Deconstructability Prediction Using Artificial Intelligence Models

Doctor of Philosophy Thesis

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Abstract

This thesis introduces artificial intelligence (AI) predictive modelling techniques for evaluating building deconstructability. It is the first research to create a deconstructability prediction model that includes variables from technical, economic, legal, social, environmental, and scheduling perspectives. The model uses advanced AI predictive models such as gradient boosting, artificial neural network, support vector machine, and random forest, among others, and can provide deconstructability prediction for different building types, including those designed for deconstruction (DfD) and those not designed for deconstruction, as well as BIM-compliant and non-BIM buildings, nearing or at the end of life.

The research uses a positivist paradigm, focusing on objectivity and quantitative methods. The research employs a systematic literature review to identify variables influencing deconstructability. This review aids the development of a deconstructability construct-based conceptual framework, guiding the creation of a questionnaire. Deconstruction professionals, such as demolition engineers, civil/structural engineers and others with deconstruction expertise, complete this questionnaire based on a single past deconstruction project.

After scrutinising all the returned questionnaires, 263 were discovered to be relevant. Since each professional responds based on a single past deconstruction project, each of the 263 questionnaires is assumed to represent a deconstruction project. These questionnaires help form two feature sets: all identified variables/features; the feature set is reduced to 22 variables using eight feature selection techniques. For consistency, the research experiments with and uses the two feature sets to develop twelve AI predictive models. The data is divided into 75% for training and 25% for testing across all feature sets.

To address the imbalance in class, the research uses an oversampling technique (i.e., the synthetic minority over-sampling technique (SMOTE)) on the training data, ensuring a balanced representation of classes for model training across different predictive models. Additionally, the research employs a 5-fold Cross-Validation (CV) to rigorously assess each model's performance. The research trains on the balanced training data and tests on the untouched 25% test set for all the AI predictive models. This provided robust and unbiased performance estimates. Importantly, this step ensured the oversampling process did not artificially inflate the models' performance metrics.

The research finds that support vector machines with the polynomial kernel (SVM-P) using all features and Artificial neural networks with multilayer perceptron (MLP) using the features deducted from the FS techniques are the two high-performing models. Among the two, the SVM-P shows the highest predictive capabilities because of its higher accuracy and AUC, even as it uses all features. These findings made it known that, though researchers have proved the use of FS for enhancing predictive capabilities in AI predictive models, their uses and advantages may depend on the problem and scenario; as such, their uses may not apply to all kinds of issues/scenario where AI predictive model is used. Additionally, the predictive modelling performance of SVM-P suggests and supports the idea that deconstructability is a multifaceted concept. This is evidenced by the fact that the highest performance was achieved when all the diverse set of variables was used.

A significant achievement of this research is the successful implementation of a generalisable and explainable AI-deconstructability predictive model that assesses building deconstructability. Another achievement is the establishment of various variables and perspectives, which provide a holistic view of the deconstructability of the building. Lastly, the AI-deconstructability predictive model developed in this research is the first AI-predictive model for deconstructability applicable to different types of buildings: DfD and non-DfD, as well as BIM-compliant and non-BIM buildings nearing or at the end of their useful life.

The findings show that AI enables deconstructability decision-making for buildings near or at the end of their useful life, leading to innovative solutions for real-world challenges. The research implications are threefold: first, it enriches the knowledge base on AI applications for deconstruction, promoting collaboration between AI researchers and deconstruction professionals. Second, deconstruction professionals leverage AI's predictive capabilities to enhance decision-making processes, with potential applications extending to industries like manufacturing, thereby contributing to sustainability across multiple domains. Finally, the research further emphasises the need to explore AI model scalability, incorporating larger samples, diverse data sources and larger industrial validation by experts. Additionally, it suggests integrating emerging technologies such as IoT and capturing technologies to enhance real-time deconstructability predictions.

Contents

Declaration

This thesis is the result of my work. It is substantially different from any previously written or submitted or is being simultaneously submitted for a degree or other qualification at the University of Hertfordshire or any other University or similar institution.

Dedication

I dedicate this thesis to the most beneficent, the merciful - Allah, the creator of heaven and earth, for providing me with the wisdom, knowledge, health, and strength to complete this study. Afterwards, my parents, my sibling, my partner, my friends, and my entire extended family.

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Research Outputs

Journal:

1. **Balogun, H**., & Alaka, H., (2023). *Artificial intelligence and machine learning for building deconstruction - challenges and opportunities*. Automation in construction. 166, 105641. **IF = 10.3**
2. **Balogun H***, Alaka H, Ajayi S., Egwim C.N., (2023). Critical factors for assessing building deconstructability: Exploratory and confirmatory analysis*. Cleaner engineering and technology. *22, 100790*. **IF = 5.3**
3. Ajayi, R.O., Alaka, H., I, Sulaimon, **Balogun, H.,** G., Wusu, W., Yusuf (2023). *Building energy performance prediction: A reliability analysis and feature selection methods. Expert system with applications. 225, 120109.* ***IF = 8.5***
4. *Egwim, C. N., Alaka, H., Demir, E.,* ***Balogun, H****., Ajayi R.,* Sulaimon, I., Wusu, G., Yusuf, W., Adegoke, M.A. (2023). Artificial Intelligence in the Construction Industry: A Systematic Review of the Entire Construction Value Chain Lifecycle. Energies.17(1):182
5. *Egwim, C. N., Alaka, H., Youlu, P.,* ***Balogun, H****., Ajayi S., Abdul, H., Oluwapelumi, E., (2023). Ensemble of Ensembles for Fine Particulate Matter Pollution Prediction using Big Data Analytics and IoT Emission Sensors. Journal of Engineering, Design and Technology.* ***IF = 2.8***
6. ***Balogun H****, Alaka H, Egwim CN, Ajayi S. (2023). A systematic review of drivers influencing building deconstructability: Towards a construct-based conceptual framework. Waste Management & Research. 41(3):512-530.* ***IF = 4.2***
7. *Egwim, C.N., Alaka, H., Demir, E.,* ***Balogun, H****. and Ajayi, S. (2023). Systematic review of critical drivers for delay risk prediction: Towards a conceptual framework for BIM-based construction projects, Frontiers in Engineering and Built Environment, 3 (1): 16-31.*
8. **Balogun, H**., Alaka, H., & Egwim, C. (2021). *Boruta-Grid-search Least square support vector machine for NO2 pollution prediction using big data analytics and IoT emission sensors. Applied Computing and Informatics.*
9. Egwim, C. N., Alaka, H., Toriola-Coker, L. O., **Balogun, H**., & Sunmola, F. (2021). *Applied artificial intelligence for predicting construction project delays. Machine Learning with Applications, 6, 100166.*

Conference:

1. Fodio S. L., **Balogun, H.**, Rasheed O. O., Olaniyi J. O., Husaini B., Ifeanyichukwu E., Olabisi J., (2024). Analysis of Machine Learning Methods for Total Organic Carbon Prediction Using Well-Log Data of Kolmani Field. IEEE 14th International Conference on Pattern Recognition Systems 2024 - *(To be presented July 2024 in London)*
2. **Balogun, H**., Alaka, H., & Egwim, C., (2021). *An application of machine learning with Boruta feature selection to improve NO2 pollution prediction. Proceedings of Environment Design and Management*
3. **Balogun, H.**, Alaka, H., & Egwim, C., (2021). *Random forest feature selection for particulate matter (PM10). Proceedings of Environment Design and Management*
4. Egwim, C., Alaka, H., & **Balogun, H.**, (2021). *Effects of building information modelling on construction project delay: A systematic review. Proceedings of Environment Design and Management.*

List of Tables

List of Figures

List of Abbreviations

ACM	Association for Computing Machinery
AEC	Architectural, Engineering, And Construction
AI	Artificial Intelligence
AI-DPM	Artificial Intelligence Based Deconstructability Predictive Model
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AR	Augmented Reality
AUC	Area Under the ROC Curve
AUROC	Area Under the Receiver Operating Characteristic Curve
BIM	Building Information Modelling
BFS	Backward Feature Selection
BREEAM	Building Research Establishment Environmental Assessment Method
CAD	Computer Aided Design
CBA	Cost Benefit Analysis
CBR	Case Based Reasoning
CDW	Construction and Demolition Waste
CE	Circular Economy
CEE	Collaboration for Environmental Evidence
CHIS	Chi-square
CIOB	Chartered Institute of Builders
CNN	Convolutional Neural Networks
CV	Cross-validation
DEFRA	UK Department for Environment, Food, And Rural Affairs
DfD	Design for Deconstruction/Disassembly
DPM	Deconstructability Predictive Model
DRL	Deep Reinforcement Learning
EFA	Exploratory Factor Analysis
ELGBM	Embedded LightGBM
EOL	End of Life
EPA	US Environmental Protection Agency
ES	Expert System
ESG	Environmental, Social and Governance
FN	False Negative
FP	False Positive
FS	Feature Selection
GDPR	General Data Protection Regulation
IDE	Institute of Demolition Engineers
IF	Image Factoring
IoT	Internet of Things
KC	Keyword Cluster
KBS	Knowledge Base System
KfCV	K-fold cross-validation
KMO	Kaiser Meyer Olkin
KNN	K-Nearest Neighbour
LCA	Life Cycle Assessment
LDA	Linear Discriminant Analysis
Lidar	Light Detection and Ranging
LOD	Level of Detail

MAR	Missing at Random
MCAR	Missing Completely at Random
MI	Mutual information
MICE	Multivariate Imputation by Chained Equation
ML	Machine Learning
MLP	Multi-Layer Perceptron
MNAR	Missing Not at Random
MR	Mixed Reality
MSA	Measure of Sampling Adequacy
OOB	Out of bag
OP	Optimization
PAF	Principal Axis Factoring
PCA	Principal Component Analysis
PRISMA	Preferred Reporting Items for Systematic Review and Meta-Analysis
RC	Reality Capture Technology
RCPSP	Resource-Constrained Project Scheduling Problem
RDX	Royal Demolition Explosive
RFE	Recursive Feature Elimination
RIBA	Royal Institute of British Architect
RNN	Recurrent Neural Network
ROC	Receiver operating characteristics curve
SHAP	Shapley Additive explanation
SFS	Forward Feature Selector
SLR	Systematic Literature Review
SMOTE	Synthetic Minority Over-Sampling Technique
SVM	Support Vector Machine
TELOS	Technical, Economic, Legal, Operational, Social
TBL	Tripple Bottom Line
TN	True Negative
TP	True Positive
UAV	Unmanned Aerial Vehicle
UK	United Kingdom
USA	United State of America
VR	Virtual Reality
XR	Extended Reality

Chapter One

1.0 Introduction

This Chapter Covers.

- *Research Background, Gap & Justification*
- *Research Question, Aim & Objectives*
- *Research Contribution, Scope & Methodology Overview.*
- *Thesis Outline*

The architectural, engineering, and construction (AEC) industry employs approximately 2.4 million individuals, representing 10% of the total workforce in the United Kingdom (UK) and 8% globally (see Figure 1.1). It also constitutes more than 6% of the country's economic output, amounting to £117 billion in 2018 (Rhodes, 2019). Similar substantial economic impacts are observed globally, including in China, the United States of America (USA), and India (Alaloul et al., 2022).

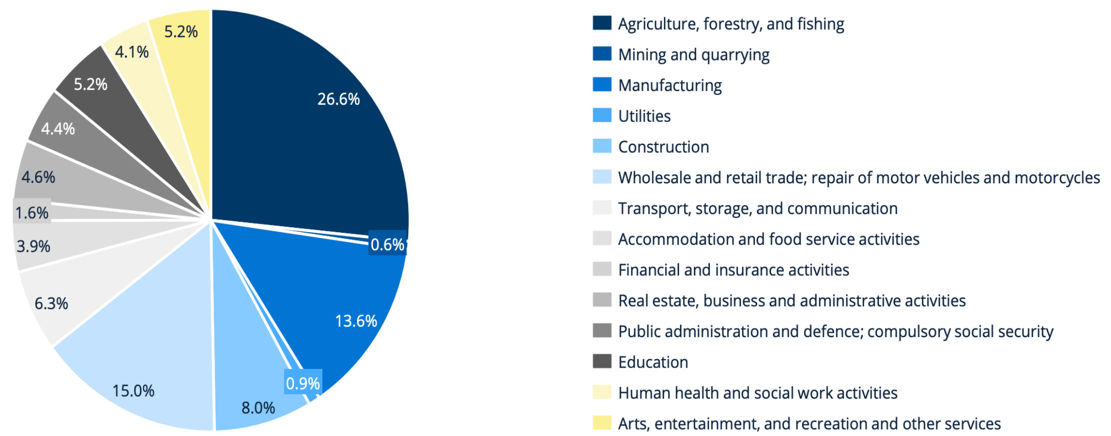

Figure 1.1: Share of employment by industry in the year 2021 (Adopted from Statista 2021)

Additionally, the industry promotes social development by improving well-being and advancing healthier communities (Altomonte et al., 2020; Chadwick, 2020; Younger et al., 2008).

Notwithstanding the undeniable positive impacts of the AEC industry on the economy and people's well-being, growing arguments highlight its detrimental effects on the socio-physical environment, including unsustainable consumption of limited natural resources, generation of waste, and atmospheric pollution. These issues can be attributed to global growth and development, particularly the increasing migration rate over the past few decades, either due to the search for better living standards or even in search of safe havens, especially for war victims. This migration trend is expected to continue; for example, the urban population is estimated to double by 2050 (United Nations, 2018; World Bank, 2020). Consequently, the pressure on natural resources for construction is expected to intensify. In the UK alone, the construction industry currently consumes around 100 million tonnes of natural resources (UK Green Building Council, 2018), while globally, it accounts for approximately 40% of total natural resource consumption (Chen et al., 2022; UNEP, 2020). These resources include water, oil, copper, limestone, and wood, to mention but a few (DEFRA, 2020a; TERI, 2017a).

Furthermore, the industry generates a significant waste volume, over 37% of the total global waste generation (Figure 1.2), primarily from construction and demolition activities (UNEP, 2020). Demolition is accountable for producing the most significant volume of waste compared to other construction activities (Balogun et al., 2022), and this is because demolition renders more than 90% of the building waste irrecoverable (Del Río Merino et al., 2010).

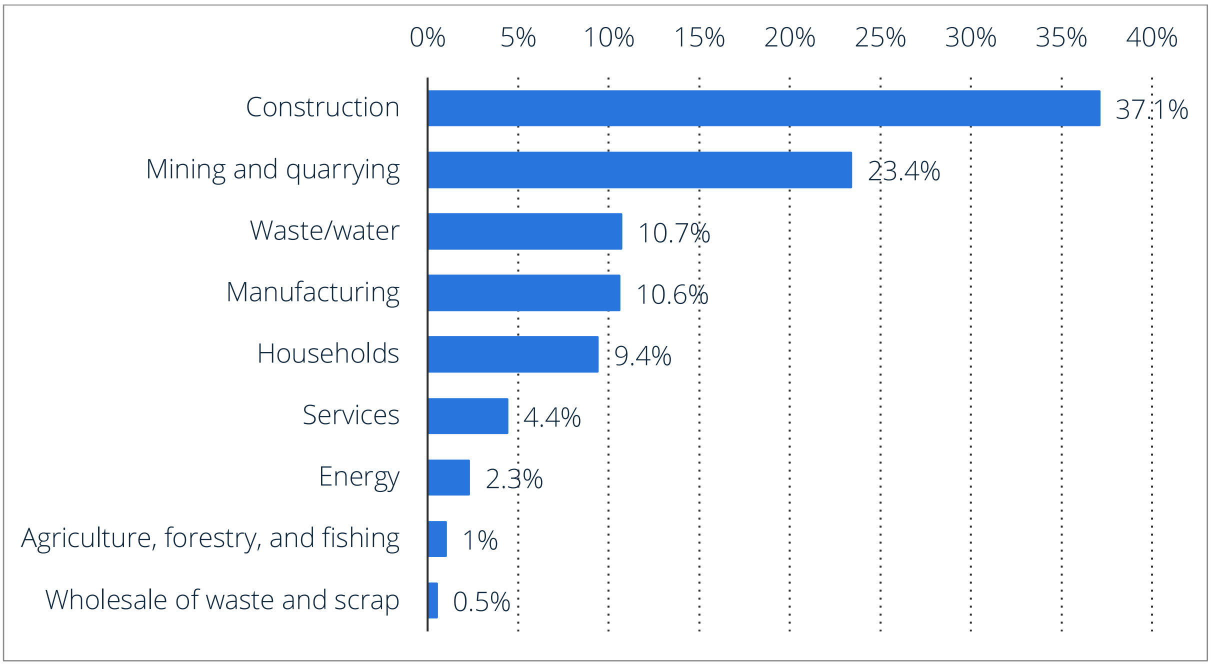

Figure 1.2: Global Waste Generation by Industry (Adopted from Statista 2021)

According to a report by the Department for Environment, Food, and Rural Affairs (DEFRA), demolition processes/activities account for approximately 62% of the total waste in the UK (DEFRA, 2020). Like the UK, demolition also contributes a significant volume to the waste stream in other countries, such as China and the USA, among others (Aslam et al., 2020; Z. Wang et al., 2024).

Furthermore, the waste from demolition activities is usually wreckage. It is heterogeneous and may contain bricks, gypsum, concrete, masonry, sand, tiles, glass, wood, plastics, asbestos, and metals. These mixtures are usually complex to sort and may harm human health.

The unruly consumption of limited and scarce resources and waste generation extends beyond environmental concerns. Disposing of construction and demolition waste (CDW) in landfills presents various challenges. For instance, densely populated areas may face space limitations. At the same time, when the rain falls, particularly in an area where CDW resides, it can cause leaching, fermentation, and the penetration of surface water and groundwater, leading to contamination of surrounding water sources and leachate issues (Istrate et al., 2020). The leachate from CDW often contains hazardous substances that can infiltrate the soil through physical, chemical, and biological processes, posing risks to soil quality. Besides, a significant proportion of CDW today is known to contain heavy metals, and the accumulation of these metals in the soil can negatively impact soil quality through various biochemical processes (Wu et al., 2022).

Furthermore, the decomposition of organic materials in landfills, along with the dispersion of waste particles by wind, can release hazardous gases such as CO_2, H_2S, CH_4, and NO_x, affecting air quality and potentially posing health risks to individuals and animals (Siddiqua et al., 2022). In addition, the issue of resource scarcity has profound economic implications. Societies heavily reliant on finite resources may face the risk of depletion, leading to political instability. Also, resource competition among powerful nations can escalate geopolitical tensions and contribute to conflicts. These factors highlight the interconnectedness of environmental issues in AEC practices with socio-environmental, political, and economic dimensions.

Several published articles have identified deconstruction as one of the most efficient and strategic plans to address socio-environmental and socio-economic concerns resulting from building construction and their end of life in the AEC industry. Deconstruction has gained popularity as a sustainable building strategy in recent years due to its ability to decrease waste and enhance resource efficiency. Deconstruction, in contrast to demolition, is the deliberate and non-destructive taking apart of a building (ISO 20887, 2020) intending to recover and reuse the materials and components (Rios et al., 2015a) rather than disposing of them in a landfill.

Deconstruction operation often starts with soft stripping, which removes all non-structural components, such as carpets, ceilings, tiles, and non-load-bearing walls, to facilitate the removal of the building's structural elements. The structural components and other components left from the soft stripping are then carefully dismantled either by specialised tools or by pieces of machinery, such as excavators and cranes. Using machinery is often faster and less labour-intensive, which may result in lower material recovery rates. Chapter two of this thesis will discuss the deconstruction process in detail.

When deconstructing buildings, recovered components may be reused nearly in their original form without significant alteration or require reform before reuse. Aside from reuse, recovered materials through deconstruction can also be recycled. Recycling entails changing the function of a component when its original use is no longer economically or ecologically sustainable. Recycling can be downcycling or upcycling. Downcycling is demonstrated by the process of breaking down recycled concrete into aggregates. Using salvaged glasses to replace additives in cement production may be called upcycling. Downcycling is well-known as the least environmentally friendly form of recovery (Zhang et al., 2020). This is because its procedures may require more energy than sustainable recovery alternatives. Although it is preferable to reuse recovered components without much modification because this implies the component still meets its functional requirements, it is worth remembering that components reused over time may be subjected to recycling at some point when they no longer serve their purpose. After years of usage, recycling becomes unavoidable.

Overall, deconstruction offers a sustainable and economically viable alternative to traditional demolition practices. It can significantly reduce waste, promote sustainability, and create economic opportunities.

1.1 Deconstruction: Barriers and Benefits

Advantages of deconstruction include waste reduction and an increase in resource recovery. Findings have clarified that deconstruction can result in a high proportion of salvaged and reused materials, ranging from 50% to 95%, depending on the project and materials involved (United States Environmental Protection Agency (EPA), 2018). The reclaimed materials could be sold, thus generating revenue while lessening the environmental effect of construction by minimising the demand for new materials and the energy necessary to produce new materials or components (Geissdoerfer et al., 2017). Similarly, by reuse and recycling, the typical cost associated with landfill tax may be reduced and/or avoided; as a result, the cost incurred for landfill disposal may be minimised.

Furthermore, by reusing resources, deconstruction may generate economic advantages by creating work opportunities and lowering the cost of new construction (Zahir et al., 2016). The construction of structures such as the pavilion at Glyndebourne Opera in Sussex (using oyster shells and corks), the Villa Welpelloo in the Netherlands (using reclaimed textile machinery and cable reels) (Kozminska, 2019), the Brighton waste house (using reclaimed carpet tiles and chalky soil) (Baker-Brown, 2016) and the 59-story Montparnasse tower in Paris, to mention but a few were partly built using recovered materials from older buildings, this possibly generates revenue reclaimed materials owners. Besides, many of the used materials were collected using basic equipment. It supposedly requires a larger workforce, often involving labour-intensive processes such as de-nailing, unscrewing, removing mortar from tiles, and cleaning marbles and slabs. As a result, potential jobs were created. Deconstruction additionally offers the benefit of preserving built heritage (Baker et al., 2021). Cities can benefit economically from retaining their built heritage. For example, Britain's well-known castles and cathedrals have contributed significantly to the economy and helped define Britain's identity (Anastasiou et al., 2022; England, 2008, 2015).

Despite its benefits, deconstruction faces several challenges, one of which is the higher cost and time required compared to traditional demolition. This is partly due to the labour-intensive nature of deconstruction, which requires skilled workers to carefully remove materials (Pons-Valladares & Nikolic, 2020). Other challenges include coordinating logistics, identifying valuable materials and ensuring their safe removal (United States Environmental Protection Agency (EPA), 2018). Additionally, technological barriers pose significant challenges;

for instance, the need for advanced tools and equipment for efficient material recovery can hinder deconstruction efforts. Access to digital platforms for tracking and managing materials and insufficient technology integration, such as Building Information Modelling (BIM), can limit the ability to plan and execute deconstruction effectively. Finally, building deconstruction requires specialised knowledge and training, which may not be readily available in some regions.

Furthermore, various issues, such as professional and governmental legislation, building design and assembly, the physical state of the materials and demand, and public attitudes often discourage deconstruction. Chapter two delves further into the challenges impacting deconstruction.

1.2 Terms and Concepts

Demolition

Thomsen et al. (2011) described demolition as the complete elimination of all parts of a building at a specific location and time. In another study by (Zahir et al., 2016), demolition was described as an engineered process to knock down buildings into debris. Equipment used to tear down buildings includes excavators, bulldozers, tearing balls and explosives such as dynamite and Royal demolition explosives (RDX) (Khandve, 2014; Pranav et al., 2015).

Deconstruction

Deconstruction is carefully knocking down a building into its components to rescue its materials for recycling, reuse, and reconstruction reasons (Rios et al., 2015b). Deconstruction is a means to an end; it exists for the appropriate recovery of building elements and materials for reuse in the most cost-effective manner (Guy, 2004). More on deconstruction will be discussed better in chapter two of this thesis.

Deconstructability

Deconstructability is a concept that evaluates the feasibility and practicality of deconstructing buildings (Akinadé et al., 2015; Guy, 2001; Guy & Ohlsen, 2003a; Kim & Kim, 2022). It extends beyond the physical aspects and considers broader implications, including structural, environmental, social, and economic factors. Deconstructability aims to determine whether deconstructing a building offers advantages over conventional demolition. This assessment involves analysing building materials, construction techniques, and potential reuse opportunities to guide decision-making.

Artificial Intelligence

Artificial intelligence (AI) is "the science and engineering of making intelligent machines" (McCarthy, 2007). Machine learning (ML) is an AI subtype where computers learn from sample data (train) to predict unseen data (test/validation) (Balogun et al., 2021; Egwim et al., 2021; Olu-Ajayi et al., 2023). With the capability of finding unknown patterns in the data, ML can solve various problems, such as discovering associations between variables, sorting subjects, making predictions based on criteria and identifying objects with similar patterns, among others. The applications of AI/ML for deconstruction will be investigated further in chapter four of this thesis.

1.3 Justification of Study

Every year, tens of thousands of buildings face demolition in the UK and the United States, as reported by the Royal Institute of British Architects (RIBA, 2021) and (The United States Environmental Protection Agency (EPA), 2018). This trend extends globally to countries like the USA, China, and various European nations (Aslam et al., 2020; Wang et al., 2024).

Shifting from demolition to deconstruction has significant benefits. By salvaging materials rather than sending them to landfills, we can reduce waste and obtain sustainable construction materials, thereby conserving resources. For example, (Guy, 2006a) argued that for every three-square fts of structural deconstruction, approximately one square ft of usable lumber can be reclaimed for future construction projects. Building upon this argument, if more buildings were deconstructed instead of demolished each year, more reclaimed materials would be available to make a substantial number of new homes.

Despite acknowledging the importance of transitioning from demolition to deconstruction, the knowledge and/or resources required to make informed decisions about a building's deconstructability are often lacking or prohibitively expensive. This knowledge should be made available to guide the decision around the deconstructability of buildings and encourage deconstruction. An initiative involving the development of a deconstructability predictive model (DPM) to help stakeholders identify buildings suitable for deconstruction, enhancing decision-making and encouraging deconstruction implementation has surfaced. However, the persistent demolition rates, as argued by (RIBA, 2021), suggest the need for a more thorough DPM that considers all variables/factors influencing existing building stocks, including those not designed for deconstruction and those non-compliant with Building Information Modelling (BIM).

1.4 Gap in Knowledge

Existing DPMs primarily concentrate on building's deconstructability prediction from perspectives such as technical, e.g., (Akinadé et al., 2015; Basta et al., 2020a) or economic factors (Rakhshan et al., 2021b; Tatiya et al. 2018a). However, this limited approach may not provide a thorough holistic understanding necessary for accurately predicting a building's deconstructability. Research sources like (Ajayi & Oyedele, 2018; Akinadé, Oyedele, Ajayi, et al., 2017) highlight the need to broaden the evaluation framework beyond technical and economic aspects to encompass various dimensions. Studies advocate for incorporating diverse perspectives, including social, environmental, legal, and scheduling, to achieve a more holistic system (Akinadé et al. 2017, 2020; Balogun et al. 2022).

Despite the proven benefits of using AI techniques over statistical models in various predictive domains such as building energy prediction (Egwim et al., 2021; Olu-Ajayi et al. 2022b, 2022a), construction project management/delay schedules (Egwim et al., 2021), and air-pollution prediction (Balogun, Alaka, & Egwim, 2021), only a few studies on deconstructability predictive models (DPM) have utilised AI techniques e.g., (Àkànbí et al., 2019; Akinadé et al., 2015). Furthermore, these existing studies, for example, (Akanbi et al. 2019; Akinade et al. 2015), mainly focus on modern buildings designed for deconstruction and compliance with Building Information Modelling (BIM). This focus neglects a significant portion of older buildings at or near the end of their useful life, which are not BIM-compliant and were not designed for deconstruction. Therefore, there is a need for a deconstructability predictive model that addresses both BIM-compliant and non-BIM-compliant buildings, as well as those intended for deconstruction (DfD) and those that are not.

Given the goal of developing a deconstructability predictive model (DPM) relevant for different building types, prioritising the AI-DPM in generalisability and interpretability is paramount for promoting DPM’s use for deconstructability assessment. In addressing these research gaps, it is essential for DPMs to

1. Incorporate extensive variable sets from a broader perspective, including technical, environmental, legal, economic, social and schedule.
2. Target both BIM, non-BIM, DfD and non-DfD buildings.
3. Be generalisable and interpretable.

1.5 Aim and Objectives

This research aims to develop an artificial intelligence-based deconstructability predictive model for buildings at their EOL or nearing EOL. To achieve this goal, research will focus on the following three objectives.

