., Ravijanya C., de Sande V.T., Riley M., Ralegaonkar R.V.	Sustainable and affordable prefab housing systems with minimal whole life energy use	Mixed method research	MM	MM	Sustainable and affordable housing	Energy building design method and code *Pre-Construction Prelim (Strategy) and Design Issues*	India
22	Pan W., Hon C.K.	Briefing: Modular integrated construction for high-rise buildings	Exploratory Technical paper Observations	ExpSt	Systems boundary criteria	High density, high rise	MiC *Pre-Construction Prelim (Strategic Definition and Prelims)*	Hong Kong

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
23	Razkenari M., Fenner A., Shojaei A., Hakim H., Kibert C.	Perceptions of offsite construction in the United States: An investigation of current practices	Mixed method research	MM	Symposium (unstructured interview), questionnaire, R-studio	Statistical Analysis attempted evaluating level of importance of each strategy, level of impact of each challenge, level of importance of each barrier, important factors when considering OSC, current major drivers, as predictability measure of the identified factors with basic stats, using mean values	OSC adoption perception, applied swot analysis *Pre-Construction Prelim (Strategic Definition and Prelims)*	US
24	Luo L., Jin X., Shen G.Q., Prof., Wang Y., Liang X., Li X., Li C.Z.	Supply Chain Management for Prefabricated Building Projects in Hong Kong	Mixed method research case study, document analysis, interviews Big data by advanced information technology (RFID)	MM	Statistical analysis (scatter plots and line graphs)	production, transportation, and assembly applied root cause analysis	supply chain management using root cause analysis *SCM/L (M &C)*	Hong Kong
25	An S., Martinez P., Al-Hussein M., Ahmad R.	BIM-based decision support system for automated manufacturability check of wood frame assemblies	Experimentation, exploratory study	Exp/ExpSt	Design-Manufacturing process mapping	Design-Manufacturing	Manufacturing *Technical Design (DI) and Manufacturing (M & C)*	No location focus, developed from Canada
26	Wang Z., Wang T., Hu H., Gong J., Ren X., Xiao Q.	Blockchain-based framework for improving supply chain traceability and information sharing in precast construction	Exploratory Study using case study	ExpSt	Process mapping, model development	precast digitalization using blockchain technology	supply chain management *SCM/L (M &C)*	No location focus, developed from China
27	Daget Y.T., Zhang H.	Decision-making model for the evaluation of industrialized housing systems in Ethiopia	Mixed method research	MM	Analytical hierarchy process (AHP), Decision support system (DSS), Expert choice comparison (ECC), Industrialized housing systems (IHSs), multi-criteria decision support system (MDSS) model	Industrialized Housing System	Decision making *Pre-Construction Prelim (Strategic Definition and Prelims)*	Ethiopia (Africa)

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
28	Andersson N., Lessing J. (Technical Paper)	Industrialization of construction: Implications on standards, business models and project orientation	Qualitative research on	Qual	Interviews	Precast digitalization	Business relationship between industrialized and project based construction *Business models (M & C)*	No specific region Swedish origin
29	Dixon-Ogbechi B.N., Adebayo A.K.	Application of the AHP model to determine prefab housing adoption factors for developers in Lagos State	Quantitative analysis	Quant	Analytical hierarchy process (AHP), Decision support system (DSS), Developers choice comparison (ECC), Industrialized housing systems (IHSs), Sensitivity Analysis	Most Important building decision factors	Building developers *Pre-Construction Prelim (Strategic Definition and Prelims)*	Nigeria
30	Wuni I.Y., Shen G.Q., Osei-Kyei R., Agyeman-Yeboah S.	Modelling the critical risk factors for modular integrated construction projects	quantitative assessment structured questionnaire	Quant	Factor analysis (PCA) fuzzy synthetic modelling (check if this is predictive)	OSC (MiC)	Critical Risk Factors (feature selection) *Pre-Construction Prelim (Strategic Definition and Prelims)*	Global View
31	Jiang W., Wu L., Cao Y.	Multiple Precast Component Orders Acceptance and Scheduling	Quantitative study (predictive in nature)	Quant	Used a heuristic algorithm and a dynamic order acceptance heuristic.	Acceptance order schedule develops a precast component order acceptance and scheduling model to maximize the total profit in a stochastic multiple orders environment	supply chain management *SCM/L (M &C)*	China
32	Yang Y., Pan M., Pan W.	'Co-evolution through interaction' of innovative building technologies: The case of modular integrated construction and robotics	qualitative(exploratory) study	Qual/ ExpSt	Content analysis exploratory analysis using case study	Scope: modular integrated construction and robotics Measures: socio-technical transitions and technology interaction theories	A new theory built Co-evolution of Innovative Building Technologies (IBTs) *SCM/L (M &C)*	Hong Kong
33	Ahmad S., Soetanto R., Goodier C.	Lean approach in precast concrete component production	Exploratory and descriptive	ExpSt	By semi-structured interviews. case study and mapping of the reinforcement work based on time study technique and time lapsed video	eliminate previously overlooked non-value added (NVA) activities to enhance the	Prefab concrete production of industrialized building system (6 storey precast building) *Manufacturing (M & C)*	Malaysia

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
					Lean process application	efficiency of the production process. lean production		
34	Zhang R., Zhou A.S.J., Tahmasebi S., Whyte J.	Long-standing themes and new developments in offsite construction: The case of UK housing	Review of government policy documents (2004-2019)	R	Bibliometric and thematic analysis	addressing the failure of meeting UK's housing challenge	housing and housing provision *Pre-Construction Prelim (Strategic Definition and Prelims)*	UK
35	Goh M., Goh Y.M.	Lean production theory-based simulation of modular construction processes	Mixed approach A case study approach, real life project study Interviews Quantitative Analysis	MM	Discrete Event Simulation (DES) Model in Arena Simulation model Mapping Sensitivity Analysis Statistical analysis	Develop a project baseline for lean production	Lean production, housing project (condominiums) *Manufacturing, SCM/L (M & C)*	Singapore
36	Zhai Y., Fu Y., Xu G., Huang G.	Multi-period hedging and coordination in a prefabricated construction supply chain	Mixed approach case study, real life study Numerical experimentation	MM	decision models, game theories comparison Numeric analysis (mathematical models)	housing project, construction lead time	buffer space hedging (supply chain management) *SCM/L (M & C)*	Hong Kong
37	Sutrisna M., Goulding J.	Managing information flow and design processes to reduce design risks in offsite construction projects	Case study, archival study Critical realist paradigm	CS	theory-oriented process-tracing, analytical technique, clarification discussion.	2 school projects (one in the UK and one in Australia	Design risks in the phases of offsite project delivery, including occupancy phase *Pre-Construction Prelim (Strategic Definition and Prelims), DI and Post Construction and Evaluation*	UK and Australia
38	Sutrisna M., Cooper-Cooke B., Goulding J., Ezcan V.	Investigating the cost of offsite construction housing in Western Australia	Case study Archival Study Critical realist paradigm	CS	Comparative data analysis	Residential	Detailed cost analysis of three offsite construction projects in WA. OSC Cost *Pre-Construction Prelim (Strategic Definition and Prelims)*	West Australia
39	Wuni I.Y., Shen G.Q.	Towards a decision support for modular integrated construction: an integrative review of the primary decision-making actors	Integrative review (SLR)	R	stage gate approach Content Analysis	MiC	Decision Making Factors (DMF) *Pre-Construction Prelim (Strategic Definition and Prelims)*	Global