1. To identify explanatory variables from all perspectives (i.e., social, economic, technical, environmental, schedule, legal) influencing building deconstructability through a systematic literature review.
2. To develop a construct-based deconstructability conceptual framework to aid data collection.
3. To investigate the explanatory variables useful in the development and selection of the best AI model with explainability and generalisability for deconstructability prediction useful for BIM, non-BIM, DfD and non-DfD buildings

1.6 Research Questions

The research questions were based on the issues identified in the 'Gap in Knowledge' and 'Research aim and objectives' sections. They are as follows:

1. What are the explanatory variables that influence deconstructability?
2. What is the significance of each identified explanatory variable?
3. What AI algorithm produces the best prediction performance on unseen datasets without losing its explainability for deconstructability prediction?

1.7 Unit of Analysis

Neuman (2003) succinctly defines the unit of analysis as "the type of unit a researcher uses when measuring." It represents the entity upon which data are collected and becomes the primary focus for analysis and interpretation.

In this research, the unit of analysis is the building. This decision stemmed from the fact that the data collected and analysed predominantly pertained to the deconstructability of buildings, and the conclusions drawn were primarily concerned with these entities.

It's important to note that the unit of analysis is frequently mistaken for the unit of observation, which refers to the entity about which data are gathered - essentially, the "who" or "what" being studied. As Tainton (1990) aptly puts it, the unit of observation is the "entity on which the original measurements are made." In this research, data were directly sourced from the deconstructed buildings, underscoring their role as the unit of observation.

1.8 Overview of Methodology

This research aimed to develop an AI-based deconstructability predictive model considering various variables and perspectives relevant to deconstructability. A systematic review of academic and industrial reports was conducted to identify these variables. Subsequently, identified variables were operationalised to form questionnaires, facilitating data collection about deconstruction projects. The collected data was subsequently used for the development of an AI-based DPM. Employing a quantitative approach, the study involved various procedures to achieve its objectives. Key aspects such as sampling, data collection, analysis techniques, and the development of the artificial intelligence predictive model for DPM were integral components of the study and are therefore briefly discussed.

Sample

The population was of the existing building stock in the UK and beyond that have reached their end of useful lives or are about to reach the end of useful lives considered for deconstruction. The sampling method is purposive and further discussed in chapter five.

Literature Review

A systematic literature review was conducted to explore existing studies that have identified variables influencing deconstructability and deconstruction practices, regardless of whether they explicitly focused on developing DPM. The identified variables were operationalised and translated into a questionnaire following the review.

Questionnaires

A survey tool was developed using the established variables from the systematic literature review to collect data. To ensure clarity and appropriateness of the survey questions, a rigorous pilot test was conducted among graduate school researchers with construction backgrounds. Following this, a purposive random sampling strategy was employed to electronically recruit participants possessing the requisite knowledge in deconstruction, given the specialised knowledge required to respond effectively to the survey questions. More on the questionnaire is further discussed in Chapter Five.

Data Analysis

The collected data served dual purposes in the research endeavour. Firstly, it was subjected to statistical analysis to explore the variables' significance and interrelationships. This analytical approach aimed to uncover insights into the factors influencing deconstructability, highlighting different perspectives on deconstructability. Secondly, the data was crucial in developing an AI-based DPM (AI-DPM). The dataset was divided into two subsets for the development of the AI-DPM: 75% for model training using cross-validation methods and 25% for extra-layer-validation/testing. This partitioning allowed rigorous evaluation of the predictive models' performance and generalisation ability. More on the analysis is discussed in chapter six.

1.9 Contribution

Academic Contribution

The primary objective of the research was to create an AI-based predictive model for assessing the deconstructability of buildings as they reach or near the end of their useful life. This effort contributed significantly to academic knowledge in several key respects. Notably, it represented a pioneering effort to expand the scope of variable consideration beyond technical-like and economic variables, aligning with the suggestion of (Akinadé et al., 2020; Akinadé et al., 2017). By incorporating additional non-technical/economical perspectives such as environmental, legal, schedule, and social into the development of the AI-DPM, the research aimed to provide a more comprehensive and nuanced understanding of deconstruction processes.

One notable contribution of the research was the systematic review to identify the diverse variables influencing deconstructability. This thorough examination was a novel approach in the field, as previous studies had not taken such a holistic perspective. By systematically analysing and synthesising existing literature, the research captured a broader spectrum of variables influencing deconstructability, enriching the academic understanding of this subject matter.

Industrial Contribution

The study underscores the significance of considering non-technical alongside technical aspects for achieving successful deconstructability. Professionals, house owners, and other stakeholders can understand variables to watch out for in buildings nearing or at the end of their useful lives for its deconstructability assessment. AI-DPM can offer rapid deconstructability assessment of buildings, whether BIM, non-BIM, DfD, or Non-DfD, at no cost. As waste management is the responsibility of the house owner/facility manager, AI-DPM can aid in understanding the deconstructability of their building nearing or at the end of life with little or no construction/deconstruction expertise, thereby setting a pace for a thorough pre-demolition/pre-redevelopment audit afterwards.

1.10 Scope

This research examines the intersection of AI and deconstruction. The two fields are broad and well-established, so defining the research scope by construction project type, lifecycle stage, and application is essential.

Construction projects are typically classified into building, infrastructure, and industrial. Buildings include both residential and non-residential structures like retail and commercial facilities. Infrastructure covers highways, bridges, and utilities, while industrial projects involve refineries and manufacturing plants. This study focuses specifically on residential buildings, which form a significant portion of the built environment and are key targets for deconstruction aimed at reducing waste and improving sustainability. Residential projects are also less complex than non-residential or industrial ones, which often require specialised handling of hazardous materials and strict regulatory compliance—areas beyond the scope of this research. Regarding lifecycle, the focus is on predicting the deconstructability of buildings at or near the end of their useful life.

In terms of implementation, AI-DPM offers a rapid deconstructability prediction and benefits architects, demolition/deconstruction engineers, waste management consultants, and other stakeholders in demolition; however, it cannot replace pre-demolition/development audits usually conducted by experts.

1.10 Thesis Outline

This thesis comprises eight chapters, as shown in Fig 1.3. The summaries of the chapters are as follows. Chapter 2 reviews key concepts relevant to the research, including the deconstruction process. It also explores the theoretical frameworks associated with deconstructability.

Chapter 3 presents a systematic literature review of academic and non-academic sources that establishes the variables influencing deconstructability. It introduces a conceptual framework derived from these variables, which aids in formulating questions for the questionnaire survey. Chapter 4 details the systematic literature review of AI and machine learning in the deconstruction landscape. It discusses the current state of AI and its subtypes, identifying potential opportunities in underexplored deconstruction areas. The chapter concludes with an analysis of the challenges affecting the implementation of AI in deconstruction activities.

Chapter 5 describes the study's methodology, outlining the options for research philosophy, ontology, epistemology, paradigms, strategies, and approaches. It justifies the selected research philosophy and approaches, highlighting their relevance to the research questions. Additionally, the chapter discusses data collection, sampling, ethics, the unit of analysis, and the object of analysis.

Chapter 6 presents the study's statistical analysis, including descriptive statistics that provide insights into the collected data and exploratory factor analysis. This chapter aims to identify potential variables useful for developing the AI-DPM. Chapter 7 discusses the development of the AI-DPM, detailing preprocessing methods such as encoding, imputation, feature selection, and handling class imbalance. It also reviews the metrics and AI algorithms used. It concludes with the complete flow of the AI-DPM, including experimentation and the selection of the generalisable and explainable AI algorithm.

Chapter 8 concludes the research with a synopsis and its main findings, outlining its contributions. This chapter also addresses the study's limitations and proposes potential directions for future research. The thesis concludes with references and appendices.

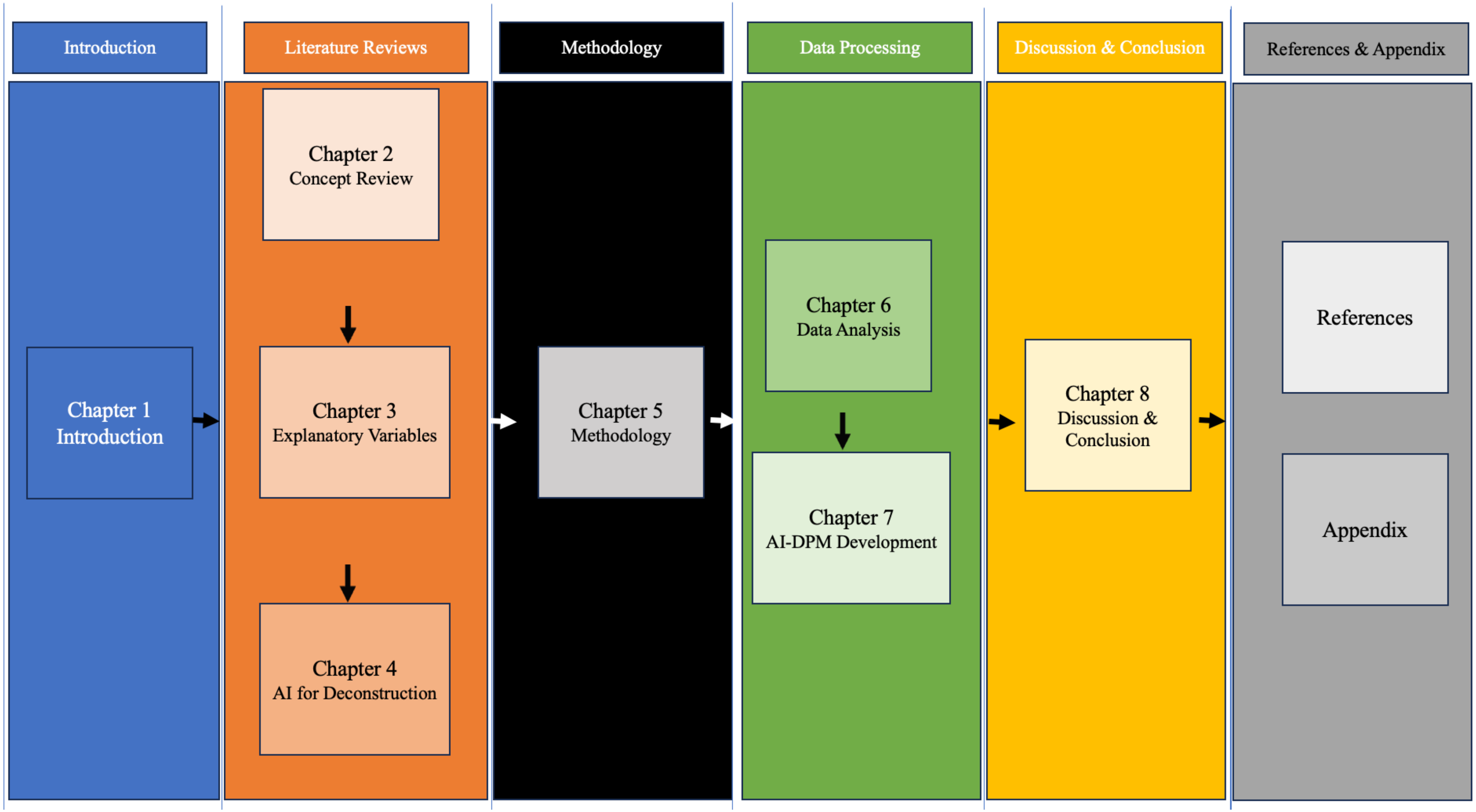

Figure 1.3: Research Thesis Structure (Created by Author)

1.11 Chapter Summary

This chapter introduced and discussed the background of the research. The chapter provided a brief on the advantages (e.g., economy, health, job creation and so on) and challenges (e.g., waste generation, pollution and more) of the architectural, engineering and construction (AEC) industry, especially at building end-of-life. At the same time, the background underscored the relevance of deconstruction over demolition and how it can turn most of the AEC challenges into opportunities and/or reduce the AEC's challenges. Additionally, the benefits and barriers to deconstruction were discussed herein. Subsequently, the chapter defined key concepts such as deconstruction, carefully dismantling a building at its end of useful life or nearing the end of life into components for reuse/repurpose. Other concepts defined in this chapter included demolition, deconstructability and artificial intelligence. Demolition was a waste-generating procedure, rendering nearly all building materials waste. Deconstructability was defined as a concept for determining the suitability of a building for deconstruction. Artificial intelligence was defined as the act of making intelligent machines.

The gap in knowledge and research questions was presented, and it exposed the need to develop a robust AI-based deconstructability considering variables from technical, economic, and other perspectives, which is the aim of the research.

A brief methodology section was presented, emphasising the utilisation of various quantitative techniques. It underscored the application of statistical methods and the development of an AI-based predictive model, drawing on a variety of variables. The section also clarified the unit of analysis and unit of observation as the building and the scope of the research were limited to residential buildings. Still, on scope, the AI-DPM only offers a rapid evaluation. However, it cannot replace the typical thorough pre-demolition audit usually carried out by experts. Lastly, the structure of the thesis was presented, having a total of eight chapters.

Chapter two contains a review of concepts and theoretical frameworks related to deconstructability.

Chapter Two

2.0 Concept & Theory Review

This chapter covers & reviews.

- *Deconstruction vs demolition*
- *Deconstruction processes and procedures*
- *Design for deconstruction (DfD) and layer theory*
- *Deconstructability & Related Frameworks*

The concept of deconstruction, also referred to as disassembly has emerged as an alternative to conventional demolition. It has gained the attention of many professionals, academicians, and the public with sustainability interest in building end-of-life. Numerous definitions of deconstruction have emerged in published articles. Among these definitions, only a few have been notable for their thorough viewpoint. One such notable definition was provided by Rios et al. (2015c), who characterised deconstruction as the meticulous dismantling of a building into its constituent parts to salvage its materials for recycling, reusing, and reconstruction. Other definitions include.

"Means to an end, and it exists for the appropriate recovery of components, sub-components for either reuse or recycling in the most cost-effective manner" – (Guy, 2004)

"Construction process in reverse". – (Greer, 2004)

"Systematic disassembly of a building to maximise recovered materials reuse and recycling" – (Chini & Bruening, 2003)

Among these various definitions, much emphasis on materials and components' recoverability was loud. In essence, deconstruction offers a pathway to extend the life of materials and components from the building near or at the end of useful lives, rather than simply sending them to landfills.

Meanwhile, demolition knocks down the entire building, eliminating and rendering all components and sub-components as waste (Thomsen et al., 2011; Zahir et al., 2016). Equipment used to tear down buildings includes excavators, bulldozers, tearing balls and explosives (Khandve, 2014; Pranav et al., 2015).

Overall, deconstruction is an engineering process of carefully dismantling materials and components that make a building for reuse or repurpose. To better understand deconstruction, its comparison with demolition is presented in Table 2.1.

Table 2.1: Demolition vs Deconstruction (Created by Author)

Characteristic	Demolition	Deconstruction
Definition	Tearing down building into waste.	Systematic disassembling of building for maximum material recovery.
Environmental Impact	Wastage of resources and disposal of waste	Encourages natural resource conservation and reduces waste disposal.
Community Employment	Not socially beneficial to communities, as it is mainly machinery dependent	The intensiveness of labour help in job creation.
Cost and Time	Swiftly implemented, with low labour cost as it often involves machines and less human labour	The economic benefit associated with the resale of recovered components makes it cost-efficient, though it takes longer.
Tools and Equipment	Heavy and big machines are mostly used	Small tools are often used
Labour	Less labour intensive, depending on heavy machine operations.	Highly labour-intensive operation
Material	Materials are inseparable and mostly sent to landfill	Material is separated into different categories, detached, prepared for reuse/recycling.
Material Disposal	A tipping fee is higher due to waste generated	Reduce the tipping fee as most of the waste is being repurposed
Structures Suitability	A typical building is built for demolition	Not all building is deconstructible.
Pollution	Generates much noise, dust, and additional waste during site clearance.	Generate less dust and noise.

2.1 Deconstruction Process

Deconstruction processes may vary depending on the deconstruction crew. However, selected processes were identified to be significant. Moreover, these processes are often likened to demolition, as illustrated in Figure 2.1.

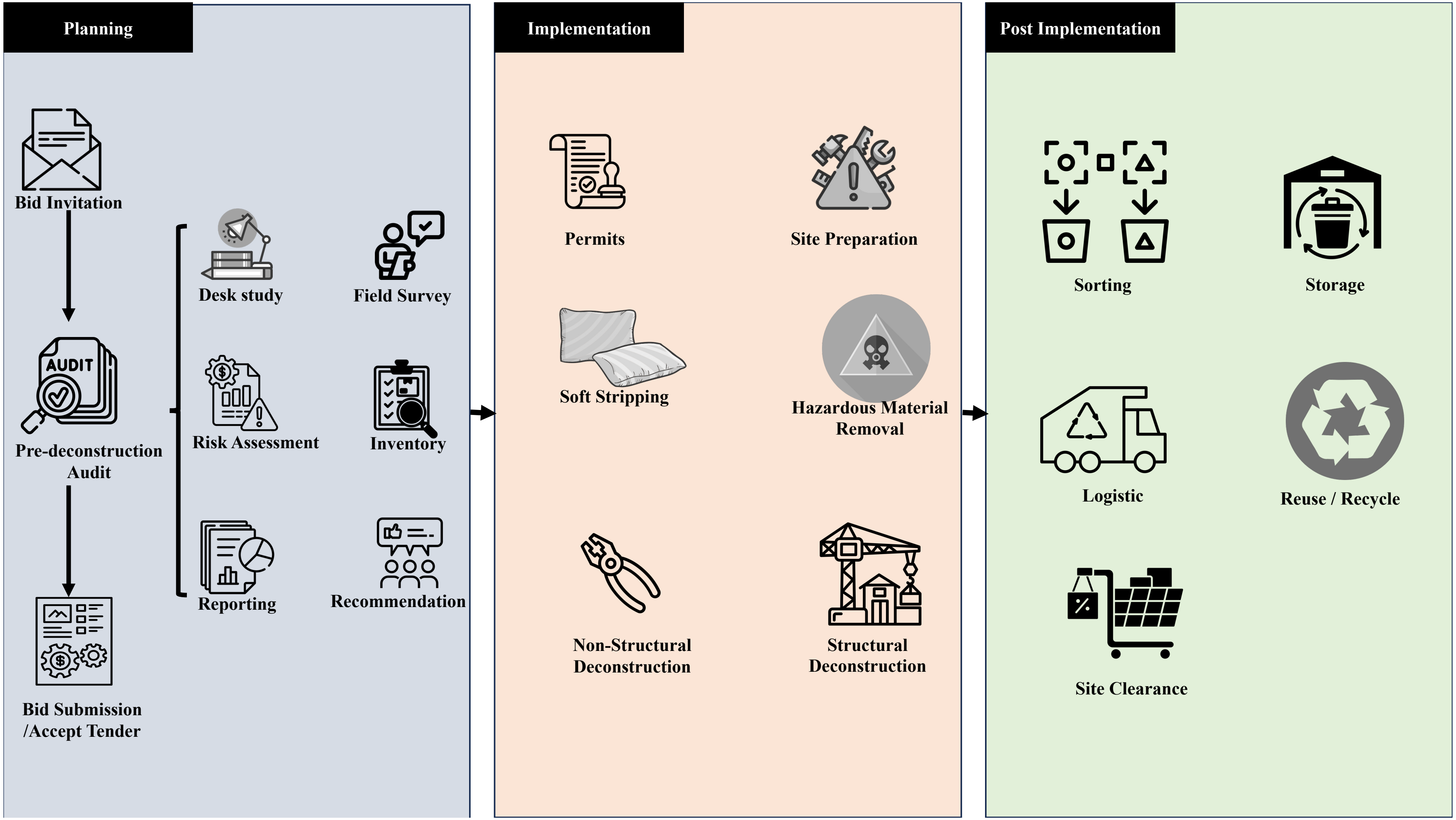

Figure 2.1: Deconstruction process (Adapted from Abdullah and Anumba, 2003 p.57; Rebekka 2017 p. 36)

The contractor kicks off the deconstruction process by soliciting bids. This involves a mandatory desk study (documentation research) and field survey in the UK, as outlined in section 7 of the UK Code of Practice, BS6187:2011. While specifically referencing the UK, similar practices were observed globally; for example, Germany follows a comparable approach.

The documentation research entails thoroughly reviewing available building records (e.g., design plans, documentation of use, inspection reports, permits, and certification, among others). It is typically conducted before/in conjunction with field surveys. It aids in estimating materials, their quantities, and any hazards they may have. Moreover, it provides insights into structural types, building ages, and details about the surrounding area, site access, and proximity to waste management facilities and salvage yards (Figure 2.2). All information from the research guides/support field survey and the extent of research may vary.

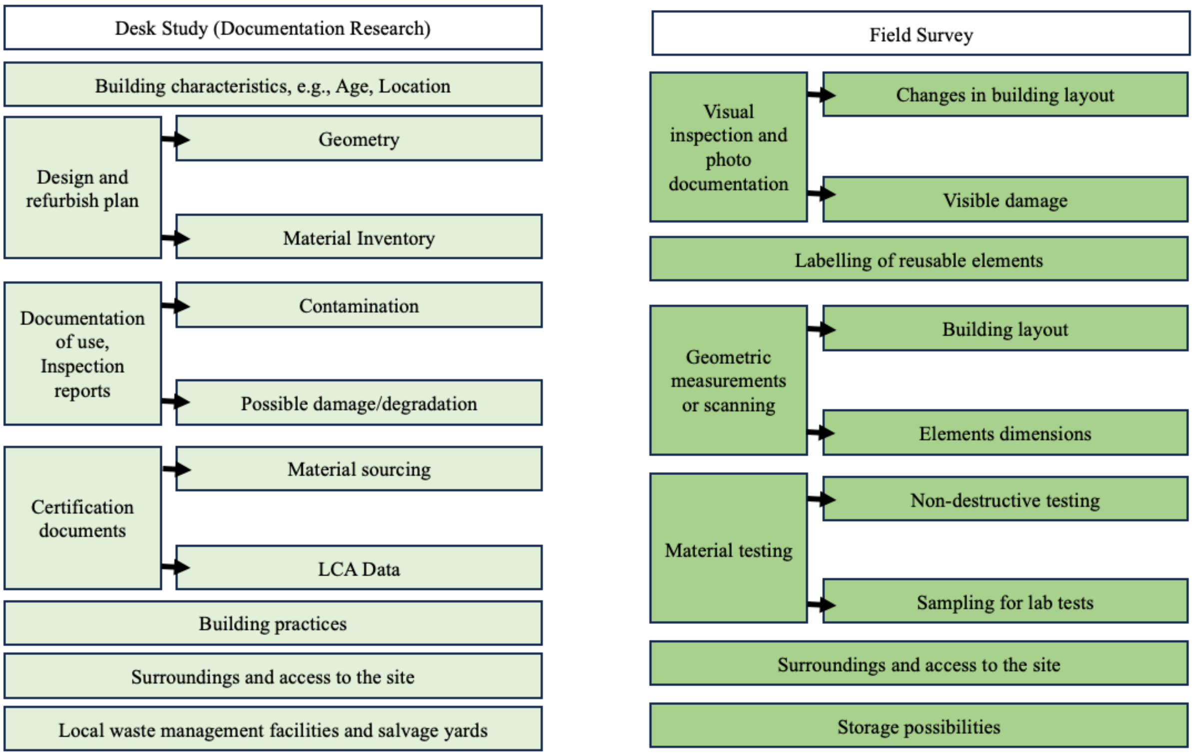

Figure 2.2: Brief on Desk Study; Field Study (Adapted from Wahlström et al., 2019)

Field surveys include steps aimed at thoroughly assessing buildings. It involves visual inspections (i.e., site visits and general analysis) to evaluate the building's condition, identify material types present and prepare necessary equipment for subsequent steps. It also involved measurements and on-site scanning to compile a comprehensive material inventory and waste declaration. Furthermore, it may involve sampling or lab tests to ascertain the quality, contamination, and level of deterioration of materials (Wahlström et al., 2019)

Contractors prepare an inventory and conduct risk assessments upon completing surveys and research. These assessments are crucial for identifying/managing potential on/off-site risks (NAHB Research Centre, 2001a; Wahlström et al., 2019). Finally, management recommendations are presented based on inventory and risk assessments. This recommendation usually includes the deconstructability of the building. This research focuses more on this phase.

Once a building has been deemed suitable for deconstruction, a comprehensive statement addressing the site's requirements, detailed sequences, and plans is prepared and submitted to the client. Subsequently, this statement is submitted as the tender document, and upon the client's approval, the contractor proceeds to the implementation (Baker et al., 2021; Margareta et al., 2019; Guy, 2006). The implementation encompasses activities such as site preparation, establishing on-site office and security, and welfare facilities. As part of the site clearance process, precautions are taken to ensure that trenches, pits, contaminants, and site drainage systems are managed in a manner that causes no hazards to health or the environment (Rebekka, 2017). Also, during this phase, the disconnection of electrical power, the capping of gas and sewer lines, the abatement of hazardous materials such as asbestos and lead, and site inspection by the building authority are carried out. Furthermore, permission must be obtained from relevant authorities, which may vary based on geographical locations. These permissions typically involve obtaining formal notification of intent, among others, from the government/council.

Subsequently, the decommissioning and soft stripping, which entails the removal of non-structural components such as the doors, frames, windows, and ceilings, among others, begins. Followed by the disassembly of the structural elements of the building. Here, careful consideration is given to the impact of removing these elements on the remaining structure and the safety of site workers and nearby individuals. Non-structural and structural elements that are retrieved are sorted, cleaned, and prepared for reuse and recycling. Items like windows and furniture can be easily reused, while materials like metal and concrete are commonly targeted for recycling. The final step involves the clearance of the site following the actual deconstruction implementation. All retrieved elements are stored or sold on-site to secondary material users at this stage (Margareta et al., 2019).

For clarity’s sake, a deconstruction process from (Guy, 2006) was presented: It started with extensive site investigations for each building. The investigations involve a visual survey and qualitative assessment of each building in the defence facility, aiming to assess the condition and identify materials used. Additionally, intrusive inspections were performed to uncover hidden material layers and determine structural elements' dimensions and layout. This involved making small openings in walls and ceilings, examining chases and plenum spaces, and inspecting beneath wooden floors. Detailed measurements were also taken for every exterior elevation, interior wall, floor, and ceiling surface. The data collected during investigations were used to create a comprehensive materials inventory, listing the type and quantity of each material found in the buildings.

2.2 Design for Deconstruction

The idea of design for deconstruction or disassembly (DfD) has emerged as a significant design development in the AEC industry, aligning with the principles of deconstruction and circular economy (CE). DfD involves designing buildings to ease future changes and disassembly, enabling component recovery (Crowther, 2005). This approach guarantees that the building components are reusable or recyclable(Guy & Ciarimboli, 2008a).

DfD recognises that most buildings have a limited lifespan and emphasises the importance of redirecting their resources away from landfills and back into the "reuse and recycle" loop. DfD aims to address the industry's high resource consumption and low recycling and reuse rates by understanding the complete lifecycle of a structure and incorporating provisions for reuse (Guy, 2001, 2004, 2006c; Guy & Mclendon, 2003; C. Kibert, 2003a; Obi et al., 2021).

Crowther (2005) outlined a set of recurring principles that form the foundation of the DfD approach, categorised based on their relevance to reuse (Figure 2.3). By applying these principles during the design process, the recovery and reintroduction of materials into the built environment can be facilitated. Whether applied during the design development stage or in assessing existing structures (regardless of whether they were initially designed with DfD principles), these practices aim to minimise the need for demolition, reduce CDW generation, and enhance material recovery.

Use of recycled and recyclable materials	Minimise the number of different types of components	Provide realistic tolerances for disassembly
Minimise the different types of material	Use mechanical not chemical connections	Use a minimum number of connectors
Avoid toxic and hazardous materials	Use an open building system not a closed one	Use a minimum number of connector types
Make inseparable subassemblies	Use modular design	Design joints and components to withstand reuse
Avoid secondary finishes to materials	Design to use common tools and equipment	Allow for parallel disassembly
Provide identification of material types	Separate the structure from the cladding	Provide identification of component type
Use A standard structural grid for set outs	Provide access to all parts and connection points	Use prefabrication and mass production
Provide on-site storage	Make components sized to suit the means of handling	Use lightweight materials and components
Retain all information of the building	Provide a means of handling and locating	Identify points of disassembly

Not Normally relevant   Relevant   Highly Relevant

Figure 2.3: Principles of design for disassembly (Adapted from Crowther, 2005)

Developing a thorough deconstruction plan that includes disassembly instructions and an assessment of building components and materials to determine their potential for reuse or recovery is necessary (Crowther , 2005). It forms an integral aspect of DfD, enabling extensive research into construction materials to identify non-toxic ones, high quality (with durability over time), and significant potential for reuse or recycling. Similarly, it helps in material selection, as it helps answer critical questions: What happens to a component at the end of its life? Can it be reused or returned to the supplier?