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
40	Wuni I.Y., Shen G.Q.P., Mahmud A.T.	Critical risk factors in the application of modular integrated construction: a systematic review	Exploratory study- A qualitative research design systematic literature review	Qual	Thematic-Content Analyses	MiC	Critical Risk Factors of MiC *Pre-Construction Prelim (Strategic Definition and Prelims)*	Global
41	Sutrisna M., Ramanayaka C.D.D., Goulding J.S.	Developing work breakdown structure matrix for managing offsite construction projects	Critical realist paradigm Archival Study of cases Discussion	CS	WBS-Matrix	Case 1: 5 volumetric classroom modules Case 2: school building (smaller nursery building and the main secondary classroom building) no detailed info provided	Work Breakdown Structure *Manufacturing (M & C)*	West Australia and England
42	Zhai Y., Zhong R.Y., Huang G.Q.	Buffer space hedging and coordination in prefabricated construction supply chain management	Literature Review	R	Game approach, model comparison, model development Comparison analysis Numerical study	Buffer space hedging Supply chain coordination	Buffer space hedging (BSH) issue in the prefabricated construction supply chain management (PCSCM) *SCM/L (M & C)*	No specific region Honk Kong origin
43	Karthikeyan V., Vinodhini E., Aparna P., Monika T., Kumar R.S.	Study on comparison between prefabricated and conventional structures	Quantitative Research	Quant	Literature review Comparative cost analysis	single and multi-storey residential buildings G+7 storey housing board colony building	precast construction industry cost effectiveness of precast concrete construction for single and multi-storey residential buildings *Pre-Construction Prelim (Strategic Definition and Prelims)*	India
44	Zhu H., Hong J., Shen G.Q., Mao C., Zhang H., Li Z.	The exploration of the life-cycle energy saving potential for using prefabrication in residential buildings in China	Mixed approach case study, (Scenario-based) Quantitative study	MM	I–O analysis (Higher order analysis) Process-order analysis Hybrid Analysis	Scenario based Tad and precast constructed building with/out energy compliance measures Case study of 2 prefab buildings in Chengdu and Shenzhen, Sichuan, China	Building Energy *Pre-Construction Prelim (Strategic Definition and Prelims) and Post-Construction and Evaluation*	China

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
45	Yuan Z., Sun C., Wang Y.	Design for Manufacture and Assembly-oriented parametric design of prefabricated buildings	Comparative/Exploratory study	ExpSt	process improvement mapping	Design Software	DfMA *Design Issues*	China
46	Arashpour M., Bai Y., Aranda-mena G., Bab-Hadiashar A., Hosseini R., Kalutara P.	Optimizing decisions in advanced manufacturing of prefabricated products: Theorizing supply chain configurations in off-site construction	Exploratory study using case study	ExpSt	three research hypotheses on optimization of supply decisions and configurations are developed and tested	Real-world precast panel production project	Optimization of purchasing decision for supply chain decision making *SCM/L (M & C)*	No specific region
47	Zhai Y., Zhong R.Y., Li Z., Huang G.	Production lead-time hedging and coordination in prefabricated construction supply chain management	quantitative analysis	Quant	decision models, comparative cost analysis	Supply chain management and site hedging of a Prefab house- a real life project	Model development for Production lead-time hedging and coordination Game theory comparison *SCM/L (M & C)*	Huizhou, Guangdong Province, China
48	Savoia M., Buratti N., Vincenzi L.	Damage and collapses in industrial precast buildings after the 2012 Emilia earthquake	Mixed approach, (discussion and case study)	MM	Ground motion analysis	prefabricated RC industrial buildings	Earthquake impact *Construction (M & C)*	Italy
49	Hanna A.S., Mikhail G., Iskandar K.A.	State of Prefab Practice in the Electrical Construction Industry: Qualitative Assessment	Quantitative study	Quant	Statistical analysis (Chi Square)	No focused project	prefab electrical components *Pre-Construction Prelim (Strategic Definition and Prelims)*	US and Canada
50	Hamzeh F., Ghani O.A., Bacha M.B.S., Abbas Y.	Modular concrete construction the differing perspectives of designers, manufacturers, and contractors in Lebanon	Mixed method research (case study and face-to-face structured interviews, survey analysis	MM	Basic statistical analysis	Lebanese Precast concrete firms	OSC adoption *Pre-Construction Prelim (Strategic Definition and Prelims)*	Lebanon
51	Anvari B., Angeloudis P., Ochieng W.Y.	A multi-objective GA-based optimisation for holistic Manufacturing, transportation and Assembly of precast construction	Quantitative study with case study	Quant	Genetic Algorithm-based (GA-based) searching technique	Manufacturing, transportation and Assembly (MtA) sectors of precast construction projects	Precast manufacturing and supply logistics (Resource scheduling) *Manufacturing and SCM/L (M &C)*	UK

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
52	Xiao J., Ding T., Pham T.L.	Seismic performance of precast recycled concrete frame structure	Experimentation (Case study)	Exp	Wen Chuan wave (WCW, 2008, N-S), El Centro wave (ELW, 1940, N-S), and Shanghai artificial wave (SHW) were selected as the input seismic waves, in the order WCW → ELW→ SHW during the test process.	a six-story precast recycled aggregate concrete (RAC) space frame structure	Seismic effect on precast building *Construction (M & C)*	Italy
53	Goulding J.S., Pour Rahimian F., Arif M., Sharp M.D.	New offsite production and business models in construction: priorities for the future research agenda	3	3	The inferential analysis of variance (ANOVA) methods	People, Process and Technology	Offsite manufacturing and production with respect to OSC adoption in the UK *Pre-Construction Prelim (Strategic Definition and Prelims)*	UK (discussion participant: UK, Netherlands and Australia)
54	Nath T., Attarzadeh M., Tiong R.L.K., Chidambaram C., Yu Z.	Productivity improvement of precast shop drawings generation through BIM-based process re-engineering	3	MM	Surveys, interview, workshop and experiments	A precast façade as an example	Productivity improvement of precast shop drawings generation through BIM-based process re-engineering *Design Issues*	Singapore
55	Demian P., Walters D.	The advantages of information management through building information modelling	Mixed method research	MM	hierarchical information paradigm	4 different facilities	Information management using 4 systems *Pre-Construction Prelim (Strategic Definition and Prelims)*	England
56	Abedi M., Rawai N.M., Fathi M.S., Fathi M.S., Mirasa A.K.	Cloud computing as a construction collaboration tool for precast supply chain management		UD				No specific region
57	Khalili A., Chua D.K.H.	IFC-based framework to move beyond individual building elements toward configuring a higher level of prefabrication		UD				No specific region
58	Lachimpadi S.K., Pereira J.J., Taha M.R., Mokhtar M.	Construction waste minimisation comparing conventional and precast construction (Mixed System and IBS) methods in high-rise buildings: A Malaysia case study	case study	CS	Quant approach, (mathematical) analysis	High rise building medium cost high rise residential buildings	Construction waste generation and management *Post Construction and Evaluation*	Malaysia

S/No	Authors	Title	Research Instrument (RI) used	RI Code	Analytical Tool used	Project type	Study focus	Location focus
59	Pan W., Sidwell R.	Demystifying the cost barriers to offsite construction in the UK	case study	CS	Basic statistical analysis (correlation analysis) Cost comparison analysis	20 medium-to-high rise residential buildings of eight projects by a leading UK housebuilder OSC and trad constructions	Cost *Pre-Construction Prelim (Strategic Definition and Prelims)*	UK
60	Jaillon L., Poon C.-S.	Design issues of using prefabrication in Hong Kong building construction	Mixed method research (questionnaire survey and case studies)	MM	Basic Statistical analysis (mean value and standard deviation for factor severity)	high rise residential buildings	Prefab adoption *Design Issues*	Hong Kong
61	Sacks R., Kaner I., Eastman C.M., Jeong Y.-S.	The Rosewood experiment - Building information modeling and interoperability for architectural precast facades	Experimentation (Case study)	Exp	3D Model design comparison	16 story office building	Architectural facades *Design Issues*	No specific region
62	Polat G.	Precast concrete systems in developing vs. industrialized countries	quantitative Study (questionnaire)	Quant	Basic statistical analysis	Precast Concrete	precast concrete system adoption *Pre-Construction Prelim (Strategic Definition and Prelims)*	US and Turkey
63	Chen Y., Okudan G.E., Riley D.R.	Sustainable performance criteria for construction method selection in concrete buildings	Mixed method research (questionnaire survey, case study (7), interviews and site observations)	MM	Ranking analysis factor analysis	Prefabrication and on-site construction method,	Decision making *Pre-Construction Prelim (Strategic Definition and Prelims)*	US
64	Kale S., Arditi D.	Innovation diffusion modeling in the construction industry	Mixed method research (survey data and 2 case studies)	MM	uses the nonlinear least-squares method, uses the dominant-less dominant analytical method	Construction industry	construction innovation diffusion model *Pre-Construction Prelim (Strategic Definition and Prelims)*	Turkey