Another crucial principle of DfD is the provision of accessible connections and the use of appropriate joinery techniques. This principle facilitates disassembly without the need for heavy equipment or excessive tools; as such, mechanical joints, such as screws, bolts, and nails, should be prioritised over chemical couplings, such as glues, welding, or binders, which make it more challenging to separate and reuse materials (Crowther, 2005).

In summary, DfD is for new construction with a deconstruction agenda, and the identified principles outlined in Figure 2.2 are very useful in promoting the recovery of materials and components. Though the guidelines were for new buildings, the principles could also benefit existing ones irrespective of whether they were initially designed using the DfD approach.

Like the deconstruction of existing buildings, DfD also has its challenges and barriers, some of which have been identified in the literature. Akinade et al. (2017a) identified the main obstacles to adopting DfD practices, specifically in the UK industry, through a series of focus groups and a literature review. Their findings are shown in Table 2.2.

Table 2.2: Barriers to DfD adoption (Adapted from Akinade et al., 2017)

Group	Identified barriers
Absence of detailed regulation for DfD	- Irregularities in legislative policies.
	- Design codes mostly do not favour reuse
	- Lack or little reward for DfD
Inadequate building design information	- Insufficient data on the recoverable materials
	- Absence of comprehensive disassembly data.
	- Insufficient knowledge regarding cost-effective techniques for material separation
Absence of large enough market for recovered components.	- Absence of a standardised classification and grading system for reclaimed materials
	- Perceived perception and risks associated with reclaimed materials.
	- Limited or inadequate performance assurances for reclaimed materials
	- Diminished visual appeal of reclaimed materials.
	- Damage or contamination of materials during recovery.
	- Storage consideration for recovered materials.
	- Transportation considerations for recovered materials.
	- No information exchange system for salvaged materials.
	- Cost of product re-certification.
Difficulty in developing a business case for DfD.	- Insurance constraints and legal warranties of reclaimed materials.
	- Changing industry standards and construction methodology.
	- Believe that DfD could compromise building aesthetics and safety.
	- Overall benefit of DfD may not happen after a long time.
Absence of effective DfD tools	- Lack of DfD analysis methodologies.
	- Existing DfD tools are not BIM compliant.
	- No tools for identifying and classifying salvaged materials at the end-of-life.
	- Performance analysis tools for end-of-life scenarios are lacking.
	- Limited visualisation capability for DfD.

Although Table 2.2 considered DfD challenges in practice, particularly in the UK, an imaginably similar challenge is faced in other parts of the world. At the same time, it is safe to assume that similar challenge is facing existing buildings at their end-of-life.

Aside from the principles, DfD also builds upon the theory of layers proposed by Duffy and subsequently expanded upon by Brand. This theory views a building not as a singular entity but as a collection of layers, each with defined functions and expected service life. According to this conceptualisation, the interfaces between these layers serve as primary points of deconstruction (Crowther, 2000) and should be designed to facilitate proper disassembly.

2.2.1 Layered Theory

The Second World War caused significant damage to the communities, leaving behind destroyed homes/properties. This crisis spurred the interest of many European researchers, including the renowned Dutch architect, John Habraken. In 1962, Habraken published the book "De dragers en de Mensen," later translated to English as "Support: An Alternative to Mass Housing." Habraken's ground-breaking research called for the fundamental reimagining of residential architecture, advocating for the active participation of dwellers in the design of their built environment. His proposal introduced the concept of the house as a process rather than a finished consumer product.

Habraken envisioned a housing structure with two levels of control: community-level control and individual-level control. The individually controlled communal parts, such as internal partitions, closets, kitchens, bathrooms, and detachable components, offer adaptability to meet the specific needs of occupants. Conversely, the community manages the base building and adheres to rules, regulations, and construction standards. This differentiation led to Habraken's building classification into changeable interiors and permanent bases (Habraken, 1962).

Expanding on Habraken's work, Frank Duffy introduced a more comprehensive framework around 1994, dividing the building into four layers. Duffy's layers included shell, services, scenery, and set. Like Habraken, Duffy recognised that each layer has a varying lifespan. The shell comprises the structure and façade, which play a crucial role in defining the longevity of a building. It is designed to withstand the test of time and maintain its functionality. Services encompass all installations and fittings within the building, while scenery refers to the interior plans. The set includes the components that undergo regular changes daily, weekly, or monthly.

In 1994, Stewart Brand built upon the research of Duffy and Habraken to propose six layers, known as the 6S model: site, structure, skin, services, space plan

(Brand, 1994). The site layer represents the permanent aspects of the building, while the structure lasts 30 to 300 years. The skin layer, including the building envelope, has an expected lifespan of approximately 20 years. Services encompass numerous installations within the building, with a lifespan ranging from 7 to 15 years. The space plan refers to the arrangement and layout of interior spaces, with an expected lifespan of 3 to 40 years. Lastly, the stuff layer represents the movable furniture and elements that adapt to daily activities (Figure 2.4).

This progression from Habraken to Duffy and to Brand demonstrates the evolving understanding of the building's composition as a series of layers with distinct functions and varying lifespans. By recognising these layers and their different rates of change, designers can develop strategies to extend a building's service life, adapt its components, and ultimately contribute to sustainable construction practices.

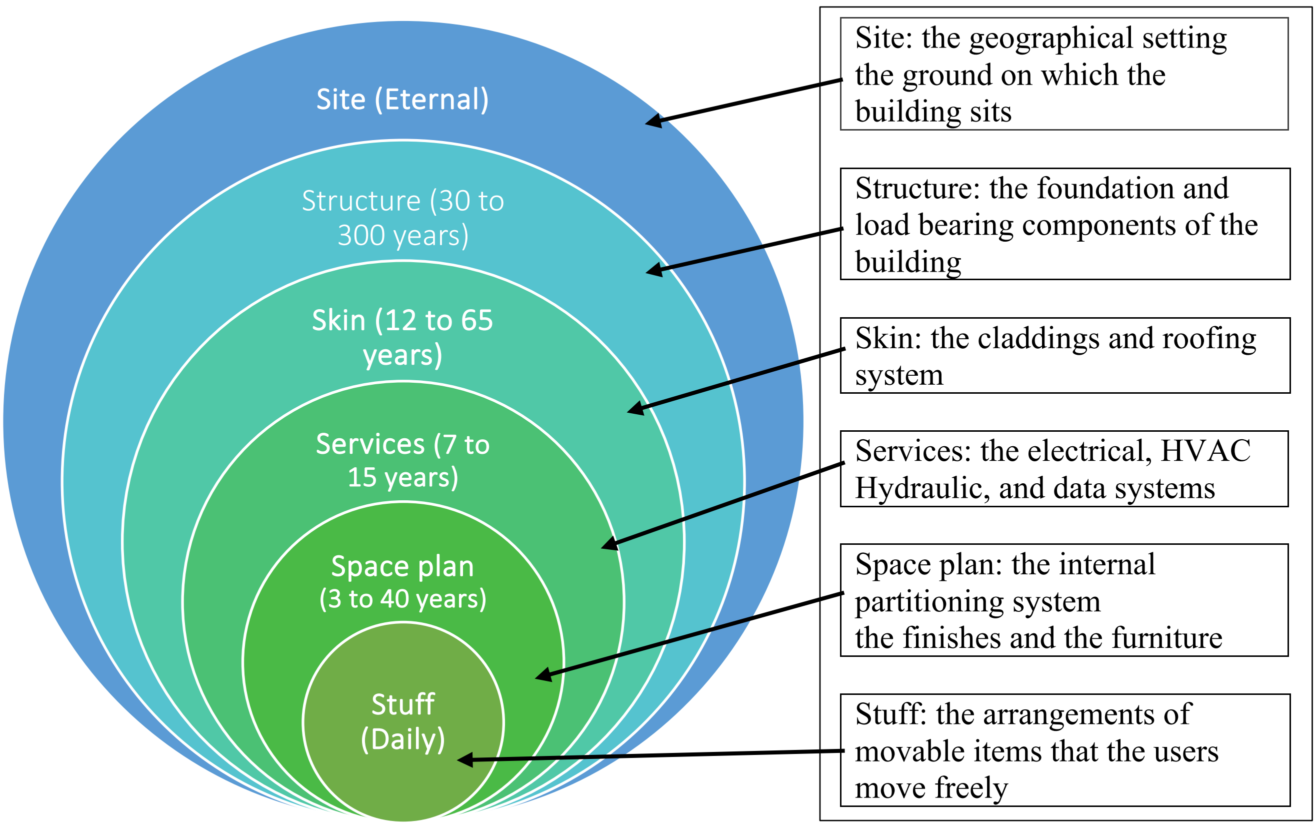

Figure 2.4: Building layers (Adapted from Brand 1994)

Understanding the makeup of a building makes deconstruction easier; however, beyond design and structural makeup, other variables need to be understood for the success of deconstruction in the built environment.

2.3 Theoretical Framework

Existing academic literature on deconstructability usually focuses on technical, economic, or both aspects (Balogun et al., 2021). Nonetheless, it is essential to explore deconstructability through other lenses beyond technical factors (Ajayi & Oyedele, 2018; Akinadé et al., 2017). As a result, this section aims to introduce theoretical perspectives and connect them to building deconstructability.

2.3.1 Triple Bottom Line (TBL)

The triple bottom line (TBL) theory, introduced by John Elkington in the mid-90s, integrates environmental and social dimensions into traditional financial performance measurements (Elkington, 1998). Also known as the 3Ps (people, planet, and profits), TBL grew to service the sustainable development paradigm, illustrated in Figure 2.5, emphasising balance among economics, environment, and society. It promotes the production of goods and services through non-polluting, resource-conserving, economically viable, and safe processes for employees, communities, and consumers (Krajnc & Glavič, 2005).

In summary, TBL aligns with sustainable development principles and offers a better approach to deconstructability. Considering economic, environmental, and social dimensions ensures a balanced approach that minimises harm and generates positive value. Embracing this theory enables stakeholders to make informed decisions that prioritise sustainability and contribute to a resilient built environment.

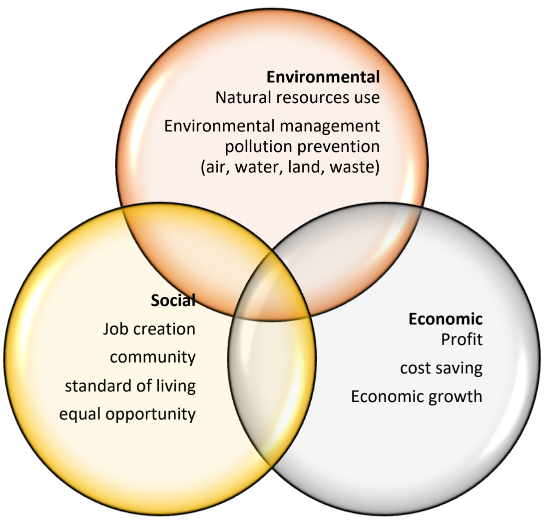

Figure 2.5: Sustainability development pillars (Adapted from Elkington, 1998)

It is important to note that scholars have recognised the applicability of TBL in deconstructability. For instance, Ding (2022) applied TBL to analyse the deconstructability of new green buildings in China, considering engineering, environmental, social, and economic factors. Similarly, other researchers such as (Ding, 2022; Ibrahim et al., 2023; Wit & Pylak, 2020) have advocated for TBL in deconstruction and sustainable construction. However, challenges remain, including the lack of standardised reporting methods and the difficulty of accurately quantifying and evaluating all three dimensions, particularly the environmental and social aspects (Goh et al., 2020). Despite these criticisms, it is justifiable that TBL is a valuable framework for deconstructability. However, some modifications may be required to address specific concerns and enhance its applicability.

2.3.2 Life Cycle Assessment (LCA)

LCA is an analytical framework that comprehensively evaluates the environmental impacts associated with all stages of a building's life, spanning from material extraction to end-of-life management. Originating in the early 1990s, LCA has gained recognition as a robust methodology for systematically analysing potential environmental consequences of the process. The LCA process entails four primary steps: goal and scope definition, life cycle inventory analysis, life cycle impact assessment, and interpretation (Muralikrishna & Manickam, 2017), as illustrated in Figure 2.6

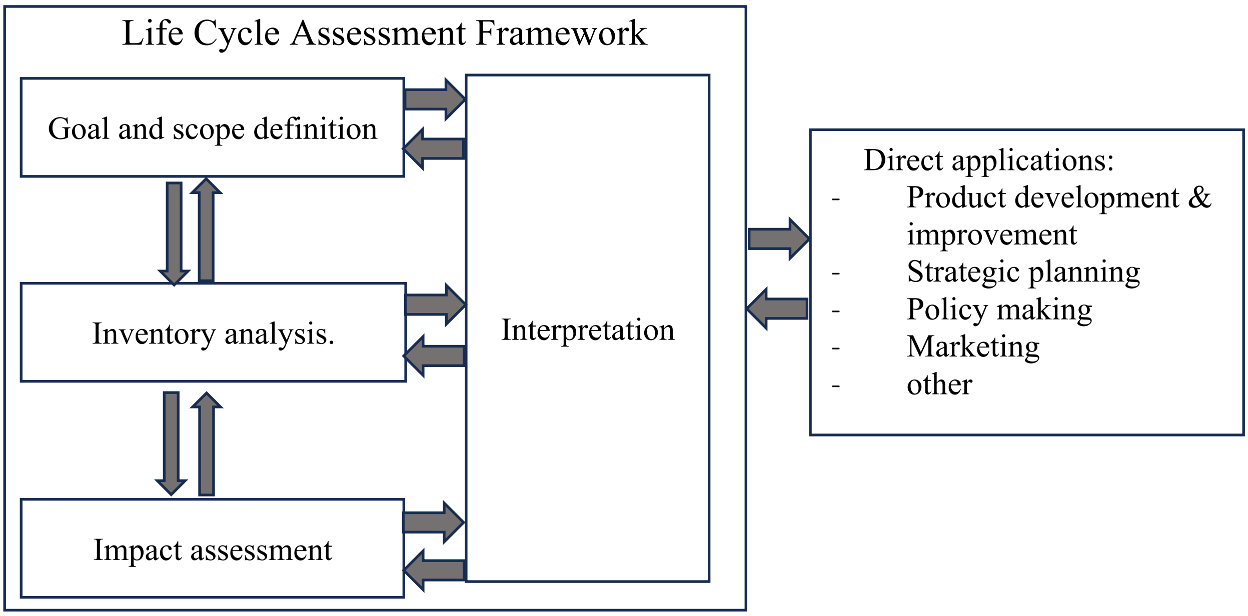

Figure 2.6. LCA Phases (Based on ISO14040)

Deconstruction, an end-of-life construction activity, requires careful consideration of environmental implications. It plays a significant role in assessing environmental impacts associated with dismantling and the material recovery processes involved in deconstruction. It offers valuable insights into environmental burdens arising from deconstruction and aids in making informed decisions.

The application of LCA to deconstructability involves several key steps. Firstly, the goal and scope of the deconstruction are clearly defined, establishing specific objectives and system boundaries. This step ensures a focused assessment. Next, the inventory analysis is conducted, which entails gathering comprehensive data on energy consumption, emissions, and resource utilisation across each stage of the deconstruction process. This data forms the basis for the subsequent life cycle impact assessment, where environmental impacts such as greenhouse gas emissions, air pollution, and energy consumption are quantified and evaluated. Finally, the assessment results are analysed in the interpretation step, and conclusions are drawn regarding the environmental performance of various deconstruction approaches.

By integrating LCA into deconstructability, decision-makers gain a deeper understanding of environmental consequences. This knowledge empowers them to make informed choices that reduce the environmental footprint of deconstruction projects. LCA serves as a valuable tool for identifying areas of improvement, optimising resource usage, and selecting strategies that maximise environmental benefits.

2.3.3 Cost-Benefit Analysis (CBA)

The cost-benefit analysis (CBA) framework initially emerged in Europe, and it application as an environmental economic theory has since spread to countries like the US, Canada, and the UK. Today, CBA is a well-established theory extensively employed by governmental and private organisations.

Harberger & Jenkins (2002) referred to CBA as a set of tools used to guide decisions regarding project implementation. It is a technique for comprehensively evaluating cost and benefit using appropriate measurement methods. Carcoba (2004) referred to CBA as a method that measures the costs and benefits of a project to determine its feasibility and evaluate its social implications. CBA is typically utilised to decide whether to undertake a specific course of action or select the best option among multiple competing alternatives (Harberger & Jenkins, 2002).

CBA has been applied in different domains, for example, disassembly sequence planning (Smith et al., 2016), recyclability assessment (Chen et al., 1994), and waste management planning (Ding et al., 2022), among others and can be applied to deconstructability. It can support the decision to implement a deconstruction project that would outweigh its costs. In terms of benefits, deconstruction can offer various advantages, such as valuable materials recovery, reduced CDW, financial incentives, and job creation. Additionally, deconstruction helps environmental sustainability by minimising resource consumption.

Conversely, there are costs for deconstruction project implementation, including labour, equipment, transportation, and potential delays in project timelines. Additionally, market demand for salvaged materials may impact the financial viability of the deconstruction project. By conducting a CBA, stakeholders can evaluate the overall economic impact of deconstruction. This analysis allows decision-makers to compare expected costs and benefits, assisting in predicting the deconstructability of the building.

2.3.4 Stakeholder Theory

The term stakeholder refers to "groups and individuals who can affect or be affected" (Freeman, 1999, 2010). Stakeholder theory aids in visualising interactions between individuals/groups. Stakeholder theory assumes that organisations have relationships with multiple groups, and these relationships influence both the company and stakeholders.

The theory contributes to the development of stakeholder management and helps organisations recognise and address the needs of individuals/groups influencing or being influenced. Stakeholder theory involves identifying stakeholders and understanding their needs and interests. It can be highly valuable in assessing deconstructability.

Stakeholder theory can assist in several ways:

- Identifying and engaging stakeholders: It stresses the importance of identifying all relevant deconstruction stakeholders. This may include homeowners, government agencies, construction firms, waste management organisations, environmental groups, and potential buyers of salvaged materials. Engaging these stakeholders early allows for a comprehensive understanding of their concerns, needs, and expectations.

- Understanding stakeholder interests and goals: It encourages analysis of stakeholders' interests, goals, and potential conflicts. It helps identify diverse views, ranging from environmental sustainability to economic viability and social equity to job creation. Understanding these interests, decision-makers can address concerns and find common ground for collaborative decision-making.
- Assessing impact on stakeholders: Deconstruction can have various effects on stakeholders, both positive and negative. Stakeholder theory facilitates the assessment of these impacts across economic, environmental, and social dimensions. This assessment includes economic development, waste reduction and cultural heritage preservation.
- Balancing stakeholder needs: Through effective communication, consultation, and collaboration, decision-makers can include stakeholder input in shaping deconstruction processes, addressing concerns, and optimising benefits for all parties involved. This helps build trust, enhance project acceptance, and create a sense of stakeholder ownership.

Overall, decision-makers can navigate complex deconstruction project dynamics, ensure transparency, and make informed choices that align with the interests and goals of all relevant stakeholders.

2.4 Implications of Theories on Deconstructability

The discussed theories have various implications for deconstructability (see Table 2.3). The triple bottom line theory balances financial gain, social aspects and environment. Cost-benefit analysis prompts deconstructability studies to adopt a relative perspective, aiming for better financial competitive advantage. Life cycle analysis directs deconstructability to focus on methods and understanding environmental impacts. Stakeholder theory aims to improve stakeholder relationships, potentially increasing the likelihood of successful deconstruction. Table 2.3 presents the basis for the possible questions on deconstructability, and it facilitates the creation of a questionnaire survey later in this research. For example, the 'people' component from 'TBL' provides the basis for social factors influencing deconstructability, and it can suggest questions like 'Would the deconstruction of the building result in an increase in job creation for the local community dwellers?'

Table 2.3: Theoretical frameworks and how they relate to deconstructability (created by author)

Theory	Theory components	Implications
TBL	People	- Would the deconstruction process provide job for locals?
	Planet	- Are there significant number of materials that are recoverable?
	Profit	- Are there any specific materials from the building that have a high demand in the market? - Are there potential customers already identified for the deconstructed materials? - Are there materials within the building that have a high intrinsic or market value?
CBA	Benefit identification	- Are there economical gains from resale values and recovery?
	Cost identification	- What is the cost associated with labour, transport, storage, hauling and landfill?
LCA	Lifecycle inventory analysis	- What are the energy and carbon footprint of the building prior to deconstruction
	Output assessment	- How much of carbon is emitted during dismantling and transportation? - How much of the materials were irrecoverable? (i.e., end up as waste) - How many materials are salvageable and reusable?
Stakeholder	Identification	- Who have the final say regarding the deconstruction of the building (building owner, contractor, or local community)?
	Interest and objective	- What is the greatest motivation behind deconstruction? (Financial gain, social responsibility, or environment)
	Collaboration and partnership	- Are there collaborative efforts and partnership established among stakeholders to enhance deconstruction? - Are there policies encouraging deconstruction? - Are there positive attitude towards reuse of salvage materials by the community?

2.5 Chapter Summary

This chapter served as a foundational introduction to key concepts relevant to the study, establishing a strong basis for the research. The chapter provided different theoretical frameworks relevant to deconstructability.

The chapter introduced the design concept for deconstruction (DfD) as a sustainable architectural approach that stresses the principles of reuse and recycling. Likewise, the chapter highlighted the significance of considering the end-of-life phase of a building and the necessity for efficient deconstruction processes to minimise waste and promote material reuse.

The chapter further outlined key principles of DfD, such as using non-chemical connections (e.g., bolt, nut, among others) and modular designs. The chapter also introduced/discussed layers theory as it helped understand typical building formation and components. The Brand's six building layers were site, structure, skin, service, space plan, etc. The layer was particularly useful as it can help identify different components in a building and possible properties of components. Also, layer theory explains layering in building design and how the intentional separation of various layers (structural, enclosure, services, and finishes) can assist the deconstruction process. The chapter emphasised the critical role of considering these layers.

Furthermore, the chapter explored various deconstruction processes. It covered planning, deconstruction implementation, and post-implementation. The chapter investigated the decision-making stage as a critical area of research. This stage holds significant importance as the primary decision to proceed with deconstruction is made during this phase.

Lastly, the chapter looked at four key theories associated with deconstructability and their implication: the triple bottom line (TBL), cost-benefit analysis (CBA), life cycle assessment (LCA), and stakeholder theory. TBL ensures a balance among economic, social, and environmental impacts. CBA evaluates economic viability by comparing costs to benefits, including socio-economic factors. LCA quantifies environmental impacts. Stakeholder theory emphasises considering all relevant parties' interests, addressing social and economic concerns, and incorporating community values into deconstructability.

Individually, most theories have only focused on one or more concerns, which may not provide a comprehensive framework for deconstructability. Also, several writers have strongly contested the claims of some of the theories in recent years. Despite the criticisms, there are still valid points from each theory that could be relevant for deconstructability. The four theories partially inform and facilitate the development of the questionnaire survey on deconstructability. The questions, variables and conceptual frameworks for deconstructability are discussed in the next chapter.

Chapter Three

3.0 Variables Influencing Deconstructability

This chapter covers.

- *Systematic literature reviews of variables influencing deconstructability.*
- *Development of deconstructability conceptual framework*
- *Development of questions/variables useful for questionnaire survey*

Assessing the deconstructability of a building, which is a feasibility assessment and practicality of deconstructing buildings when at or nearing the end of their useful lifecycle, is never an easy task. The building design, connection type, building condition, and component value would need to be assessed to make an informed decision regarding deconstructability, deciding whether deconstructing a building offers advantages over conventional demolition.

The push for a circular economy and stringent legislative frameworks becoming apparent makes deconstructability a requirement for most buildings at or near their end-of-life (EOL). For example, the circular economy statement encourages deconstructability assessment of buildings at their EOL alongside the pre-deconstruction/pre-redevelopment audit. Additionally, sustainability recognition, e.g., the Building Research Establishment Environmental Assessment Method (BREEAM), is another reason for deconstructability. Lastly, deconstructability alongside audit can shape the project's site waste management plan, which aligns with the environmental, social and governance (ESG) goals.

Deconstructability is mainly carried out using some checklist that can be likened to variables. These variables are checked during an assessment and form the basis for the perspectives from which deconstructability can be viewed. Laying on the foundation for the need to expand and look beyond technical and economic sides to deconstructability, there is a need to explore other possible variables.

The answer to this question will be illustrated by identifying variables that impact deconstructability through a review of existing literature. Afterwards, a construct-based conceptual framework for deconstructability will be developed, following the variables established through the literature review.

This study holds the potential to contribute substantially to existing knowledge by identifying variables that aid in the assessment of deconstructability, regardless of the material composition of the buildings. Moreover, it can enhance efficiency in evaluating existing buildings while raising awareness about variables that facilitate deconstruction during the design stage. It is important to note that this chapter is limited in identifying relevant variables and developing a construct-based conceptual framework for assessing the deconstructability of buildings.

3.1 Systematic literature review of variables influencing deconstructability

The typical literature review types are traditional and systematic. Traditional literature reviews are often faster to complete, making them a frequent first choice. However, their significant limitations lie in a lack of transparency and repeatability, which can compromise reliability. Systematic literature reviews, although more time-consuming, are comprehensive and reproducible, offering greater rigour and validity (Tawfik et al., 2019). In this case, a systematic literature review (SLR) would be essential to examine all relevant literature, identify variables affecting deconstructability, and construct a framework based on these findings. This approach ensures that the process is transparent and can be replicated by other researchers.

SLR is a widely accepted approach to research synthesis, offering a structured and unbiased method for locating relevant studies about the research questions (Higgins & Green, 2008). With well-defined inclusion and exclusion criteria and thorough quality assessment of studies. SLR provides a reliable and transparent pipeline to extract valuable information (Aromataris & Pearson, 2014).

To achieve a reproducible report of the complete process, the Preferred Reporting Items for Systematic Review and Meta-analysis (PRISMA) checklist (Moher et al., 2010; Page et al., 2021), one of the widely used in research fields like construction and waste management (Charef, et al., 2021; Shahruddin & Zairul, 2020) was employed to document the entire SLR process.

SLR involves a comprehensive literature search across databases. Following the approach of Rakhshan et al. (2020a), a recent article on building deconstruction, the Scopus database was used. Scopus provides research from around the world, minimising geographical biases. Additionally, Google Scholar, another widely accepted database, was used with the keyword 'deconstructability,' resulting in 31 relevant articles, which will be added to the sources from Scopus. However, the search on Google Scholar was limited to titles only to manage the number of records, as automated filtering was not feasible.

Comprehensive searching helps reduce the risk of missing essential studies (Collaboration for Environmental Evidence, 2013; Kugley et al., 2017). A pilot search was conducted on the Google search engine and the search framework on Scopus to identify appropriate keywords, reduce search bias, and establish a framework for retrieving relevant articles. The pilot search revealed that the terms 'deconstruction' and 'disassembly' are used interchangeably, while terms like 'assessment,' 'feasibility,' 'potential,' 'estimation,' 'appraisal,' and 'evaluation' were used in conjunction. To capture a broad range of research sources, ensure repeatability, and maintain consistency throughout the process, the search framework ((‘deconstruct*’ OR ‘disassembly*’) AND (‘assessment’ OR ‘feasibility’ OR ‘potential’ OR ‘estimation’ OR ‘appraisal’ OR ‘Evaluation’) AND (‘building’)) was employed, looping through 'title/abstract/keywords' of each journal.

The exclusion criteria for this research included articles written in languages other than English, mainly due to resource limitations for translation services. However, it is essential to note that excluding articles based on language is generally not encouraged in an SLR. Articles excluded in this study due to language include (Caparrós & Astarloa, 2017; Schwede & Störl, 2017), written in German and Spanish, respectively. Other articles, such as conference papers, trade journals, and book chapters, were not considered due to the focus on high-quality peer-reviewed articles (Alaka et al., 2017; Comfort & Park, 2018; Rakhshan et al., 2020a).

Applying exclusion criteria, a total of 190 articles were excluded: six were duplicates, and 184 were non-English and non-peer reviewed. After initial screening, the decision to include an article was predominantly based on its title; however, in some cases, the abstract, introduction, and conclusion were also reviewed to ensure the relevance of the selected papers.

As a result, 321 articles were excluded. Of the remaining articles, fifty showed promise and were further scrutinised. After careful review, eighteen studies were excluded: two were not readily available, and sixteen were out of scope. Overall, thirty-two studies were included in the next stage of full-text analysis.

Following the approach of Alaka et al. (2018), an additional six relevant articles were found through references and citations of the previously identified articles. These included three peer-reviewed journal articles and three reputable industry reports. 38 relevant articles were obtained to achieve the research aim and objectives (see Figure 3.1).