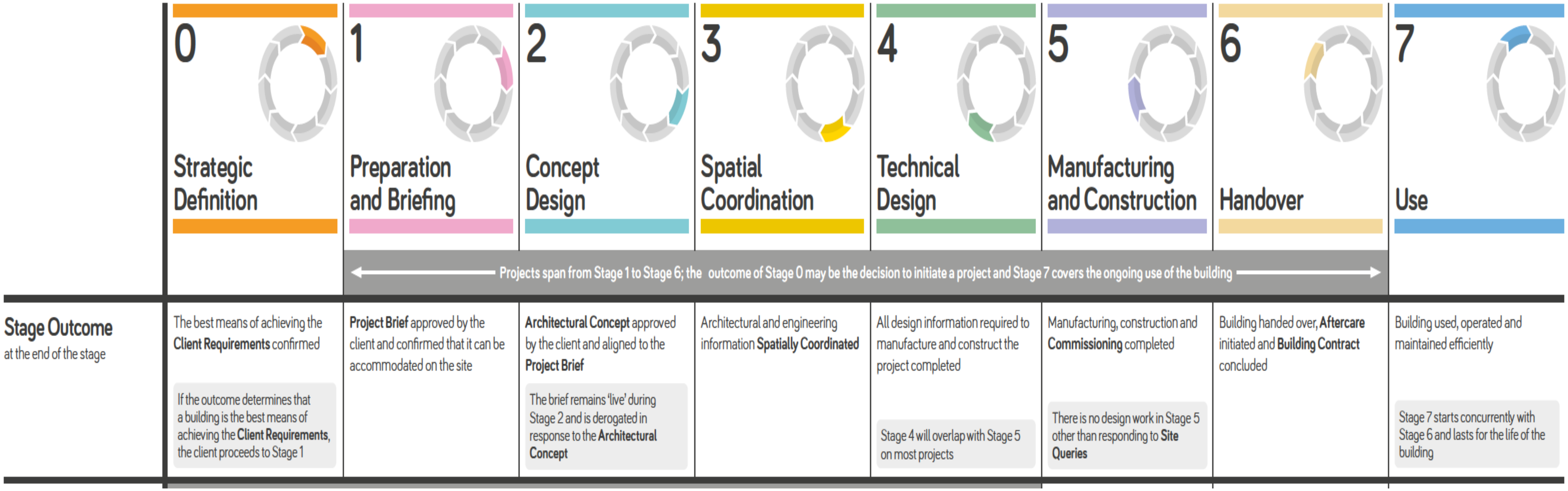

Figure 2.3.1: RIBA POW overlaid with DfMA PoW

Source: RIBA, 2021

. **Table 5.1: Demography of Interview Respondents**

Tag	Discipline/ Qualification/ Experience	Present Practise	Years of Experience (Overall)	Experience in OSC	Years of UK OSC experience	No OSC executed
R1	Architectural Technology and House building	Developing learning materials for Sustainability School	About 45 years	Yes	Over 30 years in DfMA designs	16 Mostly educational and mass housing Many were extensions to an existing building Bespoke building, restaurant extension to a theatre
R2	Architecture	Project delivery leads to higher education, primary health care, transportation infrastructure and residential building for an offsite body.	28 years	Yes	Much DfMA designs, DfMA overlay, build offsite.	50 projects using different categories of OSC approach 524 homes/units; 26 stories
R3	Furniture maker, construction technologist and manager, researcher with PhD in Construction Skills	Research Education and discipline/skill specialist, Research Lead in Building Innovation with an interest in construction industry skills	Over 10 years in the construction industry almost 4 years in building research	From an educational/ research perspective and policy development	4 years	Construction innovation hub
R4	Architecture	Consultant	0ver 30 years	Yes	Well experienced	Numerous
R5	Construction Management	Construction manager, Lecturer	Over 10 years in the industry, 6+ years in the academics	Yes Member of offsite construction community (Offsite Alliance)	> 5 years of improving construction processes	Numerous
R6	Architectural Technologist lead project management architect, OSC Consultant	Technical solution provider for OSC	Over 40 years of construction industry experience	Yes, Specialize in timber, steel, and concrete. Collaborated with an offsite home provider.	21 years in OSC	Numerous OSC projects timber frame-7 storeys, steel- 10 storeys, Vol modular-23 storeys
R7	Architecture	Architectural Office.	25 years	Yes,	Well experienced	Numerous OSC Projects mainly health care and education (also commercial and residential) not necessarily volumetric, but all other forms of DfMA
R8	Architecture	Architectural technologist, computational design coordinator of the manufacturers	5 years	Yes	4 years	New built residential buildings up to 30 storeys, high density, and low rise, façade supply of precast system, computational research on offsite construction decision making 2 designs, 1 delivery (25 stories)
R9	General practise, Chartered Surveyor	Alliance for OSC products knowledge sharing group	25 years	Marketing	Well experienced	Numerous
R10	Architecture	Technical manager at a timber engineering company, chair of an offsite group (8 OSC groups) Process improvement (strategic development position), works with the supply chain team	Well experienced	Worked with a company building fully volumetric OSC	Well experienced	Quite much

Tag	Discipline/ Qualification/ Experience	Present Practise	Years of Experience (Overall)	Experience in OSC	Years of UK OSC experience	No OSC executed
R11	Architecture, Project Manager Site Agent	Project coordinator at a windows and doors manufacturing company	13 years	Doors and windows	5 years	4 or 5 projects/month
R12	Senior Lecturer (Construction Management)	Worked at a leading offsite home developer. Former Operation Manager, Geo-Technique Officer	Over 10 years		Over 7 years	Quite much