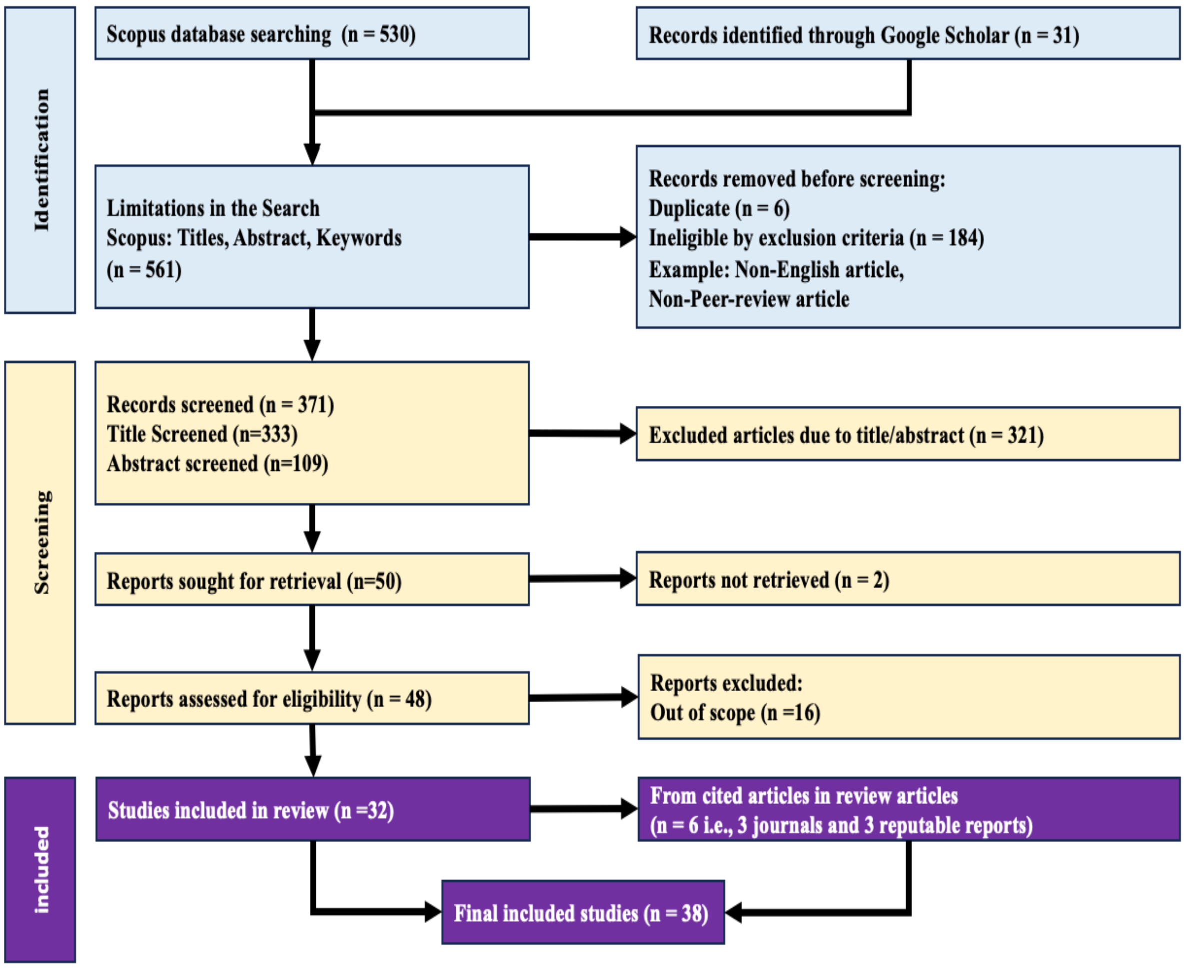

Figure 3.1: Systematic Literature Review Flow Diagram (Created by author based on PRISMA)

Following the identification of the sources, outcomes such as the source details (e.g., authors, publication year), variables, and description of the study were retrieved and summarised in Table 3.

Table 3.1: Summary Synthesis from Literature Sources

S/N	Author	variables Identified	Building type	Material	Research method	Country
1	(Bertino et al., 2021a)	- Design and plans - Underdevelopment of tools and techniques - Type & age of building - Connections - Materials and its type used in the building - Government policy - Construction techniques - Building complexity – number of components - Database for identification of materials & components (Documentation)	Residential	All	Qualitative	Undefined
2	(Cottafava & Ritzen, 2021a)	- Documentation - Material and type - Supply chain for the recovered - Design	Residential	All	Mixed method	Undefined
3	(Basta et al., 2020b)	- Use of BIM for drawings, - Identification of components, & - Provision of deconstruction plan - Different types of materials - Toxic materials - Composite and floor systems - Secondary finishes - Design - Access to components - Connections - Use of insitu - As-built plan - Standard structural grid	Residential	All	Mixed method	Undefined

S/N	Author	variables Identified	Building type	Material	Research method	Country
4	(Akanbi et al., 2019b)	- Design - Material specification - Material information	Residential	All	Quantitative	UK
5	(Hradil et al., 2019a)	- Building material - Complexity of the component - Market	Industrial	Steel	Quantitative	Finland
6	(Marzouk et al., 2019)	- Time - Cost - Undocumented building condition - Salvaged material logistics -buying & selling	Undefined	All	Quantitative	Undefined
7	(Kanters, 2018)	- Design - Materials & connections - Construction & deconstruction phase - Communication, competence & knowledge - Reuse potential & regulation	Undefined	All	SLR	Undefined
8	(Tatiya et al., 2018b)	- Component separation/connect - Low quality of recoveries - Supply chain for recoveries - Design	Residential	All	Quantitative	USA
9	(Akinade et al., 2017b)	- Government policy - Design – connection, assemblies, etc - Material related drivers – material type, quality, quantity - Site worker – cost, skill, availability	Residential	All	Mixed method	UK
10	(Machado et al., 2018b)	- material/component/connection durability - toxic material - reusability/recyclability of the material - damage - material separation	Undefined	All	Review (Literature)	Undefined

S/N	Author	variables Identified	Building type	Material	Research method	Country
		- space for equipment and manoeuvring - storage - risk assessments - as built drawings - standardisation of the component/materials/connections - tools/machinery - accessibility of connections - identification of material/information system - quality of the component/materials before deconstruction (conservation time) and damage during deconstruction - repair for reuse - cost				
11	(Akinade et al., 2015b)	- Prefabricated assemblies/demountable connections - Design - Set and type of materials/connections/component - Reusability & recyclability of material/component - Connection type - Toxic material & secondary finishes - Weight of the component/material	Residential	All	Quantitative	UK
12	(Huuhka et al., 2015)	- Connections - Material & types - Cost - High labour - Material condition & damage after deconstruction	Residential	concrete	Quantitative	Finland

S/N	Author	variables Identified	Building type	Material	Research method	Country
13	(Akbarnezhad et al., 2014a)	- Price of the material - Energy embodiment of the component - The travelling distances - Energy use associated with the recycling processes - Inflation rate and cost of designing the components for reusability - Cost associated with the recycling process - connection - Lack of information	Residential	concrete	Quantitative	Singapore
14	(J. Couto & Couto, 2010a)	- Fixed price for salvage material - Landfill tax - Material specification - Development of Suitable tool - Cost - Time & safety - Location & safety - Market value of the recovery - People/client perception - Codes & standards	Undefined	All	Qualitative	Undefined
15	(Paduart et al., 2008a)	- Design - Connection	Undefined	All	Qualitative	Undefined
16	(Leigh & Patterson, 2006a)	- Technical know how - Cost and market - Logistics of the recovery - Separation and storage - Time - Undefined law/policy	Undefined	All	Review (Literature	USA
17	(Guy, 2006d)	- Design e.g., DfD - Toxic material e.g., asbestos - Types of building material	Barack building	Timber	Quantitative	USA

S/N	Author	variables Identified	Building type	Material	Research method	Country
		- Number of building components - Type of connectors - Reusability of the material - Toxic & hazardous materials e.g., asbestos, mercury switches, leads etc - Materials recyclable				
18	(Crowther, 2005b)	- Design, e.g., DfD - Toxic material e.g., asbestos - Deconstruction purpose, e.g., relocation of building - Material and component reusable and recyclable - Connection type i.e., bolt/nut, glue - Composite material during design - Number of building components - Available building components - Toxic & hazardous materials - Secondary finishes - Deconstruction purpose	Residential	All	Review (Literature	Undefined
19	(Blengini & Di Carlo, 2010)	- Building Information/documentation	Residential	All	Quantitative	Italy
20	(C. Kibert, 2003b)	- Deconstruction purpose & design	Residential	All	Review (Literature)	USA
21	(Warszawski, 1999)	- Design – connection, key indicators for DfD, methodologies (building construct based conceptual framework)	Residential	All	Mixed method	UK
24	(Densley Tingley & Davison, 2012a)	- Material durability - Building technique e.g., volumetric construction, precast flat panel modules, tunnel formwork system, flat slabbing technology, precast foundation, hybrid concrete etc.	Residential		Quantitative	

S/N	Author	variables Identified	Building type	Material	Research method	Country
		- Site condition, - access, transportation, waste disposal, handling and storage of materials, availability and quality of electric power, water, etc., - Design				
25	(Guy & Ciarimboli, 2008b)	- Secondary finishes - Prefabricated assemblies - Composite material - Number of building components	Residential	All	Mixed method	
26	(A. R. Chini & Balachandran, 2002)	- Connection type i.e., bolt/nut, glue - Type of building components - Time, Cost & Policy	Residential	Timber	Review (Literature)	USA
27	(Webster & Costello, 2006a)	- Connection type i.e., bolt/nut, glue - Material reusable - Composite material during design - Number of building components	Residential	All	Review (Literature)	USA
28	(Andi & Minato, 2003)	- Design documentation	Residential	All	Review (Literature)	USA
29	(A. Chini & Bruening, 2003)	- Materials recyclable - Design	Residential	Timber	Review (Literature)	USA
30	(Guy & Ohlsen, 2003b)	- Labour cost - Material/Component Damage e.g., water damage, fire damage etc - Salvage material Market - Information regarding the building - Lack of skilled labour - Design i.e., DfD or not - Age of the building - Disposal fee (local tipping) - Building Material type e.g., wood, concrete, masonry etc.,	Residential	All	Undefined	Germany

S/N	Author	variables Identified	Building type	Material	Research method	Country
		- Complexity/size of the building e.g., no of floors - Number of stores/onsite storage available e.g.., one, two or more - Scheduling/time to deconstruct e.g., month, 1-6months etc - Kind of building i.e., historic or in a historic district - Kind of regulatory agency to seek deconstruction permit - Time and cost to seek/get deconstruction permit - Public policy e.g., policy that encourages deconstruction				
31	(Gorgolewski, 2006)	- Market for recycling component - Damage & Cost - Negative attitude of the public towards recovered components	Undefined	Steel	Review (Literature)	Canada
32	(Srour et al., 2012a)	- Market for recycled components - The regional recycling capacity - The total energy used to recycle & the transportation energy - Technical Knowledge - Distance from the recycling facility and the project sites - Regional purchasing habits	Residential	All	Quantitative	USA
33	(Rios et al., 2015a)	- Inaccurate quantity assessment of the recovered components - Lack of quality grading system - Lack of rules and policy encouraging the practice	Residential	All	Mixed method	USA

S/N	Author	variables Identified	Building type	Material	Research method	Country
		- Lack of technical know/skilled personnel may - Negative perception of the use of recovered components				
34	(Nakajima & Russel, 2014a)	- Low demand for the recovered components - Damages to the recovered components - The design of the building - Lack of suitable equipment for deconstruction - Sorting time - Uncertain cost factors for deconstruction - Time to deconstruct - composite materials - Lack of political initiative supporting deconstruction	Residential	Timber	Mixed method	Japan
35	(Shami, 2008a)	- Market - Incentives - Materials - Toxic materials - Quality of the salvaged material - Grading of the salvaged material	Residential	All	Quantitative	USA
36	(C. J. Kibert & Languell, 2000)	- Deconstruction cost - Industry/public attitude - Deconstruction project time - Identifying material quality & quantity - Market/resale Location e.g., onsite, or offsite - Material damage i.e., estimated amount of damage the material has	Residential	All	Mixed method	USA

S/N	Author	variables Identified	Building type	Material	Research method	Country
		- Labour cost/availability of labour & Skill level of the labour crew - Size & type of the structure i.e., number of floors, rooms etc., - Ease of removing/separating materials - Storage facility - Transportation cost - Resale - Structures containing old/rare wood species - Brick building built before 1933 - Presence of interesting/old/rare architectural features/hardwood floors - secondary finishes, e.g., presence of unpainted woods - Age of structure - Design - Availability of recycling option - Type and condition of the materials in the structure - Presence of the as built/original plan of the structure - Presence of Hazardous materials, - Cost for hazardous material handler - asbestos abatement contractor - Time of the year – depending on geographic location - Jobsite preparation – preparing site for access for transportation, dumpster locations, Time scheduling				
37	(NAHB Research Centre, 2001b)	- Project time - Code issues	Undefined	Undefined	Undefined	USA

S/N	Author	variables Identified	Building type	Material	Research method	Country
		- Market for the salvaged materials - Housing preservation - Toxic materials - Market perception of the salvaged building materials - Alternative use for the salvaged materials				
38	(NAHB Research Centre, 2000a)	- Documentation - Material type e.g., Wood framed with heavy timbers and beams, - Rare features e.g., unique woods such as Douglas, unique doors, or plumbing/electrical fixtures. - Constructed with high quality materials e.g., brick laid with - low-quality mortar (to allow relatively easy break-up and cleaning) - Structurally sound, i.e., generally weather-tight - Equipment	Undefined	Undefined	Undefined	USA

A few insights were presented to discuss the relevant literature (Table 3.1).

3.1.1 Insights from the identified literature sources

- *Project Location*

The study extracted data from the sources to investigate global trends in deconstruction. Results revealed a concentration of deconstruction projects in Europe (UK, Germany, Finland, Norway, France) and North America (USA, Canada), comprising over 60% of reported projects. Fewer projects were noted in other continents, though they were less pronounced. These findings illuminate the global distribution of deconstruction practices and sustainability initiatives, emphasising the prevailing focus in certain regions while acknowledging efforts elsewhere. They suggest a global exploration of sustainable deconstruction practices, albeit with varying prevalence across continents.

- *Data*

Most deconstruction projects sought relevant information about the building by employing direct observation and measurements. This implies that in a building deconstruction project, the primary data would likely be derived from the information gathered during the deconstruction process. This may include records of procedures followed and details about the recovered materials. Interviews with professionals and questionnaires constituted another significant method, drawing on professionals' expertise to supplement observational data, especially in the absence of access to site/other valuable documents.

- *Article Focus*

A wide range of perspectives explored across various sources were uncovered, offering valuable insights into deconstructability. One key focus was on the economic aspect, which involved analysing the financial elements, including costs, benefits, and potential economic impacts (e.g., Dantata et al., 2005b; Guy, 2006; Huuhka & Hakanen, 2015; Laefer & Manke, 2008; Tatiya et al., 2018). Understanding the economic viability of deconstruction is crucial for decision-makers and stakeholders in the deconstruction sector.

Another significant viewpoint considered the deconstruction from an environmental impact. Researchers examined ecological consequences such as waste reduction, resource efficiency, and overall environmental sustainability compared to traditional demolition methods (e.g., Ansah et al., 2021; Cottafava

& Ritzen, 2021a; Koc & Okudan, 2021; Lachat et al., 2021). This lens was essential for promoting environmentally conscious practices in construction.

Other focuses include design/technical, legal, and social viewpoints. Technical involves technologies and materials to enhance efficiency, safety, and overall effectiveness in deconstruction (Crowther, 2005). Legal focus on regulatory frameworks, permits, and legal considerations related to deconstruction practices to ensure compliance with laws and regulations (Shami, 2006; Nakajima and Russel, 2014). Furthermore, the social dimension examined societal impacts such as job creation, community engagement, and social benefits associated with deconstruction projects (Gorgolewski, 2006).

3.2 Variables established from systematic literature review

The research identified variables influencing deconstructability, as argued and highlighted across the relevant literature (Table 3.1). The presence of these variables varies significantly in the literature. For instance, labour was cited in only four out of thirty-eight sources, indicating a recognised but somewhat limited impact. In contrast, design appeared in nearly half of the literature, reflecting a broader consensus on its influence. This variation emphasises the complex nature of deconstructability, with variables differing in perceived importance across literature. Given the objective to compile all possible variables, the research presents a comprehensive selection, which is discussed below.

- *Labour and Equipment*

Labour and equipment play pivotal roles in deconstruction. Skilled and efficient labour can significantly reduce time and effort, saving costs (van den Berg et al., 2020). The availability of experienced workers is paramount to prevent delays or escalated labour expenses. Labour costs, encompassing wages and benefits, form a substantial portion of deconstruction expenditures (Guy, 2006). Complex structures may necessitate specialised labour or equipment, thereby impacting overall costs. Thus, considering variables such as labour efficiency, availability, and expenses is essential for deconstructability (Dantata et al., 2005).

- *Transportation*

Transportation exerts influence on deconstructability. Its impact encompasses various aspects, including logistics, financial considerations, and environmental implications, rendering it indispensable in planning deconstruction projects. A critical aspect impacted by transportation is an on-site market for trading recovered materials (Srour et al., 2012b). In cases where such markets are absent, transportation assumes paramount importance, moving salvaged materials to appropriate off-site locations where they can be reused, recycled, or made available for sale.

Furthermore, the geographical proximity of recycling facilities assumes considerable importance (Kibert & Languell, 2000). The distance to these centres directly affects transportation costs and operational efficiency, making strategic planning to minimise transportation distances imperative for cost savings and overall project viability. Achieving efficient transportation practices is pivotal for ensuring seamless operations during deconstruction. The smooth movement of equipment, materials, and salvaged components necessitates optimising transportation routes, utilising fuel-efficient vehicles, and exploring local recycling or reuse options to enhance cost-effectiveness and overall project success.

Beyond finance, the environmental ramifications of transportation must not be overlooked (Akbarnezhad et al., 2014). The distances covered, fuel consumption, and resulting emissions from transportation activities can significantly impact the environment. Hence, a concerted effort to reduce transportation distances, adopt eco-friendly vehicles, and prioritise local recycling facilities can effectively curtail the environmental footprint of deconstruction projects.

Furthermore, adequate access to the deconstruction site and navigational considerations in urban areas are indispensable logistical factors. Ensuring proper site access facilitates seamless transportation of equipment and materials, while meticulous planning to navigate urban settings helps mitigate traffic disruptions and environmental impacts.

- *Storage*

The absence of a readily available materials market often requires utilising storage facilities, which provide advantages for material organisation, protection, and accessibility. Proper storage streamlines operations, safeguards against damage, and enhances efficiency (Tingley & Davison, 2012). However, it is crucial to consider storage costs and balance space requirements and economic gain (Kibert & Languell, 2000). Additionally, planning the duration of storage is important to manage expenses and ensure material preservation effectively. By implementing effective storage management, deconstruction projects can be optimised, and the value of resources can be maximised (Machado et al., 2018c).

- *Demand and Supply*

Demand refers to the consumer need for salvaged materials, while supply pertains to the availability of these materials. Factors such as market trends, sustainability practices, and buyer preferences, among others, impact demand. Furthermore, the demand for recovery may be communicated through various means, including documents and established working practices. Builders may make specific requests indicating their intention to salvage structural and non-structural elements. Moreover, deconstruction contractors deeply understand the profitability of recovery practices, enabling them to identify which materials are more likely to have market value and be economically viable for reuse or recycling based on their experience and knowledge (Nakajima, 2014).

On the other hand, supply is influenced by the number of buildings being deconstructed, the types of materials used, and salvage operations, among others. When demand exceeds supply, it creates market opportunities and drives up prices, making deconstruction economically viable. Conversely, low demand or surplus supply can hinder deconstructability.

- *Value*

The market value of salvaged materials determines the project's financial viability (Couto & Couto, 2010; Couto & Couto, 2007). Valuable items like reclaimed wood, vintage fixtures, or architectural elements enhance economic feasibility by offsetting costs or generating revenue through resale.

In addition to monetary value, preserving architectural significance or historical value adds value beyond financial considerations. Reusing architectural elements and culturally significant components contributes to heritage preservation, architectural diversity, and regional context (C. J. Kibert, 2000a; C. J. Kibert & Languell, 2000). Balancing monetary and non-monetary value is crucial in determining the deconstructability of a building.

- *Quantity and Quality*

Quantity refers to the available number of salvageable materials in a building. The more materials that can be recovered and reused, the greater the potential for cost savings and revenue generation. Larger quantities of salvaged materials help offset expenses, making the deconstruction project financially viable (Machado et al., 2018c). Quality is equally important, as high-quality materials in good condition that can be easily reused or resold have higher market value (NAHB Research Center, 2000; NAHB Research Centre, 2001a).

Finding the right balance between quantity and quality is crucial. While more materials are desirable, ensuring they meet marketable and valuable quality standards is essential (C. J. Kibert & Languell, 2000; Shami, 2006, 2008b). Striking this balance ensures reasonable cost savings or revenue generation.

- *Landfill Tax and Incentives*

Financial incentives, such as grants, tax credits, or subsidies, can offset the costs associated with deconstruction. These incentives make deconstruction more attractive and feasible by reducing upfront expenses or providing financial rewards for salvaged materials (J. Couto & Couto, 2010b; J. P. Couto & Couto, 2007; Shami, 2006). They encourage project owners and developers to choose deconstruction over traditional demolition methods. A good example is the landfill tax, a government-imposed levy on waste disposed of in landfills. It is a financial mechanism to discourage landfilling and incentivise alternative waste management approaches such as recycling and reuse (Shami, 2006).

- *Remaining Service Life*

When assessing building deconstructability, it is crucial to consider the durability of the recovered materials. These materials should have a remaining lifecycle equal to or longer than the desired lifecycle of a new material. (Basta et al., 2020a; van den Berg et al., 2018, 2020a) emphasised the significance of this variable, as materials with shorter lifecycles may result in increased environmental impacts. If the construction material obtained through deconstruction needs to be replaced before the new building reaches the end of its lifecycle, it can lead to financial and environmental losses. Hence, evaluating the remaining service life of the recovered materials is essential.

- *Toxicity and Hazardousness*

Ensuring that toxic and hazardous construction materials are avoided when assessing deconstructability. One key reason is that it helps reduce the potential contamination of materials earmarked for reuse or recycling (Crowther, 2009). By preventing harmful substances, the risk of introducing pollutants into the environment during the deconstruction process can be minimised (NAHB Research Center, 2000; NAHB Research Centre, 2001a).

Furthermore, avoiding hazardous materials also plays a crucial role in mitigating risks to the health and safety of workers involved in the disassembly process. Materials such as asbestos and lead can pose significant health and environmental risks (C. J. Kibert, 2000b; C. J. Kibert et al., 2001; C. J. Kibert & Languell, 2000).

Therefore, it is vital to prioritise excluding these materials from construction materials intended for re-utilisation.

When such materials cannot be avoided, it is important to ensure their removal is easy and safe (NAHB Research Center, 2000). This entails establishing appropriate protocols and procedures for handling and disposing of these materials. Special treatment and worker protection measures may be necessary to guarantee safe handling and disposal.

- *Material Reusability and Recyclability*

Deconstructability relies on reusable materials, particularly those that can be reused without significant alterations (Akinade et al., 2015c; Basta et al., 2020c; Dams et al., 2021). Deconstructing buildings with substantial quantities of reusable materials has tremendous potential for reducing environmental impacts. This is primarily because the reuse of materials eliminates the need for resource-intensive reprocessing.

- *Damages and Deterioration*

Damages and deterioration during the dismantling of a building can render materials or connections unsuitable for reuse, posing a significant challenge to deconstruction (Huuhka, 2014; C. J. Kibert, 2000b; Nakajima, 2014). Prolonged deterioration can weaken materials or connections, making them more susceptible to damage. Moreover, certain connection types, particularly chemical connections, can hinder separation, leading to damage (Gorgolewski et al., 2006). When repairs to the damaged materials or connection are difficult or impractical, the viability of deconstruction is further compromised.

In an ideal scenario, connections should remain intact during deconstruction. Evaluating the necessity of connections and their potential for easy repair or replacement is essential to ensure successful reuse without compromising the feasibility of deconstruction. If connections cannot be preserved or repaired effectively, the possibility of reuse is undermined. Therefore, this affects the overall success of the deconstruction process.

- *Space for Equipment and Manoeuvring*

Deconstruction requires a systematic and meticulous approach to handling and manipulating materials, including de-nailing and separation (Machado et al., 2018c). However, many sites lack adequate space to accommodate these activities.

As a result, the deconstruction zone layout, building shape, and equipment size must be analysed to ensure deconstruction feasibility. This assessment considers components' size, weight, and volume to enable proper manoeuvring and removal. Additionally, controlling the built environment and space around the building is vital to ensure sufficient access to equipment. However, access to careful dismantling may sometimes be impossible, impeding the process and compromising material integrity and operation safety (Machado et al., 2018c).

- *Plans/Documentation*

A comprehensive deconstruction plan significantly enhances the feasibility of the deconstruction process (C. Liu et al., 2004). This plan, which includes technical procedures and safety measures, is vital in ensuring the smooth and safe execution of deconstruction operations.

An example is the as-built drawings, which aid in identifying specific parts and developing safe and efficient disassembly procedures, particularly when determining the order of disassembly and understanding the nature of installations and materials used in the building. In cases where as-built drawings are non-existent or outdated, it is necessary to conduct an architectural or structural design update to define disassembly procedures effectively (Rebekka, 2015).

- *Standardisation and Pre-Fabrication*

The presence of standardised and prefabricated components in a building improves deconstruction feasibility (NAHB Research Centre, 2000b). It enables better quality control and efficient replacement of components, reducing the time and procedures required for deconstruction (Crowther, 2000, 2005a, 2009). Additionally, it simplifies sorting removed materials, accelerating the deconstruction process and reducing transportation to various recycling sites. Moreover, using similar components and materials facilitates reutilisation, contributing to the overall success of deconstruction (Guy, 2001).

- *Accessibility to Parts and Connections*

Accessibility to parts and connections is crucial for deconstruction feasibility. It influences the process in various ways. Firstly, it enhances effective dismantling, resulting in quicker deconstruction. Secondly, it facilitates the extraction of valuable materials without excessive damage, thus reducing waste and maximising reuse. Moreover, accessibility improves safety by providing proper access to critical areas, minimising the risk of accidents or injuries (Crowther, 2000, 2009; Guy, 2006e). Lastly, accessibility affects cost and time, as complex access may necessitate specialised equipment or more labour-intensive methods, leading to increased deconstruction expenses and duration.

- *Number of Connections and Their Ease of Removal*

The number of connections in a building impacts deconstruction feasibility (Crowther, 2000, 2009), particularly the time, as fewer connections generally lead to a faster separation process. However, it is important to note that the ease of removing a single connection can vary depending on its type, accessibility, tools, and technologies. In some cases, a single connection might be more challenging to remove than multiple connections of easily removable types (Guy 2006). Therefore, the influence of this variable is relative.

- *Material Identification*

The efficient identification of components during deconstruction is crucial for its feasibility (Guy and Ohlsen 2003; Warszawski 1999; Crowther 2005). Various methods, such as tagging or other definitive identification techniques, can be employed to mark the parts. Implementing a marking system and definitively identifying the parts streamline the deconstruction process by aiding in the recognition and quantification of components based on their type, size, weight, and function. This organisation ensures that the disassembled parts can be easily separated and prepared for reuse or recycling, contributing to the overall efficiency and success of the deconstruction project (Crowther, 2000, 2009; Guy, 2006e).

- *Material Inventory*

A comprehensive file listing materials and components, their specifications, and essential information is highly recommended for evaluating deconstructability (Andi and Minato, 2003; Bertino et al., 2021; Basta et al., 2020). This file includes details such as lifecycle, reutilisation potential, manufacture date, resistance characteristics, special handling instructions, preservation methods, and more (NAHB 2000). It would enable informed decision-making on deconstructability, identifying opportunities for reuse.

- *Building Complexity and Structural Integrity*

The complexity of a design and its structural integrity can impact the ease and efficiency of deconstruction (Bertino et al., 2021). Buildings with intricate designs, unconventional materials, or complex structural systems may pose challenges, potentially affecting deconstruction feasibility. Assessing the technical aspects of the building, such as load-bearing capacities, material composition, and stability, is crucial in determining the feasibility of deconstruction.

- *Equipment and Tool*

The availability and suitability of equipment and tools for deconstruction tasks are important technical considerations (Couto and Couto, 2010). The right equipment and tools, such as cutting tools, material separation machinery, or lifting equipment, contribute to the efficiency and safety of the deconstruction process. Assessing the adequacy and compatibility of available equipment and tools is essential for determining the technical feasibility of deconstruction (Machado et al., 2018).

- *Expertise and Skills*

A skilled workforce with the necessary expertise and knowledge also influences the feasibility of deconstruction (Guy and Ohlsen, 2003; Akinade et al., 2017). Experts with the necessary skills may help dismantle material carefully without damage (Rios et al., 2015). Generally, it takes more time to deconstruct; however, with expertise and skills, the time may be reduced owing to past experiences and skills (Dantata et al., 2005; Srour et al., 2012). Assessing the availability of qualified personnel, including deconstruction or demolition engineers, structural engineers, and hazardous material experts, is crucial for determining the technical feasibility of the deconstruction. The expertise and skills of the workforce contribute to the efficiency, safety, and successful and timely completion of the deconstruction process.

- *Health and Safety Risk*

Reducing, controlling, and, when possible, eliminating the risks involved in dismantling a building must be a priority to preserve workers and individuals moving around the deconstruction area and material goods, including properties near the building. The risks of the process must be identified according to the activities planned, and adequate means of control must be implemented (Couto and Couto 2010).

- *Codes, Regulations and Compliance*

Deconstruction must comply with regulations and standards. These regulations may include hazardous material handling, waste disposal, air quality, and water management requirements. Ensuring compliance with these regulations is crucial for the feasibility of deconstruction (Kanter 2018). Failure to comply can result in legal and financial consequences and reputational damage.

- *Community Engagement and Support*

The local community's support and engagement can influence the deconstruction projects' feasibility. Positive community relationships, involvement, and collaboration can contribute to project acceptance, reduce potential conflicts, and facilitate the necessary permits and approvals (Kibert and Languell, 2000; Gorgolewski, 2006). Engaging stakeholders, including community members, residents, and local organisations, fosters a sense of ownership and can enhance the feasibility of deconstruction initiatives.

- *Perception and Awareness*

Public perception and awareness of deconstruction as a sustainable and environmentally friendly practice can affect feasibility (Zabek et al., 2017). Educating the public about the benefits of deconstruction, including waste reduction, resource conservation, and the creation of local employment opportunities, can foster acceptance and support for such projects. Building awareness and positive perception can contribute to deconstruction initiatives by garnering public support and minimising resistance (Gorgolewski, 2006).

- *Permits and Approvals*

Obtaining necessary permits and approvals is a legal requirement. These permits may include demolition permits, environmental permits, waste disposal permits, and other relevant authorisations (Nakajima and Russel 2014). The feasibility of deconstruction is influenced by the ability to obtain these permits and approvals on time and comply with the associated requirements (Rios et al. 2015).

- *Project Schedule*

The project schedule, including deadlines and time constraints, influences deconstruction feasibility (Leigh and Patterson 2006; Couto and Couto 2010; Marzouk et al. 2019). Projects with tight timelines may require expedited deconstruction processes, affecting the availability of resources, labour, and equipment. Obtaining necessary permits and complying with regulatory requirements can impact the timeline of deconstruction projects. Delays in securing permits or navigating complex regulations can prolong the duration of the deconstruction process and affect project feasibility.

- *Region/Seasonal Considerations*

Weather conditions and seasonal variations can impact deconstruction feasibility (Kibert and Languell 2000; Couto and Couto 2010). Extreme weather, such as heavy rain or snow, can hinder the progress of deconstruction activities and lead to delays. Planning deconstruction projects around favourable weather conditions is important to ensure efficient and timely completion.

- *Site Conditions*

The condition of the site, including the presence of hazardous materials, structural stability, and accessibility, can affect the deconstruction timeline (Basta et al., 2020). Additional time may be required for site preparation, remediation, or addressing unforeseen challenges (Tingley and Davison 2012).

3.3 Deconstructability Conceptual Framework

Inferring from identified literature sources, this research proposed a construct: bringing together interrelated variables. Subsequently, the constructs were utilised to develop a construct-based conceptual framework. The framework would be used by deconstruction experts and other stakeholders interested in reducing CDW. The framework herein aims to help generate questions and gather data to develop the AI-DPM.

The development of the conceptual framework was guided by TELOS (technical, economic, legal, operational and schedule) – a well-known feasibility framework. Additionally, the position of this study is that environmental construct replaces operation while social forms the sixth construct to form TELESS, and it was because there have been variables identified as social constructs from the SLR. The construct-based conceptual framework is thus presented in Figure 3.3.

Questions were derived from the variables identified in the systematic literature review and the conceptual framework (see Table 3.2). These questions are a foundational part of the questionnaire survey and checklist to assess building deconstructability. While they may undergo refinement following pilot testing in Chapter 5, each question is closely aligned with key variables. For instance, the variable *skill and labour* prompted the question, “How expensive is hiring skilled labour?” All questions in Table 3.2 were generated using this strategy to ensure a clear link between variables.

Economic

Market, Quantity & Quality of the recovery, Value of the recovery, transport & storage cost, deconstruction Labor cost, market pressure, damage, assessment cost, underdeveloped use for recovery, among others.

Technical

Design, Connection (e.g., accessible joints, jointing techniques), Composite material, documentation (as built plan, Architectural design), etc.

Legal

Prohibitive policy (domestic and international), practice codes, Incentives.

Scheduling/Time

Jobsite preparation, permit time, assessment time, site condition, etc.

Environmental

Asbestos, lead-based paints, chemical treated woods, mercury switches etc.

Social

Perception & awareness, community engagement etc.

Figure 3.3: Conceptual framework for deconstructability (Created by author based on retrieved literature review)

Table 3.2: Questions formed from the variables and constructs (Created by the author based on the variables identified from literature).

Construct	Variable	Possible question	Authors
Economy	Labour & equipment	1. How expensive is it to hire skilled labour? 2. What is the cost associated with acquiring or renting or maintaining the necessary equipment?	(Bertino et al., 2021b; Da Rocha & Sattler, 2009; Dantata et al., 2005a; Guy, 2006e; Koc & Okudan, 2021; Leigh & Patterson, 2006b; Machado et al., 2018c; Sanchez et al., 2020a; Tatiya et al., 2018c; van den Berg et al., 2020b; Zaman et al., 2018)
	Transport	3. what is the distance between the site and nearest market/recycling facility? 4. Are there any logistic challenges (e.g., road access, congestion, or restrictions)? 5. How expensive is transport cost?	(Akbarnezhad et al., 2014b; Bertino et al., 2021c; da Rocha & Sattler, 2009; Dantata et al., 2005a; Lachat et al., 2021; Leigh & Patterson, 2006b; Pantini & Rigamonti, 2020)
	Storage	6. How expensive is it to acquire or rent a storage facility? 7. Are there other factors that could impact storage cost (e.g., materials insurance, security)?	(Akbarnezhad et al., 2014b; Bertino et al., 2021b; Da Rocha & Sattler, 2009; Densley Tingley et al., 2017; NAHB Research Centre, 2000b; Zaman et al., 2018)
	Demand & Supply	8. Are there any specific materials from the building that have a high demand in the market? 9. Are there any restrictions or limitations on the availability of certain materials due to environmental regulations or building codes? 10. Are there potential challenges or risks associated with the supply of materials, such as the presence of hazardous substances or contamination?	(Da Rocha & Sattler, 2009; Densley Tingley et al., 2017; Hradil et al., 2019b; Koc & Okudan, 2021; Nakajima, 2014; van den Berg et al., 2020b)
	Value	11. Are there any specific components or materials within the building that have a high intrinsic or market/cultural value?	(Da Rocha & Sattler, 2009; Dantata et al., 2005a; Guy, 2006; Hradil et al., 2019a; Kibert, 2000; NAHB Research Centre, 2000; Pantini & Rigamonti, 2020; Tatiya et al., 2018; van den Berg et al., 2020b; Zaman et al., 2018)
	Quantity & Quality	12. Are there any specific materials or components within the building that have a significant quantity and can be recovered during the deconstruction process?	(Akanbi et al., 2019a; da Rocha & Sattler, 2009; Hradil et al., 2019c; Koc & Okudan, 2021)

Construct	Variable	Possible question	Authors
		13. Are there any high-quality or specialty materials within the building that have a higher market value? 14. Are there industry-standard classifications for grading salvaged materials? 15. What quantity of non-structural materials (walls, ceilings, roof, windows, and doors) and services are available for salvage or reuse?	
	Landfill tax	16. Are there any specific waste materials that are subject to higher landfill tax? 17. How expensive is landfill tax?	(Akbarnezhad et al., 2014c; Akinade et al., 2015d, 2017c; Basta et al., 2020d; C. J. Kibert, 2000b; Tatiya et al., 2018c; van den Berg et al., 2020b)
	Incentive	18. Are there any government grants or subsidies or incentives or credit for deconstruction?	(Leigh & Patterson, 2006a; Nakajima, 2014; Nakajima & Russel, 2014; Tatiya et al., 2018; Zaman et al., 2018)
Technical	Remaining service life	19. Are there significant number of materials with shorter remaining service life? 20. Are there significant number of materials with structural integrity concerns? 21. How old is the building?	(Akbarnezhad et al., 2014c; Akinade et al., 2015d; Ansah et al., 2021; Basta et al., 2020d; Bertino et al., 2021c; C. J. Kibert, 2000b; Tatiya et al., 2018c; van den Berg et al., 2020b)
	Toxicity	22. Are there any (materials now regarded as toxic or hazardous) in the building?	(Akanbi et al., 2019c; Akinade et al., 2015d; Basta et al., 2020d; Guy, 2006e; C. J. Kibert, 2000b; Tatiya et al., 2018c; Webster & Costello, 2006b)
	Reusability & Recyclability	23. Are there materials with significant reuse potential? 24. Are there materials with significant recycling potential?	(Akanbi et al., 2019a; Akbarnezhad et al., 2014a; Akinade et al., 2015a; Basta et al., 2020a; Dams et al., 2021; Guy, 2006; Kibert, 2000; Tatiya et al., 2018; van den Berg et al., 2020b; Webster & Costello, 2006)
	Damages & Deterioration	25. Are there significant number of materials that have been damaged?	(Akbarnezhad et al., 2014c; Akinade et al., 2017c; Laefer & Manke, 2008; Tatiya et al., 2018c)
	Space for tools & manoeuvring	26. Are there any specific spatial constraints that may impact use of tools or the manoeuvrability of workers?	(Akinade et al., 2017c; Cottafava & Ritzen, 2021c; Machado et al., 2018a; Tatiya et al., 2018c)

Construct	Variable	Possible question	Authors
		27. Are there any site-specific considerations such as narrow access point, low overhead, restricted areas that may impact tools and manoeuvring?	
	Data (i.e., disassembly plan, as built drawing, material inventory)	28. Has a detailed disassembly plan been developed? 29. Are as-built drawings available for building to be deconstructed? 30. Has a comprehensive inventory of the building materials been created for the deconstruction project?	(Ansah et al., 2021; Bertin et al., 2020; da Rocha & Sattler, 2009; Knoth et al., 2022; Laefer & Manke, 2008; Leigh & Patterson, 2006b; NAHB Research Centre, 2000b; Sanchez et al., 2020b; Volk et al., 2018)
	Accessibility to Parts & Connections	31. How accessible are the building material and connections? 32. Are there specific areas or materials that may pose challenge in terms of accessibility?	(Cottafava & Ritzen, 2021c; Machado et al., 2018a; Tatiya et al., 2018c)
	Connection and ease of removal	33. Are there significant number of different connection types? 34. Are the connections standardised or uniform? 35. What is the construction method?	(Akanbi et al., 2019c; Akbarnezhad et al., 2014c; Akinade et al., 2015d, 2017c; Basta et al., 2020d; Cottafava & Ritzen, 2021c; Dams et al., 2021; Guy, 2006e; Huuhka & Hakanen, 2015; C. J. Kibert, 2000b; Machado et al., 2018a; Melella et al., 2021; Paduart et al., 2008b; Tatiya et al., 2018c; Webster & Costello, 2006b)
	Building characteristics	36. What are the primary material types used in the building? 37. What type of foundation does the building have? 38. What is the average floor space of the building? 39. Are there significant composite materials in the building? 40. What is the type of framework used in the building? 41. Are there significant secondary finishes in the building?	(Akanbi et al., 2019c; Ansah et al., 2021; Bertino et al., 2021c; Diyamandoglu & Fortuna, 2015; C. J. Kibert, 2000b; Laefer & Manke, 2008)
	Material identification	42. Are there standardised classifications for identifying materials?	(Densley Tingley et al., 2017; Webster & Costello, 2006b)
	Building complexity & Structural integrity	43. Are there significant structural challenges that need to be addressed during deconstruction? 44. Are there specific architectural or design features that contribute to complexity of building?	(Akanbi et al., 2019c; Akbarnezhad et al., 2014c; Bertino et al., 2021c; Hradil et al., 2019c; Sanchez et al., 2020b; Tatiya et al., 2018c)
	Tools	45. Is there need for specialised or industry specific tools for certain tasks?	(Akbarnezhad et al., 2014c; Guy, 2006e; Machado et al., 2018a)

Construct	Variable	Possible question	Authors
	Expertise & skills	46. Do the team members possess the necessary knowledge and skills?	(Guy, 2006e; van den Berg et al., 2020b)
Environment	Health & safety risk	47. Are there any risk or potential safety hazards associated with building structural condition? 48. Have asbestos and other hazardous materials been identified within the building?	(Akinade et al., 2017; Koc & Okudan, 2021)
Social	Community engagement	49. Is the public familiar and interested in deconstruction?	(Cruz Rios et al., 2021; da Rocha & Sattler, 2009; Huuhka & Hakanen, 2015; Knoth et al., 2022; Leigh & Patterson, 2006b; Nakajima & Russel, 2014b; Volk et al., 2019; Zaman et al., 2018)
	Perception & attitude	50. How receptive is the public towards reuse and deconstruction?	
	Job creation	51. Are there gaps in skills set that deconstruction projects can help address through training & employment opportunities?	
	Social equity	52. Can deconstruction contribute to creating affordable housing option & promoting community redevelopment?	
	Cultural heritage	53. Does the building or the materials hold cultural or historical significance?	(Da Rocha & Sattler, 2009; Guy, 2006; Hradil et al., 2019a; Kibert, 2000; van den Berg et al., 2020b; Zaman et al., 2018)
Legal	Building codes	54. Is the building subjected to any specific building codes, permits or regulations that need to be considered during deconstruction?	
	Permits & approval	55. What permits are necessary and which authorities issues them?	
	Contractual	56. Was there contractual agreement?	
	Liability & insurance	57. Does the project owner insurance policy cover all deconstruction activities or does additional coverage need to be obtained?	
	Environmental	58. Are there restrictions on working hours or noise levels by the local regulations? 59. Are there any environmental policy that may impact deconstruction?	(Condotta & Zatta, 2021; Cruz Rios et al., 2021; Hradil et al., 2019c; Knoth et al., 2022; Leigh & Patterson, 2006b; Nakajima & Russel, 2014b; Volk et al., 2019; Zaman et al., 2018)

Construct	Variable	Possible question	Authors
Time	Project schedule	60. What is the proposed timeline for the deconstruction project?	(Cruz Rios et al., 2021; da Rocha & Sattler, 2009; Dantata et al., 2005b; Guy, 2006e; Leigh & Patterson, 2006b; Nakajima & Russel, 2014b; Sanchez et al., 2020b)
	Seasonal	61. Are there any seasonal factor that could impact deconstruction (e.g., extreme weather, or local events)?	
	Permit	62. How long does it take to get all necessary permits?	
	Availability of skilled labour	63. Are all required labour/expertise readily available?	
	Tools	64. Are all tools and equipment readily available?	
	Site condition	65. How long would it take to get the site in right order for deconstruction?	
	Coordination	66. How will the project adapt to changing circumstance to minimise disruptions and ensure progress?	

3.4 Chapter Summary

This chapter systematically reviewed literature (i.e., academic and non-academic). Scopus and Google Scholar databases were searched, and following the PRISMA framework, 38 articles were discovered that were relevant and used to identify variables influencing the deconstructability of buildings. From the retrieved literature sources, outcomes such as the source details (e.g., authors, publication year), variables, description of the study (i.e., building type and the location of the building) and nature of the dataset used were summarised.

The chapter further discussed the variables influencing deconstructability. These variables were later grouped under technical, economic, legal, environmental, social, and scheduling constructs following the widely accepted TELOS framework. These constructs facilitate the development of a deconstructability framework and questions for the questionnaire survey.

Examples of variables established in this chapter include labour and equipment, transportation, storage, demand and supply, value, landfill tax, and incentives. The chapter highlighted the importance of labour efficiency, availability, and costs regarding deconstructability. Other variables discussed in the chapter include transportation considerations (such as logistics and costs), storage, the economic potential of salvaged materials (including quality and market value), Incentives (such as grants and tax credits), toxicity and hazardousness, material reusability and recyclability, and damages and deterioration among others.

This chapter concludes by establishing key questions derived from variables identified in the systematic literature review and conceptual framework (Table 3.2). These questions form the basis of the questionnaire survey and a checklist for assessing deconstructability. For example, the variable *cultural heritage* led to the question, "Does the building or its materials hold cultural or historical significance?" this strategy ensures a clear alignment between variables and questions, which will be central to the data collection methodology in Chapter 5.

Chapter 4 will review artificial intelligence and its application to deconstruction, covering current uses, challenges, opportunities, and future directions. This review will provide the foundation for developing the AI predictive model, which will be explored later in this research.

Chapter Four

4.0 Artificial Intelligence for Deconstruction

This chapter covers.

- *Systematic Literature Reviews of AI applications in deconstruction*
- *Challenges facing the adoption of AI for deconstruction*
- *Opportunities for AI in deconstruction*
- *Future trends and research gaps for AI in deconstruction*

Artificial intelligence and its subfields, such as machine/deep learning, robotics, optimisation, and reality capture technologies, have brought remarkable advancements and transformative changes to various industries, including the deconstruction industry. Acknowledging AI's benefits for deconstruction, this chapter investigates AI applications and aims to pinpoint the opportunities and challenges associated with AI adoption for deconstruction. A review of existing literature focused on AI applications for planning, implementation, and post-implementation activities within the context of deconstruction was carried out. Furthermore, this chapter aims to identify and present the opportunities and challenges arising from AI for deconstruction. This chapter paves the way for realising AI's potential benefits for this sector by offering insights into key AI applications specific to deconstruction.

In recent years, the global shift towards digitisation has witnessed a rise in data-driven technologies, with artificial intelligence (AI) emerging as a key player, especially in deconstruction. With its subfields like machine learning (ML), robotics, and optimisation, AI has been instrumental in streamlining complex processes in this field. For instance, deep learning techniques have enabled the categorisation and organisation of construction end-of-life waste (Na et al., 2022), while ML predictive models have been applied to various aspects such as deconstruction cost prediction (Tatiya et al., 2018d), analysing the deconstruction process (Àkànbí et al., 2019), assessing the technical reusability of building components (Rakhshan et al., 2021c), and estimating end-of-life waste (Akanbi et al., 2020a). Robotics has demonstrated effectiveness in tasks like component finish partitioning and removal, insulation partitioning and removal, and adhesion removal (Lublasser et al., 2017a), while optimisation techniques have enhanced deconstruction process planning (Sanchez et al., 2019a; Sanchez & Haas, 2018), scheduling (Rebekka, 2015; Volk, 2017), and salvage material logistics (Akbarpour et al., 2021).

AI can revolutionise decision-making and productivity in the deconstruction industry, unlocking insights from vast datasets previously archived for future reference. Data collected from smart devices, cameras, building information modelling (BIM), and other sources can be analysed by AI to optimise deconstruction implementation and promote sustainability. In line with this, (Oluleye et al., 2023) pointed out AI's role in automating design for disassembly, material strength prediction, and reverse logistics, among the many benefits it can offer.

Owing to these benefits, AI has garnered significant attention from researchers in the field of deconstruction, leading to a surge in research works and publications. However, this proliferation of studies makes it challenging to grasp the current state of knowledge. To address this, a comprehensive review is essential to consolidate the latest advancements. Consequently, this chapter aims to summarise the current state-of-the-art AI applications in deconstruction, focusing on (a) critically reviewing existing literature on AI in deconstruction, (b) identifying and discussing the application and challenges of AI in deconstruction, and (c) identifying and discussing opportunities for AI in deconstruction.

While some related review studies in this area (Abioye et al., 2021; Akinosho et al., 2020; Baduge et al., 2022; Darko et al., 2020; Oluleye et al., 2023; Pan & Zhang, 2021; Regona et al., 2022; Saka et al., 2023; Xu et al., 2021) have made valuable contributions, it's essential to note that these studies offer a comprehensive overview from a broader viewpoint. None of them, however, have undertaken an exhaustive examination of AI applications, particularly within the context of deconstruction, which is one of the significant end-of-life activities with many benefits within the construction industry (Charef, 2022; Charef, Ganjian, et al., 2021; Charef, Morel, et al., 2021; Rakhshan et al., 2020b). This is crucial, as deconstruction presents unique challenges such as material audit, hazardous waste handling, and structural integrity assessment, which may differ significantly from broader construction contexts.

By focusing explicitly on the application of AI in deconstruction, this chapter offers insight into the current state of AI in deconstruction, challenges, and opportunities. It presents research directions for both industry professionals and researchers.

For clarification, within this systematic review context, 'deconstruction' encompasses all sustainable end-of-life activities, including selective demolition, partial demolition, and soft-stripping. Consequently, academic literature that focuses on these activities using AI will be deemed relevant to this systematic literature review.

Also, the categorisation of literature was established based on its alignment with one of three key phases: planning, implementation, and post-implementation. These stages were framed through a comprehensive review of the literature by the authors, considering the specific activities each piece of literature highlights. These stages collectively serve as a framework for classifying the literature and were inspired by the works of (Poschmann et al., 2020; Volk, 2017).

The planning phase encompasses critical activities such as tactical and strategic decision-making, planning, and inspection. The implementation involves the actual implementation, encompassing activities such as separation, grasping, handling and more. The post-implementation concerns the activities after a successful implementation, including activities like sorting, transportation to sites and recycling facilities and more.

4.1 Systematic Review Literature

Section 3.1 of this thesis outlines two types of literature reviews: traditional and systematic. Systematic literature reviews, unlike traditional, provide a transparent and reliable approach (Aromataris and Pearson, 2014). Since this chapter aims to thoroughly examine AI applications in deconstruction and derive insights from existing literature that other researchers can validate and replicate, a systematic review is suitable and can be used.

To investigate the use of AI for deconstruction, a systematic literature review following the PRISMA guidelines was used, owing to its established credibility and widespread (Abioye et al., 2021; Balogun et al., 2022b; Egwim et al., 2022; Khallaf & Khallaf, 2021). Figure 4 shows the transparent and methodical process as depicted in the PRISMA flow charts

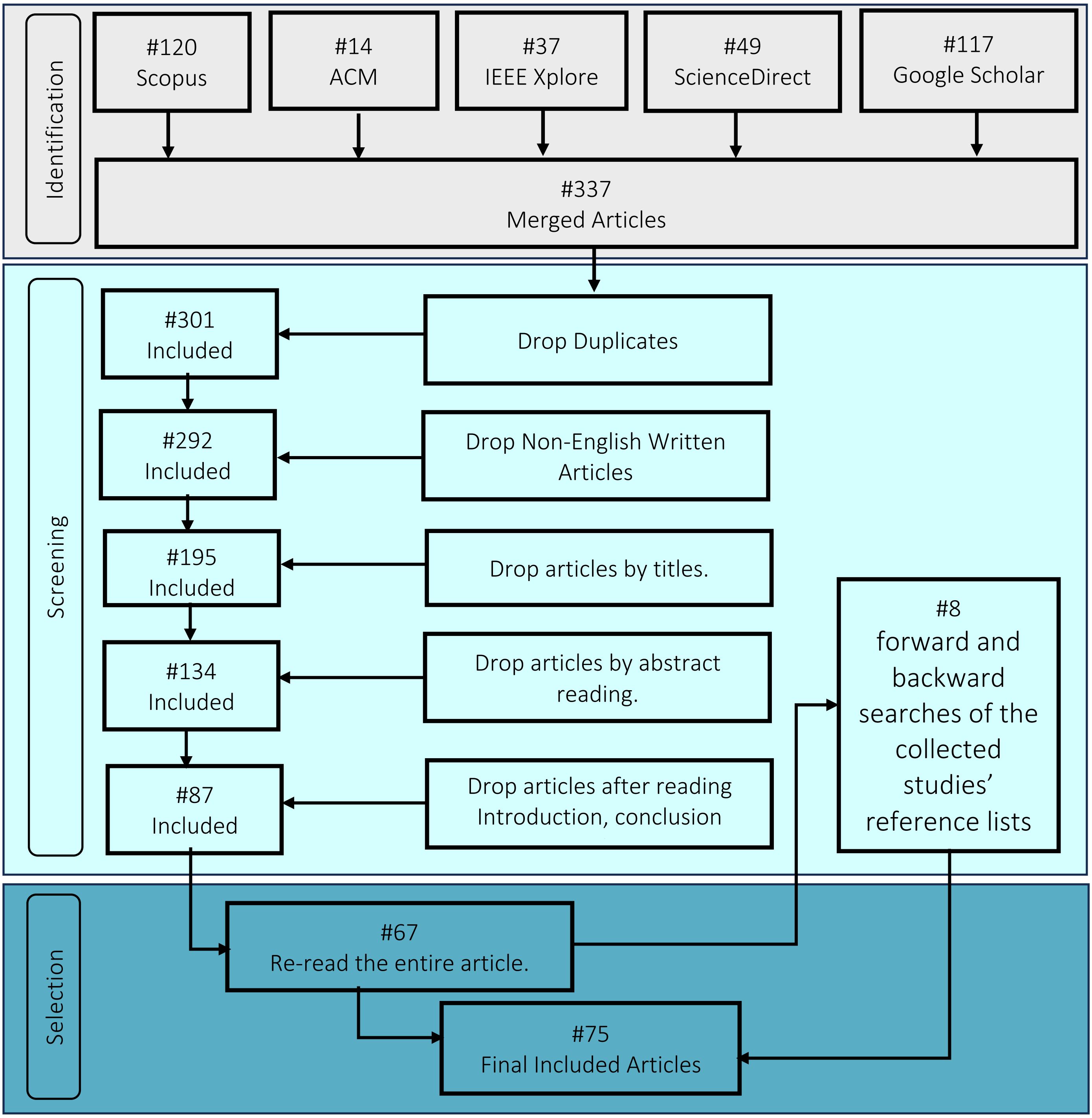

Figure 4.1: Relevant article Identification, screening, and selection (Created by the author based on PRISMA)

Figure 4.1 shows that while Chapters 3 and 4 employed systematic literature reviews, the number of databases searched increased from two in Chapter 3 to five in Chapter 4. This expansion reflects the broader scope of Chapter 4, which examines the intersection of artificial intelligence and deconstruction—a significantly broader focus than Chapter 3, which concentrated solely on variables influencing deconstruction/deconstructability. Therefore, expanding the database search in Chapter 4 is necessary and expected, given its broader research aims.

From Figure 4.1, several renowned databases, including Scopus, Association for Computing Machinery (ACM), IEEEXplore, ScienceDirect, and Google Scholar, were queried to retrieve relevant articles published until 2022. This timeframe was selected to gain insights into AI adoption's historical progression in deconstruction and identify associated challenges and opportunities.

The choice to utilise the Scopus database stemmed from its reputation as the most prominent academic database encompassing a wide range of scholarly topics. Scopus is renowned for indexing high-quality articles (Thelwall & Sud, 2022), which is another compelling reason for its inclusion in this chapter. However, relying solely on Scopus could lead to omitting relevant articles.

Consequently, additional databases such as ACM, IEEE Xplore, ScienceDirect, and Google Scholar were also searched. This deliberate search strategy aimed to mitigate the risk of overlooking pertinent articles by expanding the scope beyond Scopus. By employing a multi-database approach, this chapter aimed to gather a comprehensive collection of literature on AI applications in deconstruction, thereby ensuring a robust examination of the subject matter. Additionally, exploring multiple databases is fast becoming a norm, as seen in prominent literature reviews, e.g., (Abioye et al., 2021; Bilal et al., 2016) within the AEC domain.

Five databases were searched comprehensively to identify pertinent articles for inclusion in this review. The search strategy was around three distinct collections of keywords, a methodology inspired by (Meng et al., 2022). The design of these keyword clusters was methodically crafted to ensure a thorough search process.

a. Keyword Cluster 1 (KC1) comprises building, components, and materials. Other keywords, such as built structure and built environment, were unveiled as synonymous with building through a preliminary search on the internet.

b. Keyword Cluster 2 (KC2) incorporates keywords linked to deconstruction and sustainable recoveries, such as disassembly, dismantling, recovery, reuse, recycling, and demolition.

c. Keyword Cluster 3 (KC3) includes the elements of AI techniques. It involves general and specific keywords. Generic words such as artificial intelligence, machine learning, deep learning, intelligence, robotics, and big data, and specific terms such as neural network, reinforcement learning, model, algorithm, metaheuristics, SVM, clustering, optimisation, supervised learning, unsupervised learning, image recognition, object detection, semantic segmentation, computer vision and video analytics were all incorporated into KC3.