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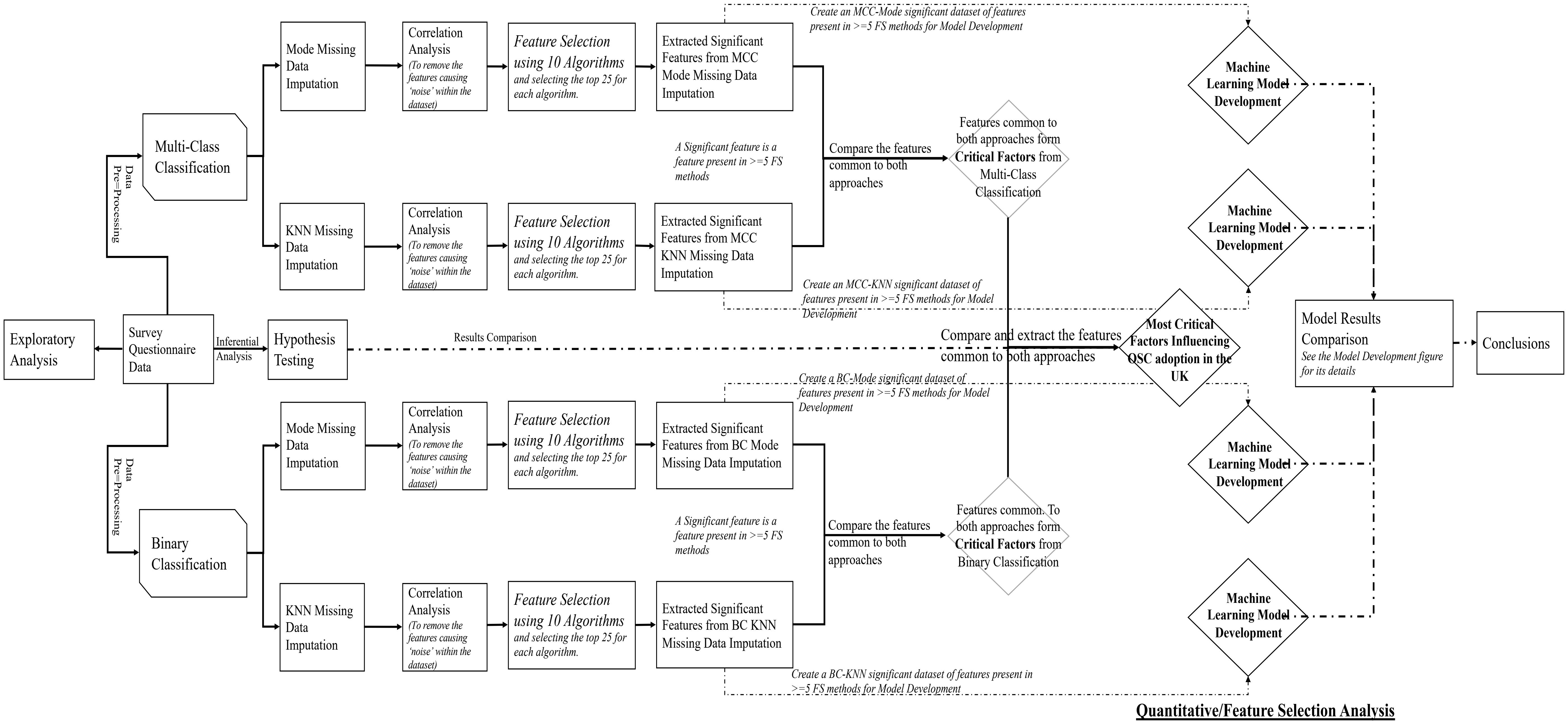

Figure 7.2: Quantitative Analysis/ Feature Selection Framework

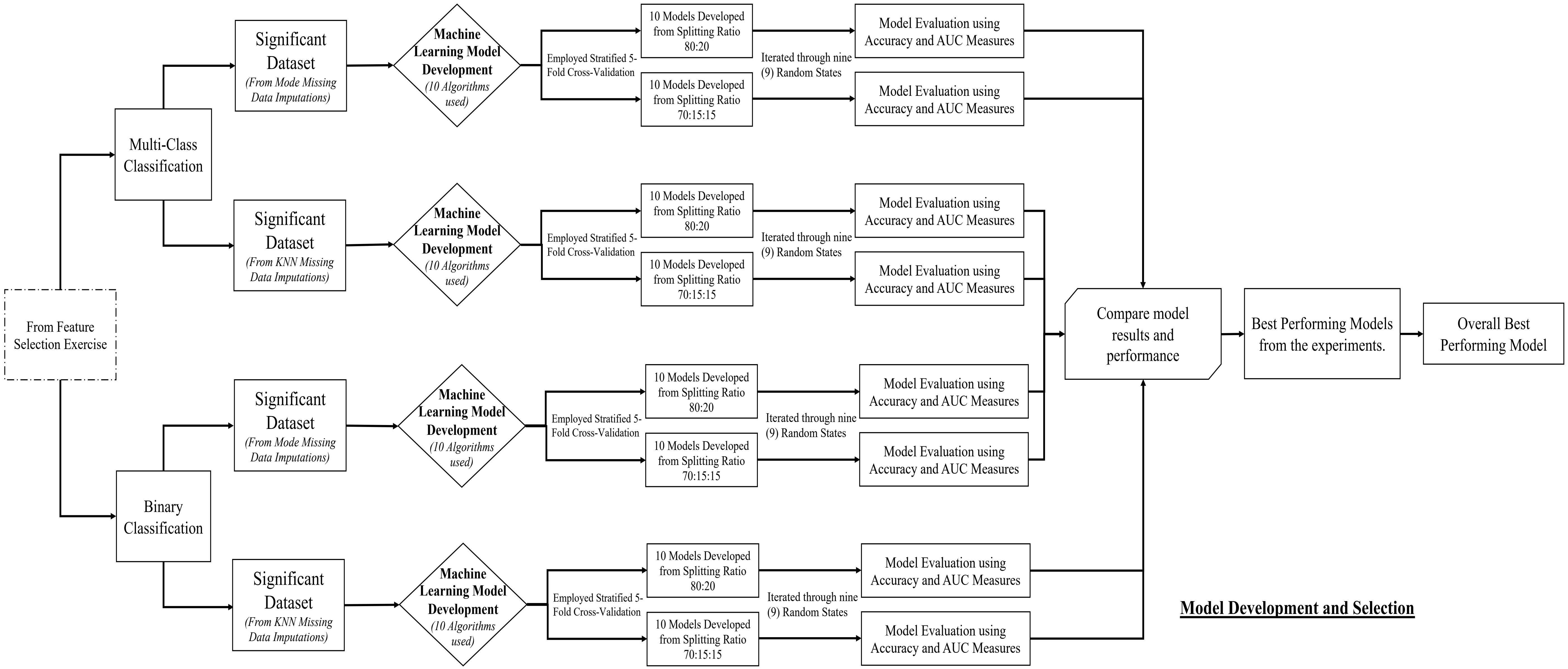

Figure 8.1: Model Development Architecture

Table 9.3a: Machine Learning Results for Random State, RS, (42)

		Multi-Class Classification								**Binary Class**							
		Mode Imputation				**KNN Imputation**				**Mode Imputation**				**KNN Imputation**			
		80:20		**70:15:15**		**80:20**		**70:15:15**		**80:20**		**70:15:15**		**80:20**		**70:15:15**	
Random State	**ML Model**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**
42	Random Forest	0.4762	0.7759	0.4583	0.7417	0.3651	0.7009	0.3750	0.6935	0.7778	0.8385	0.7083	0.7788	0.8413	0.8218	0.7708	0.7465
42	SVC	0.3651	0.7343	0.4375	0.7209	0.3651	0.7423	0.3750	0.7358	0.7937	0.8469	0.7292	0.8141	0.8254	0.8361	0.8125	0.8121
42	Logistic Regression	0.3175	0.7245	0.2500	0.6875	0.3810	0.7035	0.3333	0.6781	0.8571	0.8469	0.7292	0.8323	0.8254	0.8517	0.7083	0.8505
42	Decision Tree	0.3651	0.6009	0.3542	0.5816	0.2698	0.5539	0.2500	0.5175	0.7460	0.6836	0.7917	0.7030	0.7619	0.6950	0.6875	0.6273
42	K Neighbors	0.4286	0.6997	0.4167	0.7008	0.3651	0.6679	0.2708	0.6824	0.7778	0.8032	0.7500	0.8354	0.8095	0.7978	0.7708	0.7333
42	Gradient Boosting	0.3968	0.7037	0.4375	0.6853	0.3968	0.6837	0.3125	0.6486	0.7778	0.8110	0.7292	0.7313	0.7619	0.8086	0.8125	0.7899
42	Extra Trees	0.4286	0.7565	0.4375	0.7547	0.3810	0.6915	0.4167	0.6886	0.8254	0.8283	0.7292	0.7798	0.8254	0.8140	0.7708	0.7566
42	MLP	0.2698	0.6847	0.3125	0.6356	0.4603	0.7128	0.3750	0.6667	0.7302	0.8074	0.6875	0.7212	0.7143	0.7667	0.7292	0.7859
42	Forward Feed NN	0.2698	0.6847	0.3125	0.6356	0.4603	0.7128	0.3750	0.6667	0.7302	0.8074	0.6875	0.7212	0.7143	0.7667	0.7292	0.7859
42	Backward Feed NN	0.3333	0.6953	0.3333	0.7163	0.4286	0.7392	0.3333	0.7157	0.8413	0.8971	0.7500	0.8828	0.7778	0.8397	0.7292	0.8121