The search criteria KC1 & KC2 & KC3 were applied to the databases, combining keywords within each cluster with "OR." However, the overwhelming number of results and filter tool limitations within Google Scholar led to the end of the search as it was already reaching a point where further search appeared redundant. As a result, there is the possibility of missing articles in Google Scholar. However, searching other databases may offset biases that may be present in the Google Scholar search, and that was why other databases were explored.

The predetermined article inclusion criteria comprise (1) articles involving the application of AI or any AI subfield for deconstruction and (2) articles involving the development or integration of AI or its subfield for activities synonymous with deconstruction or closely related. Conversely, articles were excluded based on the criteria: (1) not utilising AI or its subfield for deconstruction or closely related activities, (2) non-English studies, and (3) non-peer-reviewed journal articles, conference articles, and textbooks.

Non-English language articles were excluded due to limitations in translation services, which could hinder the accurate comprehension and analysis of the research findings (Balogun et al., 2022b; Egwim et al., 2022). The decision to exclude other kinds of articles was based on the rationale that peer-reviewed and conference articles and textbooks undergo a rigorous evaluation process by experts in the field (Alaka et al., 2016). By focusing solely on English-language peer-reviewed articles, this review sought to uphold rigorous standards and minimise the risk of including potentially less reliable or lower-quality sources.

Following the refined search, the results were recorded in an Excel spreadsheet, including details such as author name, article title, and abstract. Duplicate entries were removed, and further reviews involving the examination of each article's topic and, in some cases, the abstract, introduction, and conclusion were considered to determine relevance. An Excel column for "include" or "exclude" was added along with an additional column to provide reasons for each decision. Independent reviews were performed twice for this step, and Cohen's Kappa was calculated as (0.92) and used to assess inter-rater reliability (Belur et al., 2018). In cases of disagreement between reviews, further scrutiny and readings of the articles were carried out until a consensus was reached. Also, only articles that were readily accessible were considered.

Additionally, a thorough investigation of the reference lists of the previously identified articles was conducted. This step was taken to uncover more articles following similar studies potentially (Balogun et al., 2022a; Egwim, Alaka, Toriola-Coker, Balogun, Ajayi, et al., 2021a; Egwim et al., 2022). As a result, 8 more articles were retrieved and found relevant, totalling 75 articles used for this review.

4.2 Exploratory Analysis

The exploratory analysis used a combination of thematic analysis and visual mapping, making it easier to derive actionable insights. Exploratory analysis of the identified literature aims to evaluate the selected articles and create a map of the current research landscape in AI for deconstruction. Consequently, the following perspectives: articles across different years, types of publications, the utilisation of AI and its subfields, the deconstruction undertakings using AI, and the geographical distribution (I.e., first or corresponding author's affiliation) were analysed. The time horizon for this analysis was set until 2022, corresponding to the period during which the review was conducted.

Figure 4.2 presents the publication types and their year of publication, and we can see that an average of seven publications per year was consistently maintained from 2015 onwards, with a minor decline noted in 2016. The year 2022 had the highest number of publications, underscoring the recent emergence of artificial intelligence integration for deconstruction. Similarly, this observation aligns with integrating digital technology to transform the AEC industry into a circular economy.

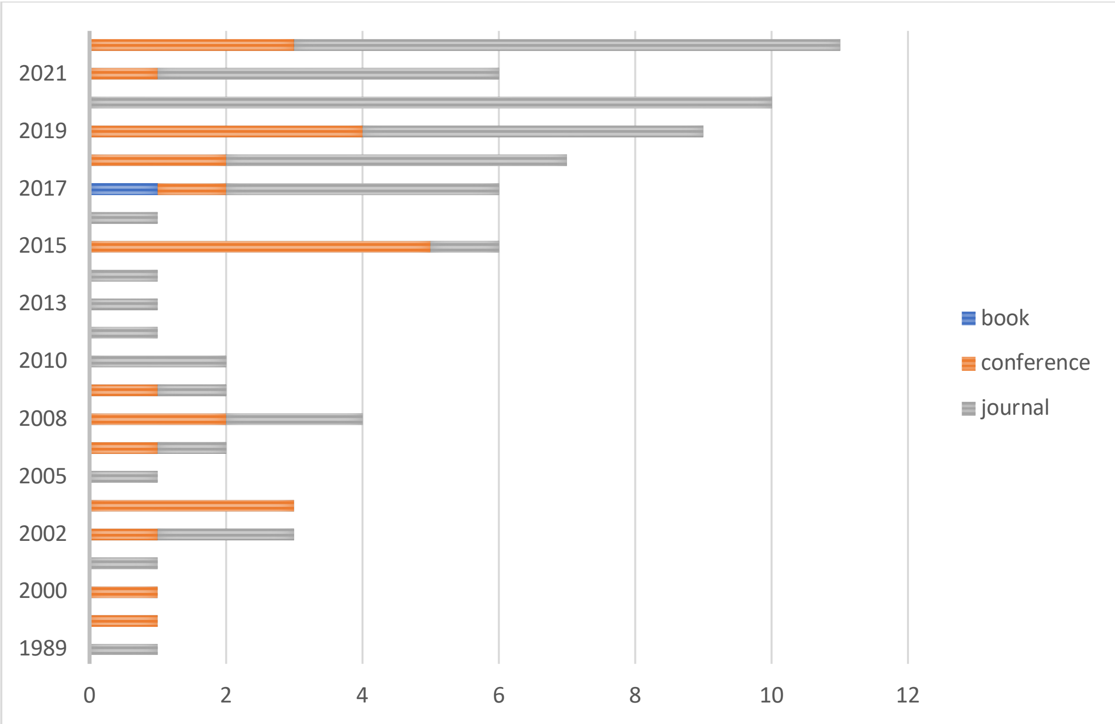

Figure 4.2: Publication types against year (Created by the author based on a literature review)

Figure 4.3 presents a Sankey Diagram created with (https://sankeymatic.com/) that visualises 75 publications on "AI for deconstruction," showing connections across publication types, years, AI technologies, deconstruction stages, and author countries. Flow widths represent the number of publications, while colours help visually trace connections across categories without specific meanings. This layout emphasises trends like the recent increase in publications and the focus on AI technologies and stages in deconstruction research.

Figure 4.3 categorises publications into Conferences (26), Journals (48), and 1 Book, with a growth trend in publication years, especially from 2018 to 2022. Key AI technologies include Optimisation (16), Robot (14), Deep Learning (17), and Machine Learning (16). Among 26 conference articles, 9 focused on building inspection using deep learning, forming the largest subset. Another 5 articles concentrated on material separation, predominantly leveraging robotics or a combination of robotics with other AI subsets. Also, conference articles featured a higher representation of separation, indicating its focus on actual deconstruction implementation, potentially due to robotics involvement. In 48 journal articles, articles focused on inspection and deconstruction scheduling predominated, employing deep learning, knowledge-based systems, and robotics. Inventory and sorting were also significant areas, predominantly utilising deep learning. Overall, AI applications were prevalent in the planning phase (59 out of 75

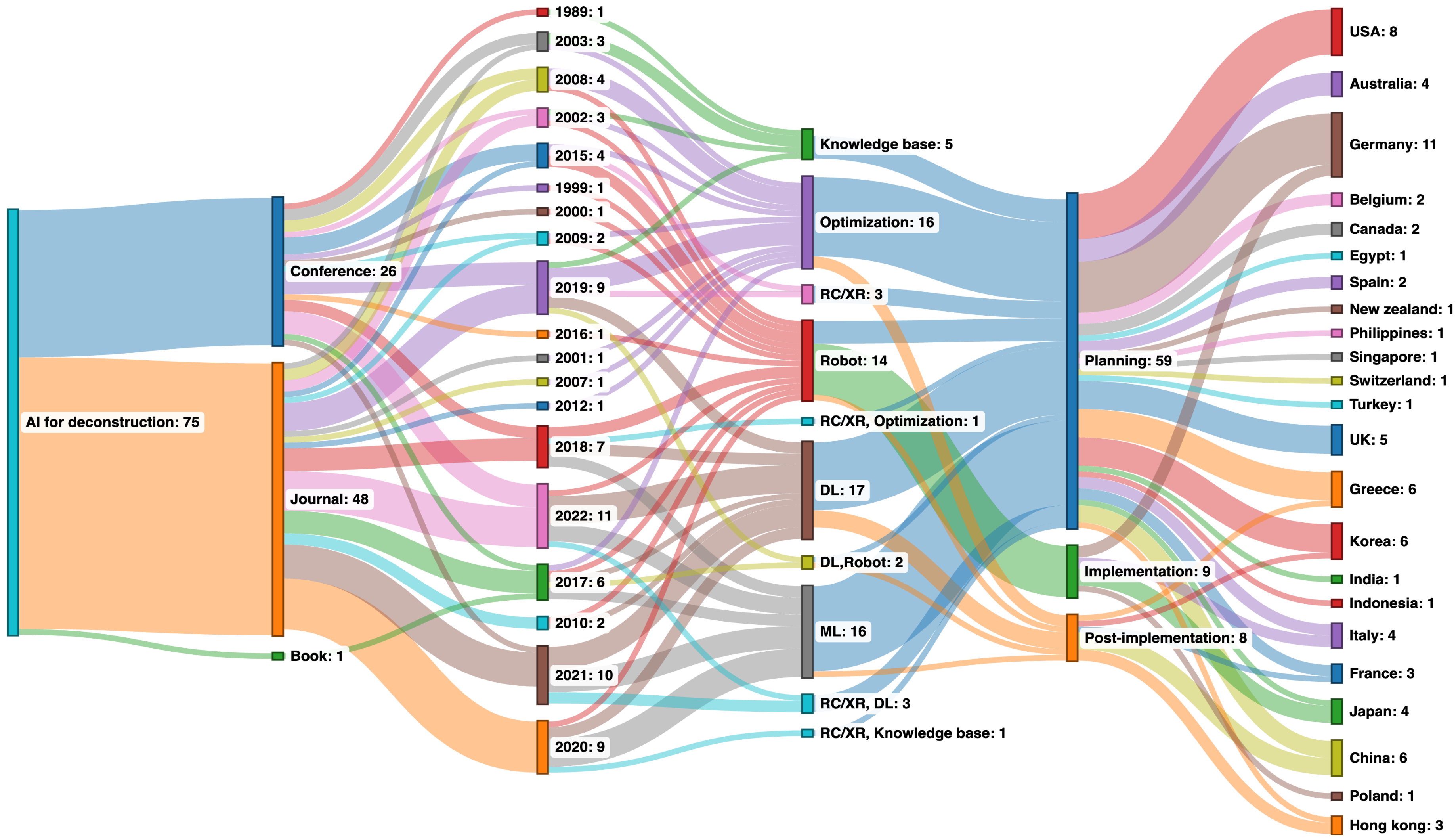

Figure 4.3: Journal types, publication year, AI types, deconstruction stages and country of author/corresponding author (Created by the author)

identified articles), highlighting planning as the key stage in deconstruction. Implementation (9 articles) and post-implementation (8 articles) received fewer mentions.

The top contributing countries are Germany (11), USA (8), China (6), and Korea (6). Germany and the United States emerged as the primary frontrunners, boasting the highest aggregate of articles. Furthermore, Europe takes the lead in this specialised area of research. One plausible explanation could be the European Union's proactive strategy to promote circular economy approaches in 2015—a strategy that garnered extensive adoption and endorsement through national initiatives. This has positioned Europe at the forefront of advancements in AI for deconstruction, solidifying its preeminent status in the field

Figure 4.4 presents the distribution of articles by publishers (i.e., publishers with a count above 2 articles). Additionally, the impact factor (Craig et al., 2014; Olavarrieta, 2022) and h-index of publishers, which serve as metrics for academic article contribution and reputation, were provided. This confirms the quality of the articles—they originate from reputable journals and conferences.

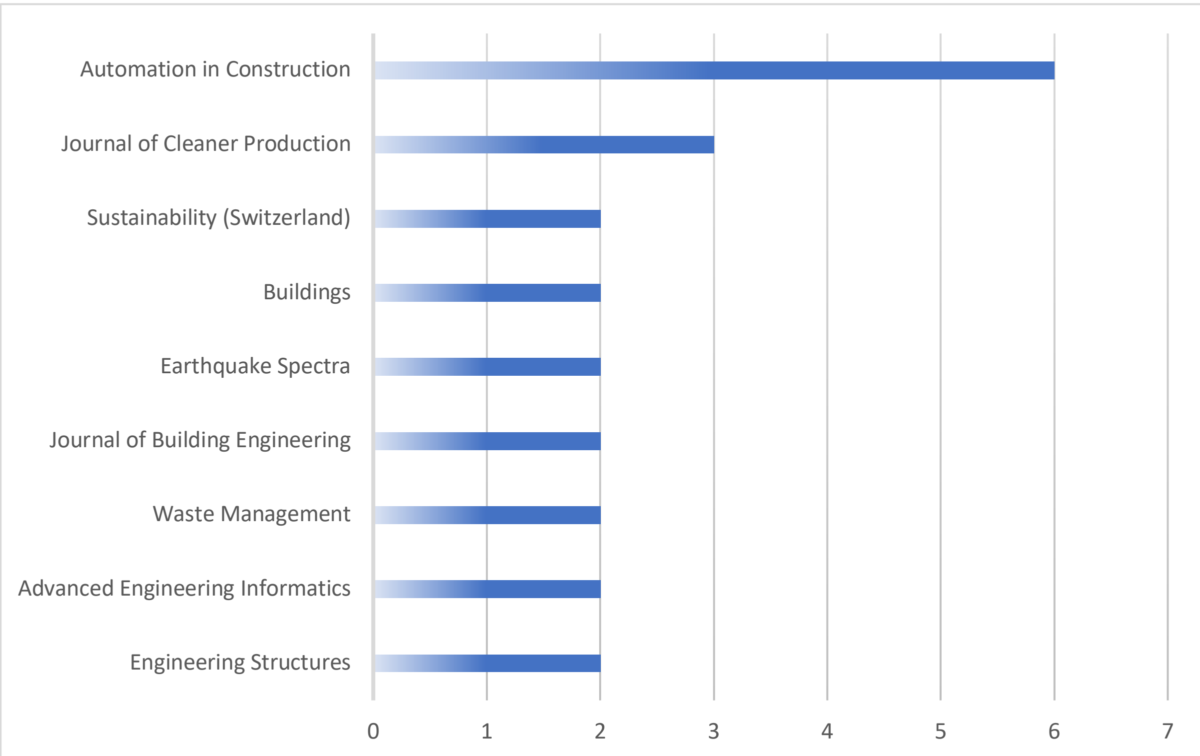

Figure 4.4: Publication counts per publisher (Created by author based on the literature review).

The Journal of Automation in Construction leads with 6 publications, boasting an impressive impact factor of 10.3 and an h-index of 157. Other significant contributors include the Journal of Cleaner Production (3 publications, impact factor: 11.1, h-index: 268), Sustainability (2 publications, impact factor: 4.0, h-index: 136), Buildings (2 publications, impact factor: 3.8, h-index: 45), and others, each contributing 2 articles.

The substantial presence of research literature in the Journal of Automation in Construction and other high-impact journals signifies a noteworthy advancement in this field, drawing attention to the newness and growing importance of this research domain. The fact that a prestigious journal has devoted many articles to this area underscores its increasing significance within the academic community. The journal's high h-index and impact factor, typically associated with respected academic publications, further validate the quality of the literature sources in this chapter.

4.3 AI and Subfields Used for Deconstruction

Artificial intelligence (AI) is the field of science and engineering dedicated to creating intelligent machines that can replicate human intelligence, with its origins dating back to 1956. Since its inception, AI has steadily garnered the attention of both scholars and the public. This enduring interest results from computing power, systems, and techniques advancements. AI has consistently played a pivotal role in people's lives, facilitating the automation of previously deemed insurmountable activities, especially in architecture, engineering, and construction (Abioye et al., 2021; Bilal et al., 2016).

There are many AI models and techniques. However, this section summarises the dominant AI techniques and models for deconstruction outlined within the selected articles, which were structured into subfields in line with (Abioye et al., 2021) categorisation. As a result, five prominent subfields stand out: Machine Learning (ML), Robotics, Optimisation, Knowledge-based systems, and Reality capture & extended reality, as illustrated in Figure 4.5.

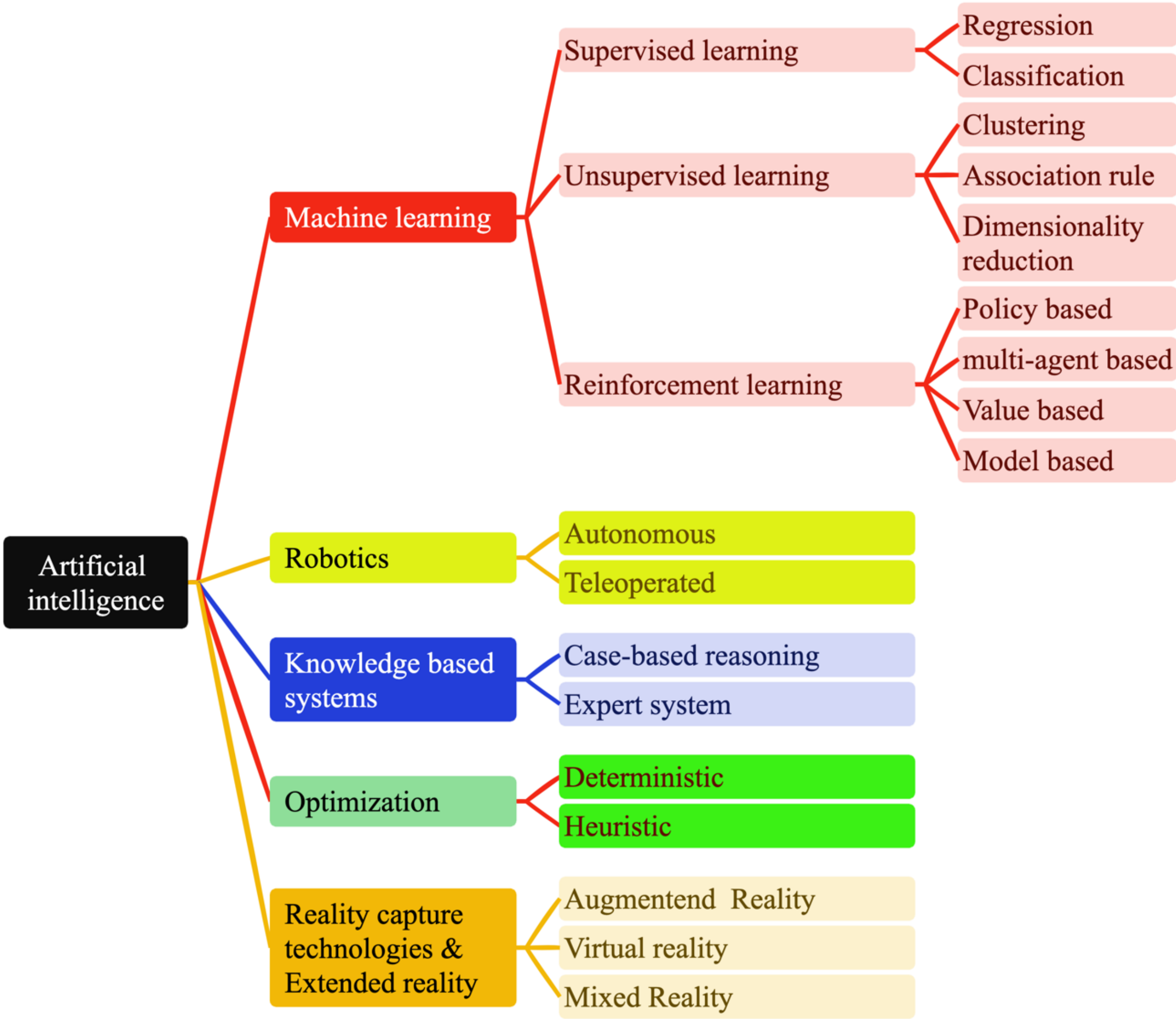

Figure 4.5: Artificial intelligence and its subfields (Adapted from Abioye et al., 2021)

Machine Learning

Machine learning (ML) involves the application of computer systems to learn from past data and make predictions on new - unseen data. ML can be classified in several ways (Figure 4.5). One way is to classify it based on the model's learning process, resulting in supervised, unsupervised, or reinforcement learning. Another classification criterion for ML is based on the complexity of the model, which can be either classical or deep learning (Xu et al., 2021).

1. Supervised learning necessitates labelled input data for training, making it suitable for solving regression or classification problems, depending on whether the labels are discrete or continuous values (Spathis et al., 2022).
2. On the other hand, unsupervised learning operates without any labelled data, focusing on finding patterns within the data autonomously. Some well-

known unsupervised learning techniques are clustering, association rule, and dimensionality reduction.

3. Reinforcement learning, the third category, involves a learning system, referred to as the agent, which interacts with the environment and receives rewards for its actions. Through this feedback mechanism, the agent learns to make decisions that maximise rewards (Uc-Cetina et al., 2022). Some well-known reinforcement techniques include value-based, model-based, multi-agent, and policy-based based, among others.

Additionally, ML may be classical ML or deep learning. In classical ML, experts manually engineer features or attributes, which are then fed into the model. As a result, the model learns from the data and makes predictions. Examples of classical ML techniques include support vector machines, decision trees, and ensemble methods, to mention but a few. The effectiveness of classical ML models largely depends on the quality of the hand-engineered features (Alaka et al., 2018; Balogun et al., 2021; Olu-Ajayi et al., 2022b, 2023).

Conversely, deep learning represents a specialised subfield of ML that centres around artificial neural networks. Neural networks are constructed with interconnected nodes, forming layers of neurons. Unlike classical ML, deep learning automatically learns feature representations directly from the data, eliminating manual feature engineering. This capability is one of the primary advantages of deep learning and has contributed to its widespread adoption in tackling intricate tasks across diverse domains. Classical and deep learning may still be formulated as supervised or unsupervised or reinforcement learning, depending on the problem scoping and objectives.

Robotics

Robotics, another significant subfield of AI, concentrates on designing and constructing robots capable of emulating human activities in the real world. These robots are engineered to carry out highly specialised tasks that might pose challenges for humans, and they come in diverse shapes and forms. Based on the functionalities, robots can be autonomous or teleoperated.

1. Autonomous robots operate independently, making decisions using intelligence gathered through their sensors and programming without direct human interventions.

2. Teleoperated robots are controlled by humans from a remote location or using some remote controls. This will be most useful in carrying out complex assignments in hazardous environments or situations where direct human presence is not feasible.

Knowledge-Based

As inferential decision-making engines, knowledge-based systems (KBS) draw upon expert knowledge or historical data to make informed decisions. KBS can be:

1. Case-based reasoning (CBR) learns by leveraging preceding problem-specific knowledge to solve new instances (Chen et al., 2022).
2. The expert system (ES) learns by amalgamating expert knowledge to devise evaluation rules for effective problem-solving (Ye et al., 2022).

Optimisation

Optimisation involves achieving the best possible outcomes while adhering to constraints (Kulkarni et al., 2017). It focuses on maximising or minimising a specific value or criterion by efficiently utilising available resources. It can be deterministic or stochastic (heuristics).

1. Deterministic refers to the systematic technique that guarantees finding optimal solutions for a given task, provided certain criteria are met. It follows a predefined set of rules and steps to search through the solution space and converges to the best possible solution. Some renowned examples of deterministic optimisation include gradient descent, linear programming, and integer programming, to mention but a few.
2. Conversely, stochastic (heuristic) methods are probabilistic methods that do not guarantee finding the global optimum. Instead, they attempt to find satisfactory solutions in a reasonable amount of time, especially for complex tasks where finding the global optimum might be computationally infeasible. Examples of methods include genetic algorithms, simulated annealing, and particle swarm optimisation, to mention but a few.

Reality Capture & Extended Reality

Reality capture technologies include the techniques and tools used to collect and generate digital representations of an object, building inclusive. Within these technologies, laser scanners, unmanned aerial vehicles (UAVs), LiDAR (Light detection and ranging), photogrammetry, videogrammetry, and digital cameras are prominent. They gather images, videos, or 3D point cloud data. Furthermore, the extension of the reality captured refers to the extended reality (XR). XR can be Virtual reality (VR), Augmented reality (AR), Mixed reality (MR) and similar reality-altering technologies that immerse users in altered realities (Al-Adhami et al., 2019; Alizadehsalehi et al., 2020; Trindade et al., 2023).

a. VR offers an immersive experience, replacing the real world with a completely simulated or virtual environment.
b. AR augments reality with computer-generated content. In AR, digital content is overlaid onto the user's real-world surroundings, allowing users to see both the real world and the additional content provided by the AR device (Wang et al., 2013).
c. MR resembles AR but facilitates deeper engagement between the virtual and the actual environment, offering users a heightened sense of realism. In MR, users get a fusion of computer-generated content within their real surroundings while also being able to actively engage with this content (Trindade et al., 2023).

To better understand these subfields, some benefits and limitations of the identified AI subfields for deconstruction were presented (Table 4.1). limitations of these AI subfields for deconstruction include data accessibility and quality, ethical concerns, essential AI proficiency tailored for deconstruction purposes and seamless integration into practical applications, potential issues with generalisation, and the criticality of validation, among other pertinent constraints.

Table 4.1: AI subfields, their benefits to deconstruction and limitations (created by author based on literature review)

Subfield	Benefits to deconstruction	Limitations	Articles
Machine Learning	- Accurate predictive models - Enhanced resource management - Precision in dismantling techniques - Optimised material auditing - Streamlined planning. - Improved efficiency - Easy integration with other technology	1. Data availability and quality 2. Explainability/interpretability 3. Generalisation and validation 4. Computational complexity 5. Human expertise and integration 6. Ethical considerations	(Akanbi et al., 2020b; Ekanayake et al., 2022; Rakhshan et al., 2021b; Tatiya et al., 2018d)
Robotics	- Adaptability to various task - Enhance productivity. - Improve safety. - Precision and consistency - Handling heavy loads - Easy integration with other technology	1. Complexity of environment 2. Cost and scalability 3. Manipulation of variable materials	(Biggs et al., 2011; Corucci & Ruffaldi, 2015; Cruz-Ramírez et al., 2010; Leea et al., 2022)
Knowledge based	- Explainability - Adaptability to varied structures. - Documentation and knowledge sharing - Easy integration with other technology	1. Dependency on expert knowledge 2. Ethical and bias considerations 3. Inability to handle uncertainty	(Fenves & Ibarra-Anaya, 1989; Sadek & Swailem, n.d.)
Optimisation	- Enhanced planning and decision making - Resource efficiency - Cost reduction - Adaptability to varied scenarios. - Optimal material recovery - Increased time efficiency	1. Computational Complexity 2. Data availability and quality 3. Trade-offs and conflicting objectives	(Queheille et al., 2019c, 2019a; Sanchez et al., 2019b; Sanchez & Haas, 2018)
Reality capture & Extended reality	- Accurate documentation - Enhanced visualisation - Improved planning - Onsite assistance and support	1. Compatibility and interoperability	(Banfi & Mandelli, 2021; Croce et al., 2021; Hu et al., 2022; Shon et al., 2022; Wei et al., 2019)

4.4 AI Application for Deconstruction

This section discusses the identified activities where AI application is employed in deconstruction, organised according to the framework from Section 4.0: planning, implementation, and post-implementation.

Figure 4.6 presents various AI applications in deconstruction processes, segmented into key areas such as Planning, Implementation, and Post-Implementation. Each branch explores specific AI techniques and algorithms tailored for distinct tasks within these stages, like inventory management, structural assessment, sorting, handling, and grading materials. Common AI techniques from Figure 4.6 are.

- You Only Look Once (YOLO) is a real-time object detection algorithm
- Convolutional Neural Networks (CNN): Image classification algorithm.
- Autoencoder: Often used for anomaly detection by learning compressed data representations.
- Support Vector Machines (SVM): Effective for classification tasks.
- Random Forest: A robust ensemble method for classification
- Logistic Regression, KNN, Decision Trees (DT), and Naive Bayes (NB) are fundamental classification algorithms.
- Analytic Hierarchy Process (AHP): A decision-making tool mostly suitable for project planning.
- Simultaneous Weighted Optimisation: Balances constraints like cost and time for optimal project scheduling.
- Path Planners: compute optimal paths for robotic navigation.

4.4.1 AI Application in Deconstruction Planning

The planning phase encompasses many activities, including inspection, project planning and scheduling, feasibility assessments, estimation of recovery rates, and thorough cost-benefit analyses (see Figure 4.6).

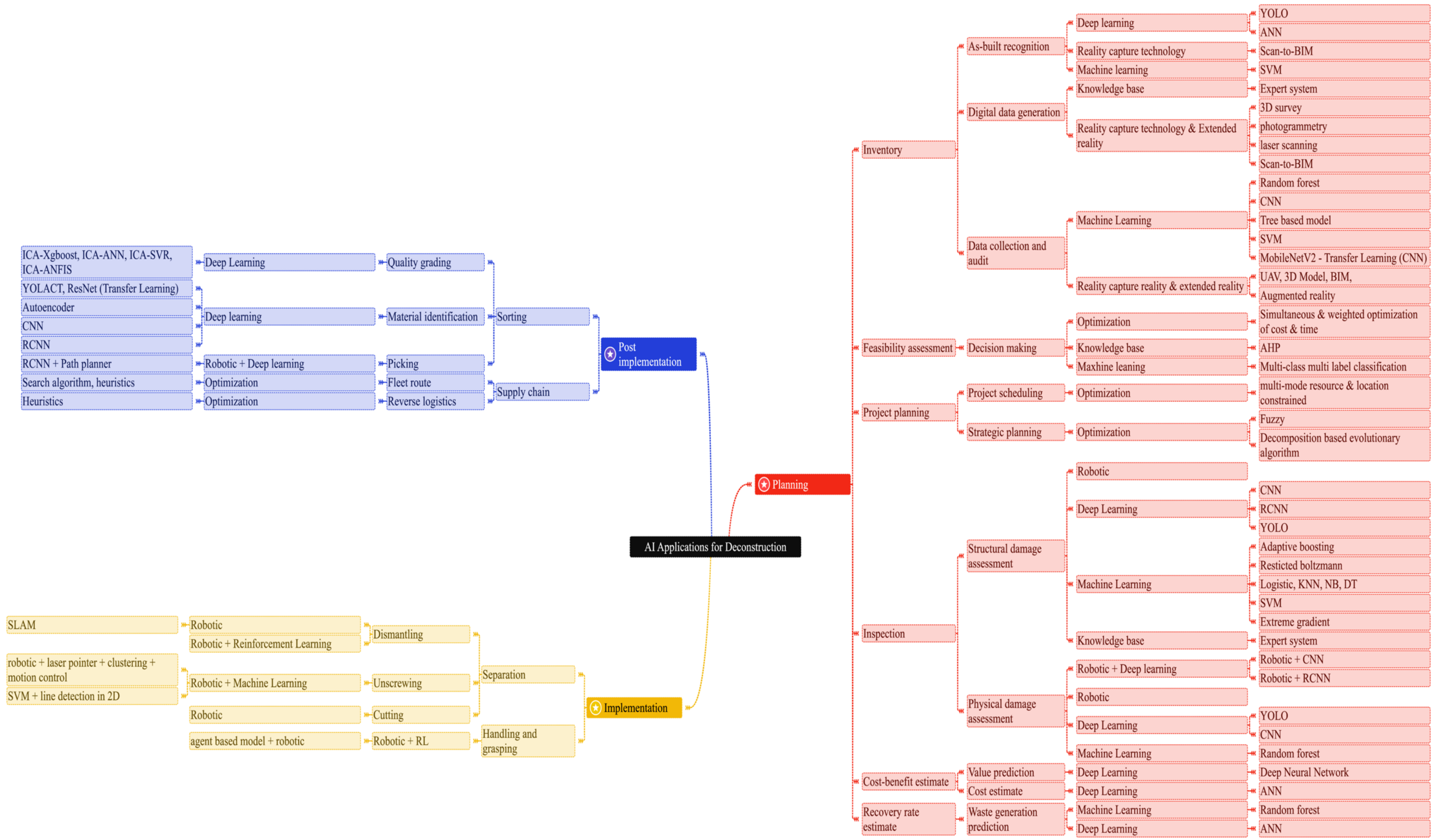

Figure 4.6. Summary of the AI application for deconstruction (Created by author)

1. Data Collection/Audit/Inventory

Deconstruction is a complex engineering process, like construction, but more challenging due to insufficient documentation. Comprehensive documentation should encompass a building's historical records, modifications, maintenance activities, and inventories over its years of existence. Examples of documents relevant to deconstruction include ownership and plot boundary documents, approval documents (e.g., permits and regulatory clearances), and strip plans of media lines and pipes (e.g., utility layouts) (Volk, 2017). Facility management, retrofits, inspections, and sampling documents offer historical facility data, aiding in maintenance understanding. Specific exposure documents are critical for safety, containing information on hazardous materials. Lastly, documentation of neighbouring buildings helps assess potential impacts on adjacent structures. These documents collectively support safe, efficient, and compliant building deconstruction processes.

Unfortunately, many existing buildings do not have this information, and thus, they suffer from incomplete, outdated, or fragmented building information, resulting in partially unknown or uncertain details. Furthermore, building information is frequently stored in an unstructured fashion, often devoid of modern formats like computer-aided design (CAD) or building information modelling (BIM), and occasionally even in non-digital formats. This absence of structured data makes it challenging to process building information directly. Consequently, material and components audits are manually possible, which implies manual measurements and examination of the existing building. A typical measurement and examination include measuring tape, torchlight, and a camera for photographs or videos.

To tackle these inventory, material audit and documentation challenges, there has been a rise in the use of reality-capturing technologies like photogrammetry, videogrammetry, laser scanning, or combinations thereof to semi-automatically or automatically capture and process building information. However, findings from this chapter posited that many of these reality-capturing technologies function more effectively when integrated with other subfields of artificial intelligence, such as machine learning and deep learning (Bassier et al., 2017; Kaplan et al., 2022) and expert systems (Doukari & Greenwood, 2020). ANN-based models were among the prominent models mostly used to augment material recognition (Brilakis et al., 2010) and data extraction (Shon et al., 2022). SVM and random forest were the other machine learning models discovered herein that are useful for data collection and material auditing in partnership with reality capture technologies such as 3D survey data, photogrammetry, and unmanned aerial vehicles, amongst others (Banfi & Mandelli, 2021; Bassier et al., 2017; Croce et al., 2021).

Despite the breakthroughs in machine learning and deep learning for recognition, detection and segmentation, its use, particularly for material audit and inventory, is still hindered by challenges, including the characteristics of the materials and components, typically inconsistent dimensions and standards, high similarity, and low variability (e.g., floor, ceiling, tiles and so on) (Brilakis et al., 2010). Also, insufficient training data, particularly for classes that form the minority, may yield poor performances for such classes (Bassier et al., 2017). Collecting more data and or augmenting the available data may be a solution to these challenges. Another challenge is the technical skills to annotate and prepare data correctly and the angle from which the data is captured (Raghu et al., 2022; Shon et al., 2022). Overcoming these challenges could facilitate utilising reality-capture technology, robotics, machine learning and even extended and immersive reality for material inventory and auditing in deconstruction.

2. Deconstruction Feasibility

Evaluating a building's deconstruction potential, termed the deconstruction feasibility at the end of its useful life, represents a pivotal activity in the planning phase. It revolves around the decision-making process of whether to proceed with deconstruction. This determination can be intricate and non-linear, particularly for existing and conventional buildings not originally designed with deconstruction.

As part of the solution to this challenge, Abdullah et al. (2003) proposed an intelligent decision support system using expert knowledge to select the most appropriate building end-of-life techniques, which include deconstruction, using criteria such as structural characteristics, site conditions, costs, experience, reusability, and time. Anumba et al. (2008) extended the work of Abdulla et al. (2003) by subjecting the different criteria to a quantitative evaluation in terms of cost. The outcome was a ranking of overall deconstruction feasibility based on their cost-effectiveness. Notably, both studies include social criteria like the health and safety of on-site workers and public acceptance. Additionally, workers' skills and prior experiences were considered factors that contributed to the economic criteria.

Similar literature surfaced afterwards, though they explored deconstruction feasibility from different points using different AI subfields. For example, deconstruction feasibility with a focus on economic gain and time optimisation (Aidonis, 2019), economic reuse potential prediction (Rakhshan et al., 2021) and technical reuse potential of components (Rakhshan et al., 2021a), among others.

Drawing from the reviewed articles, deconstruction feasibility assessment is possible using different subfields, mainly depending on the problem formulation and criteria. It is possible to use optimisation algorithms (Aidonis, 2019), expert systems (Abdullah et al., 2003; Sari et al., 2019), and machine learning (Rakhshan et al., 2021, 2021a). However, the multifaceted nature of deconstruction makes state-of-the-art feasibility assessment almost impractical, and this is because no known model has developed a holistic view of the criteria that influence deconstruction (Balogun et al., 2022). Based on this, an AI-driven predictive model considering all significant criteria from different standpoints may provide a realistic and practical feasibility assessment for deconstruction.

3. Project Planning

Effective planning is fundamental for all deconstruction activities and crucial in attaining specific project objectives. These objectives may involve cost reduction, material recovery maximisation, or both. The precise goals will vary and be influenced by factors like the building's type, urgency, stakeholder preferences, etc. Given the unique characteristics of each deconstruction project, personalised planning approaches are indispensable to address each building's distinct requirements comprehensively.

Deconstruction project planning consists of finding an optimal and feasible path for deconstruction under given constraints (Sanchez & Haas, 2018); as a result, it is often framed as an optimisation challenge and is typically categorised into two dimensions: strategic and operational (Hübner et al., 2017). Strategic planning delivers decision support for the entire project, considering time, cost, quality, resources, risk, etc. In contrast, operational planning predominantly concentrates on individual project activities, and its key objective is often to shorten the project's duration, which is commonly addressed as a resource-constrained project scheduling problem (RCPSP). Common heuristics and algorithms used for planning, generating sequences and scheduling include search techniques, optimisation techniques and genetic algorithms.

Despite the progress and utility of the optimisation techniques presented in these sources, some limitations have been observed, including limited real-life validation and a lack of automated learning of deconstruction knowledge from existing records without extensive human involvement (Queheille et al., 2019b, 2019d; Sanchez & Haas, 2018).

4. Structure and Material Inspection

The challenge of manually inspecting buildings, especially considering structural and non-structural components, has drawn attention due to safety concerns and potential damage caused by natural disasters (Roeslin et al., 2020). Despite the difficulty, these inspections are crucial for stakeholders. The exploration of AI applications in this domain has gained traction among researchers. Some have focused on AI-driven inspections of structural (Feng et al., 2020; Mangalathu & Jeon, 2018) and non-structural components (Yadhunath et al., 2022), while others covered both aspects (Rafiei & Adeli, 2017a).

Various AI subfields, notably machine learning, have been utilised, especially for image recognition and segmentation, often in integration with robotics and expert systems. For instance, Liu et al. (2017a) proposed an autonomous robot system employing recurrent neural networks for real-time visual defect detection.

Robotics has also played a pivotal role in inspection. Balaguer et al. (2002) introduced a teleoperated robot for high-rise metallic structure inspection, while Inoue et al. (2018) employed robots for wall inspection and deterioration estimation. Several studies have introduced expert systems for defect prediction (Terenchuk et al., 2018) and utilised machine learning models for seismic vulnerability assessments (Morfidis & Kostinakis, 2018; Y. Xu et al., 2022)

The classification problems retrieved from the articles were predominantly tackled, except for strength and capacity predictions (Mangalathu & Jeon, 2018). Convolutional neural networks (CNNs) were the primary choice for image detection and recognition. The most prevalent robot types used for inspections were teleoperated and semi-autonomous systems.

5. Cost-Benefit Estimate

Cost estimation is often a complex task, primarily due to uncertainties associated with the building's condition and the availability of comprehensive information regarding material states and values. This inherent complexity has led to adopting artificial intelligence (AI) techniques. Subfields of AI, such as machine learning and deep learning, have proven valuable for analysing historical project data and various variables to generate highly accurate estimates of material yields, costs, and benefits. Utilising AI in this manner helps reduce the likelihood of unforeseen expenses during the deconstruction process.

Within this context, studies have demonstrated the relevance and accuracy of artificial neural networks and case-based reasoning in cost estimation (Tatiya et al., 2018d). Additionally, the precise valuation of materials through artificial intelligence has been proposed (Haifeng & Baoming, 2021a). Among the predictive models employed for cost and benefit estimation, artificial neural networks with built-in layers emerged as the most used. This preference is attributed to the complexity of the variables involved. Furthermore, deep learning techniques like artificial neural networks are advantageous because they automatically extract features from the input data without requiring manual feature selection.

6. Recovery Rate Estimate

Accurately predicting the rates of salvageable and waste materials presents a considerable challenge, as the decision to proceed with deconstruction often hinges on the assessed value, quality, and quantity of recoverable materials within the building slated for deconstruction. In response to this challenge, AI has been increasingly explored to predict waste and salvageable material quantities precisely before commencing the deconstruction process.

As identified, Akanbi et al. (2020), Cha et al. (2022a), and Cha et al. (2020) have delved into the realm of AI, specifically employing supervised deep learning and ensemble machine learning algorithms to achieve accurate predictions of waste and recoverable material quantities. Deep neural networks and ANN logistic models were used to estimate waste quantities.

Table 4.2 summarises AI subfields in planning phase activities and sub-activities, alongside the potential opportunities. Noteworthy opportunities include leveraging robotics and deep learning algorithms to streamline material audits and optimise building material recovery.

Table 4.2: The State-of-the-art AI applications for deconstruction planning activities, sub-activities, subfields, and opportunities (Created by author)

S/N	Activity	-	Sub activities	ML	RB	KBS	OP	RC/XR	Opportunities
1	Inventory	-	As-built recognition (Brilakis et al., 2010; Ekanayake et al., 2022; Rebekka, 2015)	X				X	1. Robotics and Deep learning streamlined material audit
		-	Digital data generation (Doukari & Greenwood, 2020; Hu et al., 2022)			X		X	
		-	Data collection and material audit (Kaplan et al., 2022; Shon et al., 2022)	X				X	
2	Feasibility assessment	-	Decision making (Abdullah et al., 2003b; Sari et al., 2019)	X		X	X		1. Predictive model for feasibility assessment 2. Virtual feasibility assessment and material potential
		-	Reuse potential assessment (Rakhshan et al., 2021a, 2021c)	X					
3	Project planning	-	Schedule planning (Hübner & Schultmann, 2015; Schultmann, 2003)				X		1. AI-driven insights for strategic planning and task prioritization
		-	Strategic planning (Xanthopoulos et al., 2012a)				X		
4	Inspection	-	Structural damage assessment (Harirchian et al., 2020; Hwang et al., 2021; Mousavi et al., 2022; Y. Xu et al., 2022)	X	X	X			1. XR-enabled building inspection
		-	Physical damage assessment (Ekanayake, 2022; Rafiei & Adeli, 2017b)	X					
5	Cost-benefit estimate	-	Value prediction (Haifeng & Baoming, 2021b)	X					1. AI and XR high-value material recognition 2. Knowledge-based market demand estimate
		-	Cost estimate (Tatiya et al., 2018e)	X		X			
6	Recovery rate estimate	-	Waste generation estimate (Akanbi et al., 2020d; Cha et al., 2022b)	X					1. Deep learning for the material recovery rate

ML - Machine learning and this includes deep learning, RB – robotics, KBS-knowledge based systems, OP-Optimisation and RC/XR – reality capture technology and extended reality.

From Table 4.2, the prospect of a predictive model for assessing deconstruction feasibility using multidimensional criteria and applying extended and immersive reality for virtual feasibility assessments and material potential identification stands out.

Furthermore, Table 4.2 shows the limited utilisation of robotics in planning activities, primarily attributed to cost and expertise constraints (Abioye et al., 2021). Additionally, while reality capturing exhibits substantial benefits within inventory activities, its integration and use with extended reality still need to be explored, showcasing its untapped potential in enhancing deconstruction planning activities. Thus, robotics integrated with machine learning, deep learning, digital technologies like IoT, and extended reality should be more utilised in deconstruction planning activities. This underscores a critical gap in harnessing these advanced technologies to their full potential within deconstruction planning activities.

4.4.2 AI Application for Implementation

Robotics plays a pivotal role across various deconstruction implementation activities. It is instrumental in separation, dismantling, handling, and grasping tasks, as well as sub-activities like de-nailing and cutting, as illustrated in Figure 4.6. This is due to the inherent physical nature of typical deconstruction tasks.

Robots have been developed for dismantling interior components, such as ceiling panels (Cruz-Ramirez et al., 2008; Cruz-Ramírez et al., 2010), ceiling beams (Biggs et al., 2011) and partition removal (Lublasser et al., 2017b). Conversely, robots designed for dismantling structural components, like walls, have also been developed (Leea et al., 2022). They have also been explored for multitasking purposes (Lee et al., 2015), aiming to maximise productivity and reduce deconstruction operation times.

The integration of robots with other subfields, particularly machine learning, deep learning, reality-capturing technology, and expert systems, is evident in most of these studies. For instance, Leea et al. (2022) introduced an autonomous deconstruction robot equipped with a vision system capable of collecting environmental feedback. While considering hardware capabilities and human expert inputs, this system can automatically and precisely cut concrete walls. Additionally, it includes a grasping module to ensure safe wall cutting without damaging other building elements. Similarly, Biggs et al. (2011) developed a teleoperated robot designed explicitly for unscrewing suspended ceiling beams. This robot utilises laser scanning and clustering techniques to locate beams and features a motion control module for navigating between screws. While the robot performed admirably, occasional issues with skipped screws were encountered.

The findings from this chapter underscore that most developed robots for various deconstruction activities largely remain in their experimental stages, posing a challenge in evaluating their practicality for real-world deconstruction practices. Furthermore, while these robots hold promising potential applications, their deployment on actual deconstruction sites faces hurdles due to the inherent unstructured nature of building end-of-life scenarios (Lublasser et al., 2016). Despite the potential for reinforcement learning to address these challenges, its exploration in this domain still needs to be explored.

4.4.3 AI Application for Post-Implementation

The aftermath of deconstruction implementation presents several challenges, some of which can be strenuous, dangerous, or technically demanding. Post-implementation involves sorting and grading salvageable materials to separate reusable items from waste, picking and loading, planning logistics for the recovered materials, and more, as illustrated in Figure 4.6.

Studies in this field have explored the use of AI, including machine learning, deep learning models and robotics, to address these challenges. Table 4.3 summarises the subfields used for post-implementation (created by the author).

Table 4.3. Summary of subfields used for post-implementation activities and sub-activities.

Activities	Sub-activities	ML	RB	KBS	OP	RC/XR	Opportunities
Sorting	Grading (Dao et al., 2019)	X			X		Sorting and grading automatio through adaptive learning
	Material classification (Xiao et al., 2020)	X	X				
Supply chain	Reverse logistics (Xanthopoulos & Iakovou, 2009)				X		AI-driven Reverse logistics
	Fleet route (Xanthopoulos & Iakovou, 2009)				X		

Findings in this chapter revealed the use of AI subfields, such as optimisation for post-implementation activities. For instance, Xanthopoulos et al. (2012b) proposed and formulated the supply chain task for recovered materials as an optimisation problem. Also, Duan et al. (2021) investigated the prediction of compressive strength in recycled aggregate using meta-heuristic search techniques (ICA) and Xgboost. They developed a hybrid model called ICA-Xgboost, which was argued to outperform other models such as ICA-ANN, ICA-SVR, and ICA-ANFIS.

Additionally, studies have explored machine learning and deep learning with robotics for sorting and classifying salvageable materials. Examples include real-time waste classification and sorting systems using deep learning techniques like YOLACT and ResNet-50 (Na et al., 2022). In a similar study, Wang et al. (2019) introduced a robot capable of identifying materials, picking them up, and loading them. This robot utilised a Recurrent Convolutional Neural Network (CNN) for object detection and employed deep learning techniques for path planning and motion control. Several other studies, such as those by (Ku et al., 2021; Z. Wang et al., 2020; Xiao et al., 2020), adopted a similar approach involving robots, deep learning, and image-based technologies. Convolutional Neural Networks (CNN) and its variants, including Faster CNN, Recurrent CNN, Region-based CNN, and Masked RCNN, were among these studies that commonly used deep learning models for image recognition. While these proposed solutions demonstrate relevance, it's important to note that most are still in their experimental stages and may require further refinement for practical on-site use.

4.5 Challenges Facing AI for Deconstruction

So far, this chapter has pinpointed potential prospects and upcoming patterns in using AI for deconstruction. Recognising and deliberating on the leading obstacles is crucial to deepen our understanding in this domain. Figure 4.7 presents the opportunities, challenges, directions for future research, and evolving trends from the literature review. Five notable challenges affecting the utilisation of AI for deconstruction from the literature review are presented below.

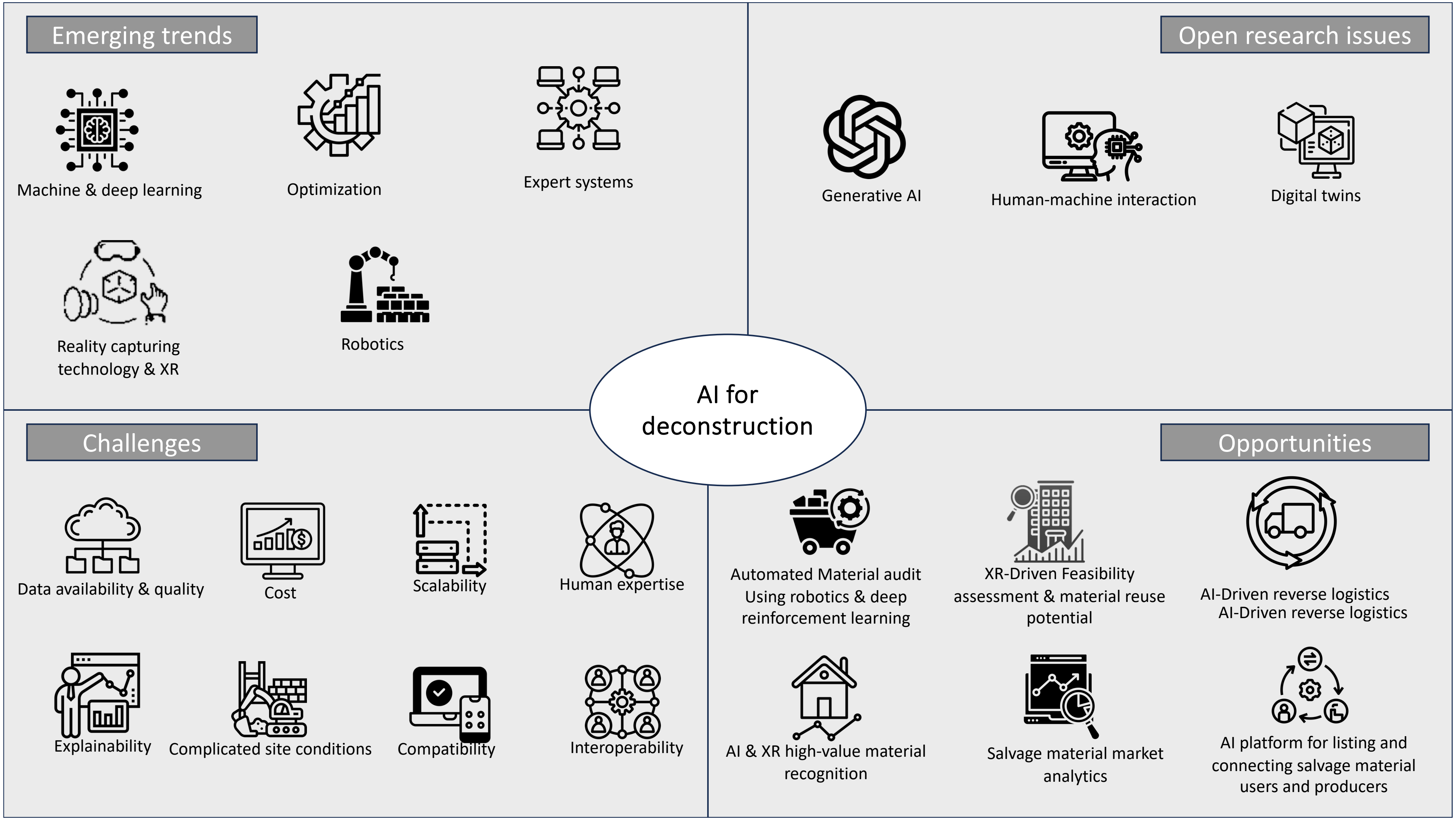

Figure 4.7: AI for deconstruction: opportunities, challenges, trends, and future directions (Created by the author based on a literature review)

1. Data Availability and Quality

This review uncovered a significant issue: a need for publicly available real-life datasets suitable for training AI in deconstruction. Most of the existing data used for developing AI in this field is privately owned.

This scarcity of accessible data has hindered the adoption of AI in deconstruction, as AI heavily rely on ample data (Balogun, Alaka, & Egwim, 2021; Balogun, Alaka, Egwim, et al., 2021b, 2021a; Egwim, Alaka, Toriola-Coker, Balogun, & Sunmola, 2021; Olu-Ajayi et al., 2023). Furthermore, there needs to be more focus on sustainable end-of-life and limited data availability specifically tailored for deconstruction (Akbarieh et al., 2020). Although some studies utilised a few open-source datasets, especially for waste classification and sorting, many needed more quality (Na et al., 2022). Other efforts have been made to collect datasets from the internet, but these often need to represent real-world deconstruction sites (Ekanayake, 2022).

Furthermore, using transfer learning and pre-trained models streamlines AI model training, particularly in machine and deep learning, and minimises data requirements by leveraging existing knowledge for new tasks. Adapting prior model learning to related tasks or domains is beneficial, especially for activities like material sorting (L. Liu et al., 2017b; Na et al., 2022). However, despite these advantages, the data quality problem still needs to be solved (Sun & Gu, 2022).

Overall, the absence of a tailored dataset for deconstruction poses a significant challenge in leveraging AI for deconstruction. If this challenge still needs to be addressed, it could stagnate the evolution of digital deconstruction. To overcome this obstacle, we recommend establishing a secure data-sharing platform to encourage developing and validating more AI solutions tailored for deconstruction. Additionally, data challenges may be tackled shortly with the rise in the use and integration of reality-capturing technologies, including unmanned aerial vehicles (UAV), sensors, laser scanners and others.

2. Cost and Scalability

The undeniable benefits of AI in deconstruction are offset by substantial initial expenses, dissuading smaller firms and subcontractors, significant players in the industry (Aguilar-Fernández & Otegi-Olaso, 2018; Low et al., 2020). This leaves firms with the trade-off between AI adoption's return on investment and associated expenses. Additionally, ensuring AI's adaptability to diverse deconstruction workflows and project sizes is pivotal for broad acceptance. However, integrating these AI applications smoothly across different projects and firms poses a scalability challenge, adding complexity to their widespread application.

3. *Human Expertise and Explainability*

Deconstruction, a specialised field, makes it challenging to find individuals proficient in deconstruction and AI development. AI's intricate nature and subfields create a barrier as their inner workings are often hard to interpret, hindering adoption. This lack of transparency may lead deconstruction professionals to hesitate to trust AI solutions without understanding how they arrive at conclusions. Addressing this requires developing AI models that are not just effective but also transparent and interpretable.

Collaborations between AI experts and deconstruction industry professionals can bridge these gaps by fostering innovation tailored to the unique needs of deconstruction. Such collaborations aim to create models offering insights into decision-making processes, fostering trust among deconstruction stakeholders and potentially accelerating AI adoption in the industry.

4. *Complicated Site Conditions and Uncertainties in Buildings*

Over time, buildings naturally deteriorate due to weather and accidents, rendering their conditions uncertain. Furthermore, typical sites are primarily complex and complicated (Xu et al., 2021). These challenges significantly impact the feasibility and effectiveness of adopting AI for deconstruction. The unpredictable state of buildings complicates the use of AI solutions, which rely on accurate data for decision-making. The uncertainties hinder the AI's ability to predict and assess salvageable materials and optimise strategies effectively, among other possibilities.

To boost AI adoption in deconstruction, it's vital to tackle uncertainties and complex site conditions. Leveraging advanced technologies like IoT, sensors, and adaptive and reinforcement learning for autonomous decision-making and accurate building assessments can mitigate these challenges.

5. *Compatibility and Interoperability*

Deconstruction is a specialised domain within construction, and like construction, professionals within deconstruction are conventional in their ways, so ensuring AI solutions seamlessly integrate with existing tools and systems used in the deconstruction process is essential. Challenges arise when AI solutions need help to fit into current workflows or lack efficient data exchange with other on-site tools.

Addressing these challenges involves tailoring AI applications for easy integration within the industry's infrastructure. This aims to have AI systems complement and enhance, rather than disrupt, established practices. For instance, when AI tools seamlessly communicate with inventory management or structural analysis systems, they optimise decision-making during deconstruction. Ultimately, prioritising compatibility and interoperability not only streamline operations but also significantly boosts efficiency in deconstruction activities.

4.6. Opportunities and Future Direction

The chapter's findings suggest the need for further research to explore AI's potential in deconstruction fully. Therefore, some opportunities and future research directions are outlined below (See Figure 4.7).