Table 9.3b: Machine Learning Results for Random State, RS, (45)

		Multi-Class Classification								Binary Class							
		Mode Imputation				KNN Imputation				Mode Imputation				KNN Imputation			
		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15	
Random State	ML Model	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance
45	Random Forest	0.3810	0.6740	0.2083	0.6316	0.3810	0.6997	0.2083	0.5966	0.7460	0.7512	0.7083	0.7475	0.8095	0.8128	0.7500	0.7657
45	SVC	0.3333	0.7099	0.2917	0.6507	0.4603	0.7497	0.3125	0.6598	0.7460	0.7691	0.7292	0.7475	0.8254	0.8158	0.8333	0.8606
45	Logistic Regression	0.3492	0.6568	0.2083	0.6084	0.4286	0.7026	0.2292	0.6233	0.7619	0.7847	0.6667	0.6848	0.7937	0.8361	0.8125	0.8626
45	Decision Tree	0.2381	0.5222	0.1667	0.4665	0.2698	0.5339	0.1667	0.4768	0.6190	0.6226	0.6250	0.6182	0.7937	0.7925	0.6042	0.5303
45	K Neighbors	0.3651	0.6591	0.2917	0.6605	0.4444	0.6575	0.3333	0.6076	0.6667	0.6806	0.6875	0.6960	0.7460	0.7482	0.7500	0.8121
45	Gradient Boosting	0.3175	0.6267	0.2500	0.5842	0.3810	0.6807	0.2500	0.5935	0.6984	0.6579	0.6667	0.7414	0.7778	0.7859	0.7500	0.7980
45	Extra Trees	0.3651	0.6801	0.2083	0.5906	0.3175	0.6865	0.2708	0.6241	0.7778	0.7392	0.7500	0.7394	0.7937	0.7841	0.7708	0.7495
45	MLP	0.3016	0.6355	0.3125	0.6135	0.3810	0.6910	0.2917	0.6427	0.7302	0.7261	0.6458	0.7333	0.8730	0.8313	0.8125	0.8525
45	Forward Feed NN	0.3016	0.6355	0.3125	0.6135	0.3810	0.6910	0.2917	0.6427	0.7302	0.7261	0.6458	0.7333	0.8730	0.8313	0.8125	0.8525
45	Backward Feed NN	0.2540	0.6439	0.2917	0.5847	0.4444	0.7036	0.3542	0.6162	0.7460	0.7189	0.7292	0.7495	0.7937	0.8074	0.8125	0.8889

Table 9.3c: Machine Learning Results for Random State, RS, (50)

		Multi-Class Classification								Binary Class							
		Mode Imputation				KNN Imputation				Mode Imputation				KNN Imputation			
		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15	
Random State	**ML Model**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**
50	Random Forest	0.4762	0.7285	0.3125	0.7334	0.3333	0.6547	0.2708	0.6570	0.7937	0.8457	0.8750	0.8889	0.7619	0.8349	0.8542	0.8939
50	SVC	0.4127	0.7585	0.3750	0.7401	0.3492	0.7013	0.3542	0.7079	0.7302	0.8696	0.8333	0.8990	0.7778	0.8684	0.8542	0.9051
50	Logistic Regression	0.3016	0.7190	0.3333	0.6723	0.3810	0.6893	0.2708	0.6286	0.7619	0.7584	0.8542	0.8929	0.7778	0.8373	0.8125	0.8869
50	Decision Tree	0.3810	0.6093	0.3125	0.5917	0.3016	0.5518	0.2917	0.5599	0.6349	0.5891	0.7292	0.7303	0.6984	0.6495	0.8333	0.8242
50	K Neighbors	0.3810	0.6954	0.3750	0.6949	0.3175	0.6397	0.3125	0.6730	0.7937	0.8343	0.7500	0.8313	0.8571	0.8355	0.8750	0.9242
50	Gradient Boosting	0.3968	0.6854	0.3542	0.7019	0.3333	0.6688	0.3333	0.6025	0.7937	0.8433	0.8542	0.8929	0.7778	0.8110	0.9167	0.9172
50	Extra Trees	0.3968	0.7039	0.2917	0.7042	0.3333	0.6689	0.3333	0.6537	0.7619	0.8523	0.8542	0.8636	0.7460	0.8505	0.8542	0.8949
50	MLP	0.4127	0.6793	0.3542	0.6064	0.3175	0.6513	0.2292	0.5963	0.7460	0.7859	0.8333	0.8687	0.7937	0.8565	0.8750	0.9192
50	Forward Feed NN	0.4127	0.6793	0.3542	0.6064	0.3175	0.6513	0.2292	0.5963	0.7460	0.7859	0.8333	0.8687	0.7937	0.8565	0.8750	0.9192
50	Backward Feed NN	0.4444	0.7028	0.3125	0.6673	0.3175	0.6687	0.2500	0.6352	0.7937	0.8349	0.8333	0.9010	0.7460	0.8146	0.8542	0.8949

Table 9.3d: Machine Learning Results for Random State, RS, (55)

		Multi-Class Classification								Binary Class							
		Mode Imputation				KNN Imputation				Mode Imputation				KNN Imputation			
		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15	
Random State	**ML Model**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**
55	Random Forest	0.3651	0.6773	0.2917	0.6568	0.4127	0.7147	0.2917	0.6804	0.7778	0.8278	0.7500	0.7596	0.7619	0.8433	0.7708	0.7525
55	SVC	0.3333	0.7295	0.3958	0.6541	0.3810	0.7477	0.4583	0.6785	0.8095	0.8517	0.7708	0.8303	0.8095	0.8505	0.8125	0.8121
55	Logistic Regression	0.3651	0.7264	0.3750	0.6171	0.4603	0.7297	0.4375	0.6519	0.7778	0.7727	0.7708	0.8444	0.7937	0.7955	0.7708	0.8929
55	Decision Tree	0.2540	0.5343	0.1875	0.4870	0.3492	0.5896	0.2292	0.5006	0.6667	0.6118	0.7083	0.6606	0.6825	0.5933	0.6458	0.5606
55	K Neighbors	0.3016	0.6342	0.3958	0.5804	0.3333	0.6648	0.3542	0.6293	0.7302	0.7123	0.6667	0.7444	0.7778	0.7817	0.7708	0.7354
55	Gradient Boosting	0.3492	0.6913	0.3750	0.6299	0.4286	0.7254	0.4583	0.6706	0.7143	0.7404	0.7083	0.7313	0.7302	0.8002	0.7708	0.8081
55	Extra Trees	0.3333	0.6665	0.3542	0.6637	0.3968	0.7186	0.3750	0.6532	0.7619	0.8068	0.7500	0.7717	0.7619	0.8373	0.7917	0.7737
55	MLP	0.2381	0.6298	0.2500	0.5471	0.3333	0.6747	0.3125	0.5898	0.7460	0.7859	0.7500	0.8081	0.8095	0.7907	0.8333	0.8283
55	Forward Feed NN	0.2381	0.6298	0.2500	0.5471	0.3333	0.6747	0.3125	0.5898	0.7460	0.7859	0.7500	0.8081	0.8095	0.7907	0.8333	0.8283
55	Backward Feed NN	0.3968	0.7077	0.3125	0.6084	0.3333	0.6793	0.3542	0.6171	0.7778	0.8385	0.7500	0.8465	0.7619	0.7895	0.8333	0.8808

Table 9.3e: Machine Learning Results for Random State, RS, (60)

		Multi-Class Classification								Binary Class							
		Mode Imputation				KNN Imputation				Mode Imputation				KNN Imputation			
		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15	
Random State	Model	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance
60	Random Forest	0.4286	0.7013	0.3750	0.6936	0.4921	0.7698	0.3958	0.7135	0.6984	0.7721	0.6875	0.6828	0.7460	0.7572	0.7083	0.7101
60	SVC	0.4286	0.7153	0.4167	0.6760	0.4127	0.7571	0.4167	0.7104	0.7937	0.8098	0.6667	0.6485	0.8254	0.8385	0.7708	0.7273
60	Logistic Regression	0.3016	0.6769	0.2708	0.6561	0.3651	0.7042	0.3750	0.6707	0.7302	0.6902	0.6458	0.5818	0.8095	0.8062	0.7292	0.6970
60	Decision Tree	0.2698	0.5333	0.3333	0.5730	0.3333	0.5806	0.1875	0.4817	0.6349	0.5891	0.6250	0.5636	0.6984	0.6196	0.7083	0.6242
60	K Neighbors	0.3810	0.7025	0.4167	0.6731	0.4444	0.7742	0.4583	0.7212	0.7778	0.7584	0.6667	0.6303	0.7937	0.7524	0.7083	0.6859
60	Gradient Boosting	0.3175	0.6530	0.3125	0.6435	0.4444	0.7416	0.2708	0.6654	0.7143	0.7392	0.6875	0.6727	0.6667	0.6914	0.7292	0.6424
60	Extra Trees	0.3968	0.6894	0.2708	0.6701	0.3968	0.7538	0.3542	0.6844	0.7460	0.7494	0.6875	0.6798	0.7302	0.7159	0.7292	0.6758
60	MLP	0.3333	0.6591	0.3333	0.6233	0.3968	0.6990	0.3125	0.6217	0.6667	0.6998	0.5625	0.5333	0.7778	0.7512	0.7292	0.7152
60	Forward Feed NN	0.3333	0.6591	0.3333	0.6233	0.3968	0.6990	0.3125	0.6217	0.6667	0.6998	0.5625	0.5333	0.7778	0.7512	0.7292	0.7152
60	Backward Feed NN	0.3810	0.6823	0.3125	0.6575	0.4286	0.7366	0.4375	0.7215	0.7460	0.6854	0.6458	0.5939	0.7460	0.7620	0.6667	0.6707

Table 9.3f: Machine Learning Results for Random State, RS, (65)

		Multi-Class Classification								Binary Class							
		Mode Imputation				KNN Imputation				Mode Imputation				KNN Imputation			
		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15	
Random State	**ML Model**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**
65	Random Forest	0.3651	0.6700	0.3750	0.6482	0.4127	0.7123	0.3542	0.6644	0.7143	0.7010	0.6458	0.5758	0.7619	0.7339	0.6875	0.5939
65	SVC	0.4286	0.7266	0.3542	0.6661	0.4127	0.7467	0.3542	0.6917	0.7302	0.7524	0.6458	0.5939	0.7619	0.7835	0.7083	0.6263
65	Logistic Regression	0.3333	0.6891	0.2708	0.6684	0.3651	0.6616	0.3750	0.6370	0.7619	0.7548	0.6667	0.6586	0.7778	0.8062	0.6667	0.6505
65	Decision Tree	0.2857	0.5369	0.3125	0.5541	0.2857	0.5362	0.3125	0.5657	0.6190	0.5927	0.6042	0.5485	0.6825	0.6531	0.5833	0.4970
65	K Neighbors	0.2857	0.5976	0.2292	0.5759	0.3651	0.6891	0.2500	0.6055	0.7460	0.7225	0.5625	0.5414	0.7460	0.7404	0.6458	0.6515
65	Gradient Boosting	0.3651	0.6185	0.1875	0.5758	0.3651	0.6837	0.3125	0.6391	0.7778	0.7093	0.6458	0.6020	0.7619	0.7524	0.6458	0.6626
65	Extra Trees	0.2698	0.6952	0.3542	0.6264	0.3651	0.7102	0.3958	0.6193	0.7143	0.7452	0.6458	0.6081	0.7143	0.7398	0.6667	0.5697
65	MLP	0.3175	0.6046	0.2708	0.6295	0.3968	0.6713	0.4583	0.6686	0.7143	0.6890	0.5833	0.5455	0.6825	0.6734	0.6458	0.6182
65	Forward Feed NN	0.3175	0.6046	0.2708	0.6295	0.3968	0.6713	0.4583	0.6686	0.7143	0.6890	0.5833	0.5455	0.6825	0.6734	0.6458	0.6182
65	Backward Feed NN	0.4127	0.6634	0.3333	0.6714	0.4286	0.6854	0.3750	0.6679	0.7619	0.7978	0.6458	0.6404	0.7460	0.7895	0.7083	0.6242

Table 9.3g: Machine Learning Results for Random State, RS, (70)

		Multi-Class Classification								Binary Class							
		Mode Imputation				KNN Imputation				Mode Imputation				KNN Imputation			
		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15	
Random State	ML Model	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance
70	Random Forest	0.4921	0.7518	0.3750	0.7039	0.3651	0.7198	0.3958	0.6925	0.6349	0.7530	0.7708	0.8364	0.7302	0.7775	0.7500	0.8343
70	SVC	0.4603	0.8130	0.4792	0.7687	0.4603	0.7924	0.4167	0.7463	0.7302	0.7548	0.7917	0.8121	0.7460	0.7990	0.7292	0.8040
70	Logistic Regression	0.4286	0.7513	0.3750	0.7118	0.3968	0.7449	0.4167	0.7052	0.6984	0.7177	0.7917	0.8343	0.7460	0.7679	0.7292	0.8061
70	Decision Tree	0.3968	0.6174	0.3750	0.5912	0.3492	0.5932	0.2708	0.5402	0.5714	0.5437	0.6875	0.6818	0.6825	0.6232	0.6250	0.5818
70	K Neighbors	0.3651	0.7406	0.4167	0.6804	0.4444	0.7176	0.3958	0.6586	0.6667	0.6878	0.7500	0.7788	0.7143	0.7530	0.7500	0.7929
70	Gradient Boosting	0.4286	0.7536	0.3750	0.6936	0.3492	0.7137	0.3125	0.7066	0.6508	0.7440	0.7917	0.8364	0.7302	0.7679	0.7292	0.8162
70	Extra Trees	0.4444	0.7417	0.3958	0.7194	0.3492	0.6756	0.3125	0.6643	0.6667	0.7584	0.7083	0.8182	0.7143	0.7392	0.7083	0.7919
70	MLP	0.4762	0.7607	0.3958	0.7032	0.4762	0.7409	0.4167	0.7035	0.5873	0.6926	0.7708	0.7717	0.6667	0.7703	0.6875	0.8061
70	Forward Feed NN	0.4762	0.7607	0.3958	0.7032	0.4762	0.7409	0.4167	0.7035	0.5873	0.6926	0.7708	0.7717	0.6667	0.7703	0.6875	0.8061
70	Backward Feed NN	0.4127	0.7108	0.3750	0.6992	0.4127	0.7436	0.3542	0.7117	0.6984	0.7464	0.7292	0.8424	0.6984	0.7799	0.7500	0.8162

Table 9.3h: Machine Learning Results for Random State, RS, (75)

		Multi-Class Classification								**Binary Class**							
		Mode Imputation				**KNN Imputation**				**Mode Imputation**				**KNN Imputation**			
		80:20		**70:15:15**		**80:20**		**70:15:15**		**80:20**		**70:15:15**		**80:20**		**70:15:15**	
Random State	**ML Model**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**	**Accuracy**	**AUC Performance**
75	Random Forest	0.3968	0.7042	0.4583	0.6986	0.4444	0.7169	0.3125	0.6861	0.7619	0.8672	0.8125	0.8657	0.7778	0.8140	0.8333	0.8717
75	SVC	0.3492	0.7621	0.4167	0.7441	0.4127	0.7696	0.3750	0.7338	0.7460	0.8194	0.7708	0.8828	0.7302	0.8050	0.8125	0.9051
75	Logistic Regression	0.381	0.7381	0.3750	0.7130	0.4444	0.7527	0.3958	0.7190	0.6825	0.7943	0.7083	0.8182	0.7302	0.8493	0.7917	0.8566
75	Decision Tree	0.3175	0.5575	0.2708	0.5320	0.2222	0.5118	0.2292	0.5164	0.7302	0.7620	0.7083	0.6788	0.6984	0.6346	0.7292	0.6758
75	K Neighbors	0.4286	0.6518	0.5833	0.7650	0.3175	0.6835	0.3333	0.6707	0.7302	0.7117	0.8125	0.8162	0.7778	0.7476	0.8125	0.8596
75	Gradient Boosting	0.3492	0.6822	0.4167	0.7039	0.4444	0.7180	0.3125	0.6298	0.7302	0.7883	0.7917	0.8505	0.6984	0.7644	0.7708	0.8727
75	Extra Trees	0.4286	0.6795	0.3958	0.6984	0.3810	0.6994	0.3333	0.6678	0.7143	0.7709	0.7500	0.8788	0.6984	0.7554	0.7500	0.8596
75	MLP	0.3651	0.6908	0.3750	0.6429	0.3968	0.7049	0.2708	0.6236	0.6984	0.7990	0.7292	0.8505	0.7302	0.8230	0.8333	0.8828
75	Forward Feed NN	0.3651	0.6908	0.3750	0.6429	0.3968	0.7049	0.2708	0.6236	0.6984	0.7990	0.7292	0.8505	0.7302	0.8230	0.8333	0.8828
75	Backward Feed NN	0.3651	0.7216	0.4583	0.7189	0.4127	0.7517	0.3750	0.6995	0.7302	0.8230	0.7708	0.8646	0.7619	0.8134	0.7917	0.8848

Table 9.3i: Machine Learning Results for Random State, RS, (80)

		Multi-Class Classification								Binary Class							
		Mode Imputation				KNN Imputation				Mode Imputation				KNN Imputation			
		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15		80:20		70:15:15	
Random State	ML Model	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance	Accuracy	AUC Performance
80	Random Forest	0.4603	0.7725	0.4792	0.7849	0.3175	0.7096	0.2917	0.7177	0.7460	0.7996	0.7500	0.7556	0.7460	0.8140	0.7500	0.8121
80	SVC	0.3968	0.7712	0.3958	0.7769	0.3651	0.7912	0.5208	0.7696	0.7619	0.7811	0.7292	0.7293	0.7619	0.8026	0.7500	0.7596
80	Logistic Regression	0.3651	0.7525	0.3958	0.7362	0.3492	0.7642	0.2292	0.6655	0.7302	0.8038	0.7500	0.7253	0.7778	0.8110	0.7708	0.7616
80	Decision Tree	0.2698	0.5498	0.4167	0.6384	0.2540	0.5240	0.1875	0.4881	0.5873	0.5700	0.6458	0.5606	0.5397	0.5359	0.7083	0.6788
80	K Neighbors	0.3810	0.6742	0.4375	0.6898	0.3810	0.6992	0.4375	0.7045	0.6825	0.7315	0.6875	0.7273	0.7619	0.7919	0.7708	0.7828
80	Gradient Boosting	0.4127	0.7236	0.3958	0.7005	0.3016	0.6958	0.3333	0.6695	0.7302	0.8122	0.6875	0.7273	0.7460	0.7644	0.7292	0.7657
80	Extra Trees	0.4286	0.7224	0.5000	0.7593	0.3810	0.6849	0.3125	0.6994	0.7302	0.7972	0.7292	0.7364	0.7619	0.8008	0.7500	0.7586
80	MLP	0.4444	0.6864	0.3542	0.6707	0.3651	0.6750	0.3542	0.6469	0.6825	0.7787	0.6250	0.7455	0.7460	0.7811	0.7083	0.7354
80	Forward Feed NN	0.4444	0.6864	0.3542	0.6707	0.3651	0.6750	0.3542	0.6469	0.6825	0.7787	0.6250	0.7455	0.7460	0.7811	0.7083	0.7354
80	Backward Feed NN	0.4127	0.7053	0.5208	0.7643	0.4286	0.7302	0.3333	0.6776	0.7302	0.7883	0.6667	0.7212	0.7619	0.8050	0.7292	0.7232

Table 9.3j: Machine Learning Best Results Table for Random State, RS, (42-80) Iterations

		Multi-Class Classification								**Binary Class**							
		Mode Imputation				**KNN Imputation**				**Mode Imputation**				**KNN Imputation**			
		80:20		**70:15:15**		**80:20**		**70:15:15**		**80:20**		**70:15:15**		**80:20**		**70:15:15**	
Random State	**ML Model**	**Accuracy**	**AUC Performanc e**	**Accuracy**	**AUC Performanc e**	**Accuracy**	**AUC Performanc e**	**Accurac y**	**AUC Performanc e**	**Accuracy**	**AUC Performanc e**	**Accuracy**	**AUC Performanc e**	**Accuracy**	**AUC Performanc e**	**Accuracy**	**AUC Performance**
	Best Results	Rando m Forest, RS 70 0.4921	SVC, RS 70 0.8130	K Neighbors , RS 75 0.5833	Random Forest, RS 80 0.7849	Rando m Forest, RS 80 0.4921	SVC, RS 80 0.7912	SVC, RS 80 0.5208	SVC, RS 80 0.7696	Logistic Regression , RS 42 0.8571	Backward Feed NN, RS 42 0.8971	Rando m Forest, RS 50 0.8750	Backward Feed NN, RS 50 0.9010	MLP, RS 45 Forward Feed NN, RS 45 **0.8730**	SVC, RS 50 0.8684	Gradient Boosting , RS 50 0.9167	KN, RS 50 0.9242

***Best results for Accuracy are highlighted in green and best AUC performance are highlighted in yellow.**

Best Models from Multi-Class Classifications (Mode Missing Data Imputation)

Table 9.4a: Detailed Performance of models with high Accuracy (Multi-Classification, Mode Imputation, Splitting Ratio 80: 20)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
70	Random Forest	1	1	1	1	1	{'2': 76, '3': 58, '5': 42, '1': 41, '4': 35}		0.3934	0.4407	0.4064	0.4921	0.7518	{'2': 19, '3': 15, '5': 10, '1': 10, '4': 9}	{'n_estimators': 100, 'max_depth': None}

Table 9.4b: Detailed Performance of models with high AUC performance (Multi-Classification, Mode Imputation, Splitting Ratio 80: 20)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
70	SVC	0.7509	0.6643	0.6803	0.7063	0.9326	{'2': 76, '3': 58, '5': 42, '1': 41, '4': 35}		0.4978	0.4118	0.4114	0.4603	0.8130	{'2': 19, '3': 15, '5': 10, '1': 10, '4': 9}	{'C': 1.0, 'kernel': 'rbf'}

Table 9.4c: Detailed Performance of models with high accuracy (Multi-Classification, Mode Imputation, Splitting Ratio 70:15:15)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Val Precision	Val Recall	Val F1 Score	Val Accuracy	Val AUC	Val Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
75	K Neighbors	0.5638	0.5317	0.5404	0.5455	0.8614	{'2': 66, '3': 51, '5': 36, '1': 36, '4': 31}		0.266	0.2795	0.2627	0.2766	0.5472	{'2': 14, '3': 11, '5': 8, '1': 7, '4': 7}		0.5983	0.5503	0.5596	0.5833	0.765	{'2': 15, '3': 11, '5': 8, '1': 8, '4': 6}	{'n_neighbors': 5, 'weights': 'uniform'}

Table 9.4d: Detailed Performance of models with high AUC performance (Multi-Classification, Mode Imputation, Splitting Ratio 70:15:15)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Val Precision	Val Recall	Val F1 Score	Val Accuracy	Val AUC	Val Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
80	Random Forest	1	1	1	1	1	{'2': 66, '3': 51, '5': 36, '1': 36, '4': 31}		0.3236	0.3049	0.3001	0.3404	0.7057	{'2': 14, '3': 11, '5': 8, '4': 7, '1': 7}		0.4634	0.4477	0.4484	0.4792	0.7849	{'2': 15, '3': 11, '1': 8, '5': 8, '4': 6}	{'n_estimators': 100, 'max_depth': None}

Best Models from Multi-Class Classifications (KNN Missing Data Imputation)

Table 9.4e: Detailed Performance of models with high Accuracy (Multi-Classification, KNN Imputation, Splitting Ratio 80: 20)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
60	Random Forest	1	1	1	1	1	{'2': 76, '3': 58, '5': 42, '1': 41, '4': 35}		0.5347	0.4657	0.4811	0.4921	0.7698	{'2': 19, '3': 15, '5': 10, '1': 10, '4': 9}	{'n_estimators': 100, 'max_depth': None}

Table 9.4f: Detailed Performance of models with high AUC performance (Multi-Classification, KNN Imputation, Splitting Ratio 80: 20)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
80	SVC	0.8044	0.7192	0.7454	0.75	0.9282	{'2': 76, '3': 58, '5': 42, '1': 41, '4': 35}		0.4185	0.3191	0.3088	0.3651	0.7912	{'2': 19, '3': 15, '5': 10, '1': 10, '4': 9}	{'C': 1.0, 'kernel': 'rbf'}

Table 9.4g: Detailed Performance of models with high accuracy (Multi-Classification, KNN Imputation, Splitting Ratio 70:15:15)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Val Precision	Val Recall	Val F1 Score	Val Accuracy	Val AUC	Val Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
80	SVC	0.8206	0.7432	0.7683	0.7682	0.9479	{'2': 66, '3': 51, '5': 36, '1': 36, '4': 31}		0.5073	0.3477	0.3529	0.3830	0.7664	{'2': 14, '3': 11, '5': 8, '4': 7, '1': 7}		0.7146	0.4476	0.4737	0.5208	0.7696	{'2': 15, '3': 11, '1': 8, '5': 8, '4': 6}	{'C': 1.0, 'kernel': 'rbf'}

Table 9.4h: Detailed Performance of models with high AUC performance (Multi-Classification, KNN Imputation, Splitting Ratio 70:15:15)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Val Precision	Val Recall	Val F1 Score	Val Accuracy	Val AUC	Val Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
80	SVC	0.8206	0.7432	0.7683	0.7682	0.9479	{'2': 66, '3': 51, '5': 36, '1': 36, '4': 31}		0.5073	0.3477	0.3529	0.383	0.7664	{'2': 14, '3': 11, '5': 8, '4': 7, '1': 7}		0.7146	0.4476	0.4737	0.5208	0.7696	{'2': 15, '3': 11, '1': 8, '5': 8, '4': 6}	{'C': 1.0, 'kernel': 'rbf'}

Best Models from Binary Classifications (Mode Missing Data Imputation)

Table 9.5a: Detailed Performance of models with high accuracy result (Binary Classification, Mode Imputation, Splitting Ratio 80:20)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
42	Logistic Regression	0.7193	0.5325	0.6119	0.7937	0.8299	{0: 175, 1: 77}		0.8125	0.6842	0.7429	0.8571	0.8469	{0: 44, 1: 19}	{'C': 1.0, 'solver': 'lbfgs'}

Table 9.5b: Detailed Performance of models with high AUC performance (Binary Classification, Mode Imputation, Splitting Ratio 80:20)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
42	Backward Feed NN	1	1	1	1	1	{0: 175, 1: 77}		0.7647	0.6842	0.7222	0.8413	0.8971	{0: 44, 1: 19}	{'hidden_layer_sizes': (100,), 'activation': 'tanh', 'solver': 'adam'}

Table 9.5c: Detailed Performance of models with high accuracy result (Binary Classification, Mode Imputation, Splitting Ratio 70:15:15)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Val Precision	Val Recall	Val F1 Score	Val Accuracy	Val AUC	Val Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
50	Random Forest	1	1	1	1	1	{0: 153, 1: 67}		0.6	0.2143	0.3158	0.7234	0.8009	{0: 33, 1: 14}		0.8462	0.7333	0.7857	0.8750	0.8889	{0: 33, 1: 15}	{'n_estimators': 100, 'max_depth': None}

Table 9.5d: Detailed Performance of models with high AUC performance (Binary Classification, Mode Imputation, Splitting Ratio 70:15:15)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Val Precision	Val Recall	Val F1 Score	Val Accuracy	Val AUC	Val Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
50	Backward Feed NN	1	1	1	1	1	{0: 153, 1: 67}		0.6364	0.5	0.56	0.766	0.7597	{0: 33, 1: 14}		0.7059	0.8	0.75	0.8333	0.9010	{0: 33, 1: 15}	{'hidden_layer_sizes': (100,), 'activation': 'tanh', 'solver': 'adam'}

Best Models from Binary Classifications (KNN Missing Data Imputation)

Table 9.5e: Detailed Performance of models with high accuracy result (Binary Classification, KNN Imputation, Splitting Ratio 80:20)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
45	MLP	1	1	1	1	1	{0: 175, 1: 77}		0.8235	0.7368	0.7778	0.8730	0.8313	{0: 44, 1: 19}	{'hidden_layer_sizes': (100,), 'activation': 'relu', 'solver': 'adam'}
45	Forward Feed NN	1	1	1	1	1	{0: 175, 1: 77}		0.8235	0.7368	0.7778	0.8730	0.8313	{0: 44, 1: 19}	{'hidden_layer_sizes': (100,), 'activation': 'relu', 'solver': 'adam'}

Table 9.5f: Detailed Performance of models with high AUC performance (Binary Classification, KNN Imputation, Splitting Ratio 80:20)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
50	SVC	0.8769	0.7403	0.8028	0.8889	0.9567	{0: 175, 1: 77}		0.6923	0.4737	0.5625	0.7778	0.8684	{0: 44, 1: 19}	{'C': 1.0, 'kernel': 'rbf'}

Table 9.5g: Detailed Performance of models with high accuracy (Binary Classification, KNN Imputation, Splitting Ratio 70:15:15)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Val Precision	Val Recall	Val F1 Score	Val Accuracy	Val AUC	Val Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
50	Gradient Boosting	0.9706	0.9851	0.9778	0.9864	0.9972	{0: 153, 1: 67}		0.5833	0.5	0.5385	0.7447	0.684	{0: 33, 1: 14}		0.8667	0.8667	0.8667	0.9167	0.9172	{0: 33, 1: 15}	{'n_estimators': 100, 'learning_rate': 0.1, 'max_depth': 3}

Table 9.5h: Detailed Performance of models with high AUC performance (Binary Classification, KNN Imputation, Splitting Ratio 70:15:15)

Random State	Model	Train Precision	Train Recall	Train F1 Score	Train Accuracy	Train AUC	Train Support		Val Precision	Val Recall	Val F1 Score	Val Accuracy	Val AUC	Val Support		Test Precision	Test Recall	Test F1 Score	Accuracy	AUC Performance	Test Support	Best Parameters
50	KNeighbors	0.7586	0.6567	0.704	0.8318	0.8802	{0: 153, 1: 67}		0.75	0.6429	0.6923	0.8298	0.7457	{0: 33, 1: 14}		0.8	0.8000	0.8000	0.8750	0.9242	{0: 33, 1: 15}	{'n_neighbors': 5, 'weights': 'uniform'}