1. Robotics & Deep Reinforcement Learning for Audit

Integrating deep reinforcement learning (DRL) for material audit during deconstruction can revolutionise how robots identify, classify, and handle various building materials. By utilising DRL, robots equipped with sensors and cameras can learn to classify materials which are typically difficult to distinguish accurately (Brilakis et al., 2010). This technology allows the robots to continuously improve their material recognition abilities over time, enhancing the precision and efficiency of material audits. Additionally, DRL empowers these robots to develop optimised sorting strategies, learning to prioritise materials for recycling, reuse, or specific processing based on their properties. This approach not only streamlines the material audit process but also maximises resource recovery and promotes a circular economy.

2. XR-Driven Feasibility Assessment and Material Reuse Potential

Exploring extended reality (XR) in assessing material reuse potential and evaluating deconstruction feasibility is a significant opportunity for future research. By leveraging XR technologies like augmented reality (AR) and virtual reality (VR), researchers can create immersive mock-ups that analyse and visualise potential salvageable material for reuse or recycling from buildings. These simulations could provide valuable insights into recovered materials' condition, usability, and suitability for repurposing. Additionally, XR-driven feasibility assessments can virtually simulate and evaluate the deconstruction process, allowing stakeholders to assess challenges, optimise methodologies, and make informed decisions before physically undertaking the deconstruction. This innovative approach streamlines decision-making processes and contributes to more efficient, cost-effective, and sustainable practices within the deconstruction industry.

3. AI-Driven Reverse Logistics

Integrating AI subfields like robotics, optimisation, reality-capturing systems, and machine learning models presents a transformative opportunity for reverse logistics. By deploying these innovations, the intelligent screening of recovered materials at collection points can be readily automated. Furthermore, the advanced capabilities in optimisation algorithms can help solve complex tasks as intricate as path and route optimisation. This streamlines the redirection of the retrieved materials to locations suitable for repurposing or further processing. Leveraging this innovative approach to select the most efficient routes would reduce transportation time while maximising opportunities for material recovery. This convergence of AI-driven technologies would significantly contribute towards more efficient, sustainable, and streamlined materials management in reverse logistics operations within deconstruction.

4.7 Chapter Summary

The potential impact of AI on various industries, particularly in tackling and enhancing overall productivity, is undeniable. The deconstruction sector, facing productivity issues and numerous hurdles, stands to benefit significantly from AI's transformative capabilities. With the rapid evolution of digital technologies, AI has the potential to synergise and magnify the effects of these technological advancements within the deconstruction process.

This chapter thoroughly investigates the application of AI for deconstruction, encompassing an analysis of recent and relevant studies covering various uses of AI within deconstruction. This chapter aims to gauge the extent to which AI has been employed for deconstruction processes, exploring its utilisation across diverse activities. We provided an overview covering AI concepts, types, and subfields, revealing their uses within deconstruction. Furthermore, we outlined the limitations and benefits of each AI subfield, offering a summary of their contributions to the field of deconstruction.

Several well-known databases, including Scopus, Association for Computing Machinery (ACM), IEEEXplore, ScienceDirect, and Google Scholar, were searched to retrieve relevant articles published until 2022. This decision was reached to have a comprehensive collection of studies on AI applications for deconstruction, ensuring a robust examination of the subject.

Based on the gathered data, we categorised AI subfields into five: machine learning, robotics, optimisation, knowledge-based systems, reality-capture technologies, and extended reality. Additionally, we organised the applications of these subfields within the context of deconstruction into three phases: planning, implementation, and post-implementation. This structuring allows for a comprehensive understanding of how these AI subfields are utilised at different stages of the deconstruction process, from initial planning to the actual implementation and subsequent post-implementation activities.

The chapter's findings underscored that machine learning, deep learning, optimisation, and knowledge-based systems emerged as prominent AI subfields extensively employed in deconstruction activities. Conversely, the exploration and utilisation of robotics, reinforcement learning, and extended reality remained comparatively limited within the AI literature dedicated to deconstruction. Furthermore, despite generative AI's advancement and hype in other studies (Saka et al., 2024), their potential contributions to deconstruction processes remain largely unexplored and underutilised.

The chapter highlights that AI integration in deconstruction is gaining momentum owing to emerging trends like reality-capturing technologies and BIM. However, many are still in their conceptual or laboratory phases. Moreover, we identified challenges impeding the adoption of AI for deconstruction and provided actionable recommendations to overcome these hurdles. Overall, this chapter is a valuable resource for researchers and industry practitioners, offering insights into relevant AI uses and ongoing research within deconstruction.

Furthermore, this chapter provides an overview of what already exists (i.e., the AI application areas and the subfields employed) and some challenges from the existing literature affecting AI for deconstruction. Also, this chapter suggested possible areas in which deconstruction professionals can exploit AI for efficiency and productivity (see Figure 4.7). This chapter highlights areas yet to be explored and open for research. This will help and serve as a starting point for deconstruction practitioners and academics in ways that support the AI skill force without deconstruction domain expertise to understand areas where AI can be used for deconstruction purposes. Also, the chapter will help deconstruction practitioners just starting on AI adoption to note subfields and methods that are possibly relevant/feasible for deconstruction activities.

Despite its contributions, it is essential to acknowledge the limitations of this chapter. The chapter focused solely on journals, conferences, and textbooks, possibly neglecting valuable insights from other literature types. Consequently, the research findings may present a partial overview of the available literature on AI for deconstruction. Furthermore, the chapter primarily examined the methodologies employed in the articles rather than focusing on their results. This narrow focus may have limited this discussion and hindered the thorough validation of the methods used.

These limitations highlight areas for future research. Subsequent studies could address these shortcomings by incorporating data from various sources, evaluating the results, and validating methods employed in the literature. The next chapter is the research methodology, discussing the data collection, sampling, and ethics, among others, necessary for this research.

Chapter Five

5.0 Methodology

This chapter covers.

- *Methodology choices including philosophy, ontology, epistemology, approach, enquiry, strategy, unit of observation & analysis*
- *Data collection, ethics, sampling and data analysis*
- *Data quality and reliability*

This chapter discusses the choice of methodology to develop an AI-based deconstructability predictive model (AI-DPM). The chapter presents the philosophical assumptions, theoretical approach, enquiry methods, and strategy, among others, with justifications. An overview of the research methodology is given in Table 5.1.

Table 5.1: Methodologies summary (Adapted from Saunders et al., 2019)

Realm of choice	**Available choices**	**Adopted choice**
Philosophy	positivism, critical realism, interpretivism, and pragmatism	Positivism
Ontology	Realist, relativist	Realist
Epistemology	Objectivist, subjectivist, constructionist	Objectivist
Theoretical approach	Deduction, induction, abduction	Deduction
Method of enquiry	Quantitative, qualitative, and mixed methods	Quantitative
Strategy	Experiments, surveys, archival, documentary, case studies, ethnography, action research, grounded theory, narrative inquiry	Survey
Data collection method	Interviews, observations, artefacts, questionnaires, focus groups	Questionnaire
Data analysis methods	Various techniques	Reliability analysis, Exploratory Factor analysis
Unit of Analysis		Building

5.1 Research Philosophy

Research philosophy refers to assumptions developed, either deliberately or unconsciously, at the various stages of research, all of which inexorably shape methods and research findings (Crotty 1998). These assumptions are mainly of ontological, epistemological, and axiological. Ontology concerns assumptions about the nature and reality of things. It involves the researcher's interpretation of the study object and phenomena and how he perceives and approaches the object. Epistemology refers to acceptable, valid, reliable, and legitimate knowledge. Lastly, axiology refers to the researcher's role and value and how that impacts the research process. Additionally, these assumptions can either be objective or subjective. For example, the ontological perspective can either be objectivism which ‘holds that social entities exist external to and independent from social actors’ or subjectivism ‘which holds that social phenomena are created through the language, perceptions, and consequent actions of social actors’ (Saunders et al., 2019, p.159). These assumptions, together with the subjectivism and objectivism standpoints give rise to varying philosophies including positivism, critical realism, interpretivism, and pragmatism.

a. Positivism

It is the philosophical position of natural and physical scientists born from the works of the Vienna circles, Francis Bacon, and Auguste Comte (Saunders et al., 2019). Positivism sees social entities as physical objects: real, observable, and measurable, mostly quantitative and could draw on law-like generalisations (i.e., theory) which can be tested and confirmed through highly structured methodologies. Positivism might hypothetically test and confirm the existing theory and could deduct knowledge (deduction) or may follow an inductive approach, developing new theories and hypotheses, which can be tested and confirmed (Saunders et al., 2019). Positivism centres on empiricist methods designed to yield accurate data and findings uninfluenced by human bias and values.

b. Critical realism

It is concerned with understanding what we see and feel in terms of the underlying reality structures that affect visible occurrences and was born from the work of Bhaskar, in the late twentieth century (Saunders et al., 2019). Its ontological standpoint is subjectivism, and that is the same for epistemological and axiology standpoints. It sees reality as independent and external, not accessible through observation and knowledge as done in positivism. It embraces epistemological relativism which recognizes that knowledge is a social construct and does not exist independently (Bhaskar 2008), and lastly, axiologically, critical realism emphasises values of sociocultural backgrounds and experiences (Saunders et al., 2019).

c. Interpretivism

It is a subjectivist philosophy born from the work of French, German and English researchers (Saunders et al., 2019). It emphasises that human beings are different from physical phenomena because they create meanings. Interpretivists study meanings to create new, richer understandings of organisational realities. Empirically, interpretivism focuses on individuals' lived experiences and cultural artefacts and seeks to include their participants as well as their interpretations in their research.

d. Pragmatism

It employs a diverse set of research methodologies, the selection of which is influenced by the nature of the research issues. It was developed from the work of Charles Pierce, William James, and John Dewey (Saunders et al., 2019). It tries to integrate objectivism with subjectivism, facts and values, and contextualised experience. It accomplishes this by considering the functions that theories, conceptions, ideas, and hypotheses play as tools for action.

5.1.1 Research Philosophy Adopted

This study adopts positivism, aligning with a hypothetico-deductive model that builds on verifying a priori hypothesis and experimentation by operationalising variables and measures; results from hypothesis testing are used to help inform theory and contribute to the literature (Park et al., 2020). Studies aligned with positivism generally focus on identifying explanatory associations or causal relationships through quantitative approaches, where empirically based findings from large sample sizes are favoured—in this regard, generalisable inferences, replication of findings, and controlled experimentation have been principles guiding positivism (Creswell and Creswell, 2018; Robson and McCartan, 2016).

5.2 *Research Approaches*

Deduction, induction, and abduction are prominent research approaches that play crucial roles in theory formation. Deduction involves testing theoretical claims and typically begins by establishing causal relationships between variables (Saunders et al., 2015). This approach encompasses five key steps: formulating a research question based on an existing theory, transforming the question into hypotheses, collecting data to test the hypotheses, analysing data, and verifying or modifying the original theory based on the findings (Saunders et al., 2019).

On the other hand, induction involves the development of theories based on the analysis of gathered data. This approach derives hypotheses from previously collected evidence (Saunders et al., 2015). Lastly, abduction combines elements of both deduction and induction, moving back and forth between theory and data. Abduction starts with the observation of an unexpected event and aims to generate a plausible explanation for its occurrence. According to Van Maanen et al. (2007), certain theories may effectively explain observed phenomena more than others, and these theories can facilitate the discovery of further unexpected observations throughout the research process.

5.2.1 Approach Adopted

The deductive research approach was chosen for this study due to its ability to explain variable relationships. By operationalising the established variables into quantifiable facts, the deductive approach is justified as it enables a systematic examination of these relationships. Moreover, the predominantly quantitative nature of the research data and the need for a structured methodology that allows for replication further validate the suitability of the deductive approach.

Another noteworthy characteristic of deduction that aligns with this research is its capacity for generalisation. By utilising a sample of sufficient size, it becomes possible to draw inferences about the broader deconstructability, extrapolating from the findings of the sample. This allows for broader implications and insights to be derived from the research.

Moreover, the deductive approach aligns with the positivist philosophy, which emphasise the importance of structure, quantification, generalisability, and testable hypotheses. By adhering to these principles, the deductive approach provides a solid foundation for conducting scientific research, further supporting its appropriateness in this study (Saunders et al., 2019).

5.3 Research Strategies

A research strategy can be defined as a plan outlining how a researcher intends to address research questions. It serves as the methodological bridge between the researcher's philosophical standpoint and the subsequent selection of data collection and analysis methods (Denzin and Lincoln, 2018). Consequently, the choice of research strategy is primarily guided by the research questions and objectives at hand.

Several research strategies have been identified in the literature, including experiments, surveys, archival and documentary analysis, case studies, ethnography, action research, grounded theory, and narrative inquiry. Among these strategies, the first two—experiments and surveys—are primarily or exclusively associated with a quantitative research design. The subsequent two strategies—archival and documentary analysis, and case studies—may incorporate elements of both quantitative and qualitative research or adopt a mixed design that combines the strengths of both approaches. Finally, the last four strategies—ethnography, action research, grounded theory, and narrative inquiry—are primarily or exclusively linked to a qualitative research design.

5.3.1 Strategies adopted.

The study used a survey strategy. The decision to utilise a survey strategy in this study aligns with the common understanding that surveys are often associated with a deductive research approach. Additionally, the chosen strategy is well-suited to address research questions that seek to explore the "what," "where," and "how," aspects of the variables influencing deconstructability. By employing a survey, the study aims to provide valuable exploratory and descriptive insights, allowing for a comprehensive examination of deconstructability. The survey strategy offers the opportunity to collect data from a large sample size, enabling the generation of statistically significant findings and facilitating a broader understanding of deconstructability.

5.4 Research Methods

There are three primary research methods: quantitative, qualitative, and mixed methods (Saunders et al., 2019). Quantitative research relies on numerical data, utilising techniques like questionnaires and statistical analysis to gather and interpret information. In contrast, qualitative research focuses on non-numeric data, using methods such as interviews and data categorisation to capture rich descriptions and understandings.

Lastly, the mixed method combines elements of quantitative and qualitative methods. It is common for studies to integrate these methods, leveraging their strengths to address research objectives effectively. For example, a research design may incorporate a structured questionnaire supplemented with open-ended questions to capture nuanced perspectives that extend beyond pre-defined response options. Additionally, follow-up interviews may be conducted to gain deeper insights based on questionnaire findings. In some cases, qualitative research data can also be subject to quantitative analysis or inform the design of subsequent questionnaires.

Furthermore, these three methods were further divided into two sub-types each. The mono-methods refer to the use of one single data collection technique and corresponding analytical procedure. Multi-method refers to the use of more than one data collection technique and more than one analytical procedure.

5.4.1 Research method adopted.

The utilisation of quantitative research designs is commonly associated with positivism, particularly when employing predetermined and highly structured data collection techniques. However, it is important to note that it is now widely recognised as a misrepresentation to suggest an exclusive connection between positivism, deduction, and quantitative research design (Bryman, 1988; Walsh et al., 2015). As argued by Saunders et al. (2019), quantitative research designs can also be conducted within the realms of realist and pragmatist philosophies. Considering the quantitative nature of data collection, the adoption of a deduction approach, and the positivist philosophy, the chosen research methodology for this study is quantitative.

Quantitative research primarily focuses on examining relationships between variables, which are measured using numerical scales and analysed through a variety of statistical and graphical techniques. It often incorporates measures to ensure analytics validity, like an experimental design. Additionally, the data analysis will involve a mixture of analytical techniques, including conventional statistical approaches and machine learning techniques. This comprehensive approach facilitates a thorough exploration of the research questions and contributes to robust and evidence-based findings.

5.5 Data Collection Methods

Data collection methods are generally categorised into two types: primary and secondary. Primary data is firsthand information that has not been altered or published. Researchers gather primary data directly, making it specific to their study and tricky to substitute with secondary sources. This specificity is essential for research requiring precise, unbiased information, such as positivism. While primary data improves research quality, it is resource-intensive, requiring careful design/planning. Primary data sources include experiments, surveys, interviews, and questionnaires (Taherdoost, 2021).

In contrast, secondary data is pre-collected and published, gathered by others for different purposes. This type of data, commonly found in literature reviews, provides background information and aids in designing studies or comparing results with primary data.

5.5.1 Justification for using a questionnaire.

The survey approach often involves using questionnaires, which rely on structured, close-ended questions like multiple-choice and Likert-scale formats. Due to a lack of data from the deconstruction project, as discussed in Chapters 3 and 4, a questionnaire survey was chosen for this research. No publicly available deconstruction database existed, and the study aimed to develop an AI-DPM, which is difficult to achieve through secondary data. Additionally, data privacy restrictions and general unavailability hindered accessing essential documents like building plans and inventories. These factors necessitated using a questionnaire for data collection.

5.5.2 Advantages and Disadvantages of the Questionnaire

The questionnaire ensures uniform exposure to questions and options for all respondents, minimising potential bias and oversight. This helps to avoid bias in the questioning method. It also ensures respondents can address all queries, knowing their anonymity and the building's identity are protected. Additionally, it offers cost-effective data collection, particularly by utilising online distribution methods.

However, disadvantages include the inability of respondents to seek clarifications on unclear questions, restricting their ability to express their views fully. Closed-end questions may also limit respondents' capacity to share unique or nuanced experiences. Lastly, electronically distributed questionnaires may encounter low response rates (Holtom et al., 2022).

5.5.3 Pilot Questionnaire

The variables identified from the systematic literature review in section 3.1 were utilised to construct a preliminary questionnaire. This questionnaire was piloted with over ten professionals and academics specialising in construction and deconstruction. The primary objective of the pilot study was to ensure the clarity, organisation, simplicity, length, and relevance of the survey questions before broader distribution.

Feedback from the pilot study emphasised the need to organise questions into sections and to refine/rephrase specific questions for precision and conciseness. Additionally, unnecessary questions were identified and subsequently removed based on this feedback. All suggestions and feedback were carefully integrated into the final questionnaire (see Appendix A for a comprehensive/final sample of the questionnaire)

5.5.4 Ethics Approval

Following the pilot study, the finalised questionnaire was submitted to the university's research ethics committee for review and received approval under reference number cBUS/PGR/UH/05259. This ethics approval ensures compliance with strict standards for data security, participant confidentiality, and overall safety. All collected data is securely stored on encrypted systems, accessible only to the researcher. Participants were fully informed of their rights, including anonymity, confidentiality, voluntary participation, and the option to withdraw at any time without consequence. These measures safeguard participant welfare and ensure ethical compliance throughout the study.

5.6 Unit of Analysis

The unit of analysis refers to the person or object from which data is gathered, answering the questions of 'what' and 'who' is being studied, representing the entirety of the subject under investigation (Trochim 2006). This concept is often confused with the unit of observation, which pertains to the entity where measurements are taken (Tainton 1990). While the unit of observation deals with data collection, the unit of analysis guides the analysis, interpretation, and conclusion (Kumar 2018). So, in most cases, both are the same, but not always.

This research gathers data from construction experts with experience in deconstruction projects, focusing specifically on buildings at their end-of-life stage. The research centres on these buildings as the unit of observation and the unit of analysis, with the experts providing data based on projects they have been directly involved in.

5.7 Sampling

In this research, non-probability sampling methods, purposive and snowballing, were utilised. The link to the survey questionnaire was distributed/directed at deconstruction experts and professionals. These professionals were identified by exploring various reputable professional bodies, groups, forums, and renowned companies operating within and beyond the United Kingdom (UK). Prominent organisations and entities, including the Institute of Demolition Engineers (IDE), the Chartered Institute of Builders (CIOB), and the Royal Institute of British Architects (RIBA), among numerous others, were contacted to ensure the broadest possible reach.

A panoply of communication channels, including but not limited to widely recognised professional networking platforms like LinkedIn, were adroitly harnessed to establish fruitful and meaningful connections with these esteemed professionals (Kayam & Hirsch, 2012; Koranteng & Wiafe, 2019). Additionally, conventional means of communication, such as emails, were effectively utilised to reach these highly regarded experts. The data collection phase spanned an extended period from November 2021 to June 2022, allowing for an exhaustive gathering of vital information.

647 deconstruction professionals were contacted (via emails, phone, and physical visits to deconstruction/demolition companies/sites) with several back-and-forth reminders. Additionally, Google Ads and other channels such as LinkedIn and Twitter saw that the total number of questionnaire survey link clicks reached 2831, which is the total number of respondents reached out to. Of the total respondents, 301 responded and completed the survey (i.e., 10.6% return rate). However, because the research is interested in deconstruction projects, a total of 263 professionals were confirmed to have worked on at least one deconstruction

project in the past. This represents the valid data retrieved – indicating 263 deconstruction projects (i.e., 87% valid rate). While it's possible that some respondents may have worked on the same project, this figure reflects substantial firsthand expertise in deconstruction, which supports the research objectives even if there is some overlap in project experience.

The data recovered is relatively small but sufficient and satisfactory for analysis, following the central limit theorem requirement of 30 samples (King et al., 2018; Zhang et al., 2022). In addition, the samples considered in this research exceed the 36 used in similar research (Nunes et al., 2019) or even 90 used (Rakhshan et al., 2021a, 2021c).

5.7.1 Data Quality and Reliability

The survey questionnaire was divided into sections. Section A embarked on the inquiry into the professional's deconstruction expertise, specifically probing their involvement in leading or participating in previous deconstruction projects. In the event of a negative response, the subsequent questions were rendered redundant, effectively terminating the survey. Conversely, an affirmative response would prompt the professionals to provide additional insights into their roles, including their job titles and the number of years of experience amassed in the field of deconstruction. This strategic addition of supplementary details was conceived to augment the quality of the collected data.

Furthermore, respondents were instructed to confine their responses to a single deconstruction project they had previously worked on, instilling a sense of coherence and focused analysis within the collected dataset.

5.8 Descriptive Analysis

Data collected through a questionnaire survey were quickly explored. This was to understand the dataset's structure. A descriptive analysis involving a visual summary of the retrieved data was carried out. This foundational step is essential as it sets the stage for more advanced analysis (i.e., statistical/AI modelling) and understanding of overall data; few visual summaries are presented; see Figures 5.1 to Figure 5.6.

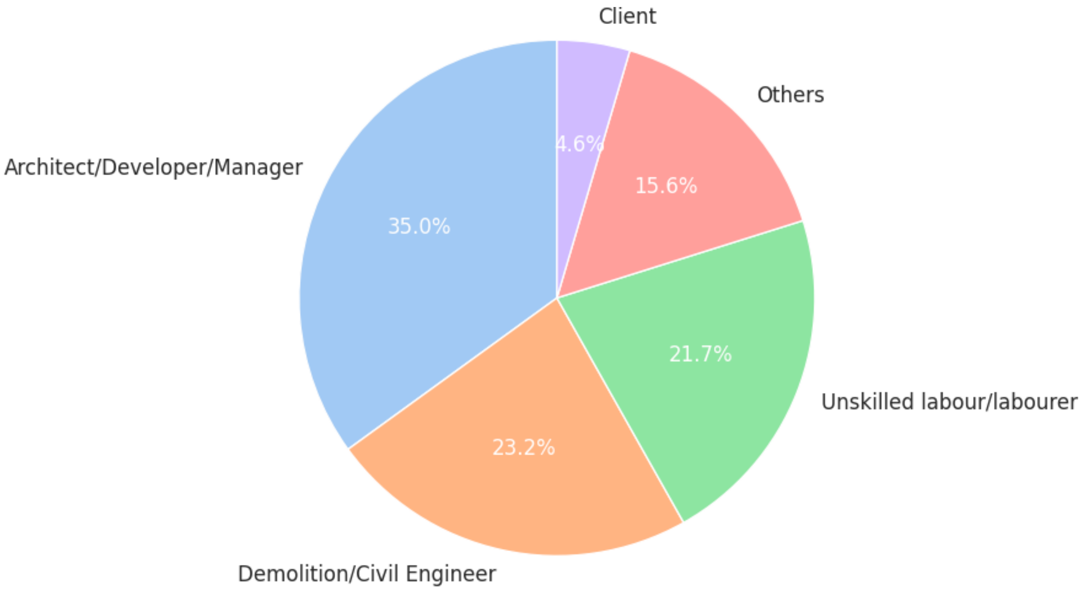

Figure 5.1: Distribution of the profession of the deconstruction experts (created by author)

Figure 5.1 presents the title distribution of the respondents. The profession with the most significant proportion was architect/developer/manager. The Client occupies smaller portions. Figure 6.1 emphasises the prominent representation of higher-level managerial/technical roles, further validating data quality.

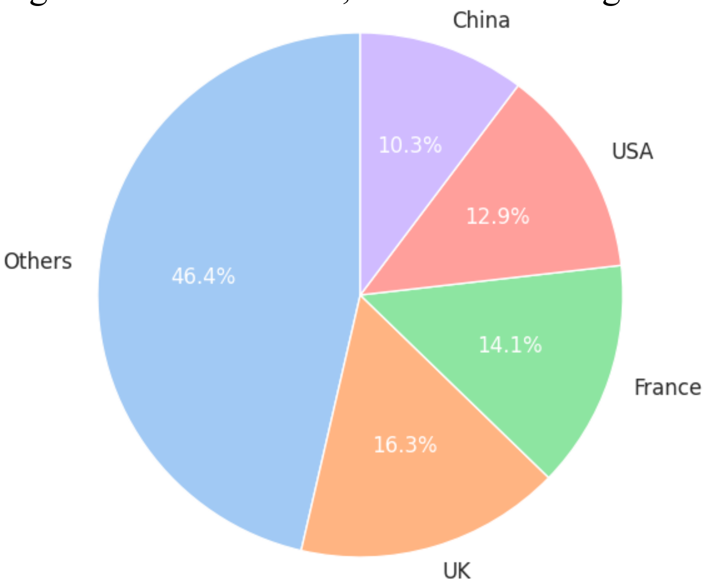

Figure 5.2: Locations of projects each questionnaire represents (created by author)

Figure 5.2 shows the geographical distribution of the deconstruction projects. The figure was segmented into five sections, each corresponding to a different project location: China, France, Others, the UK, and the USA. The largest, labelled "Others," occupies a significant portion, indicating that many deconstruction projects were in countries not explicitly listed. This distribution highlights the global nature of deconstruction projects and suggests a diverse set of project locations among the survey respondents.

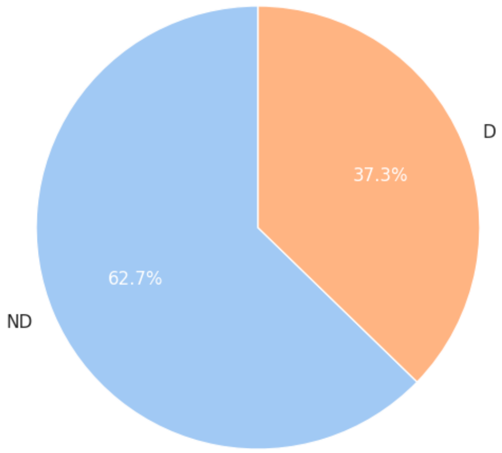

Figure 5.3: Deconstructability distribution of the completed projects (Created by author)

Figure 5.3 presents the distribution of deconstructability. The 'D' indicates deconstructible, and 'ND' indicates non-deconstructible. The proportion of the deconstructible building was smaller than the non-deconstructible.

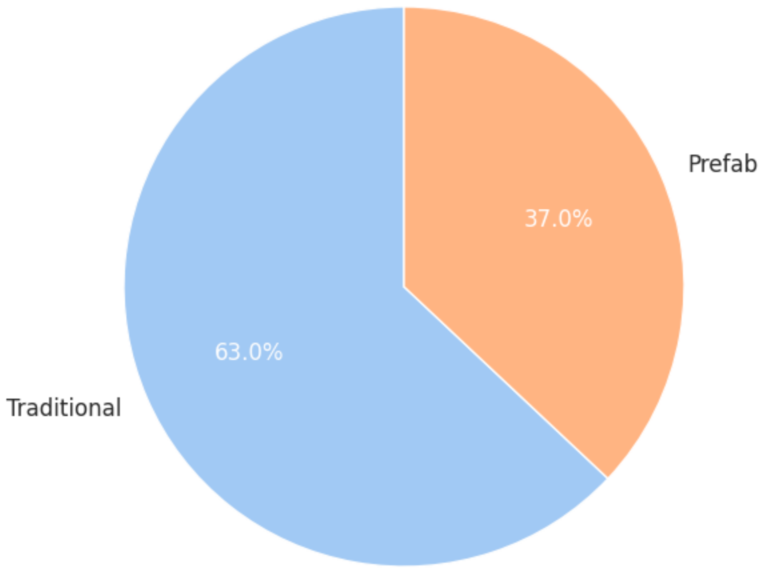

Figure 5.4: Building Methods (Created by author)

Figure 5.4 shows the building methods distribution. The traditional, usually built using non-separable connections, was considered the most common. This explains the reason for less deconstructible buildings, as seen in Figure 5.3.

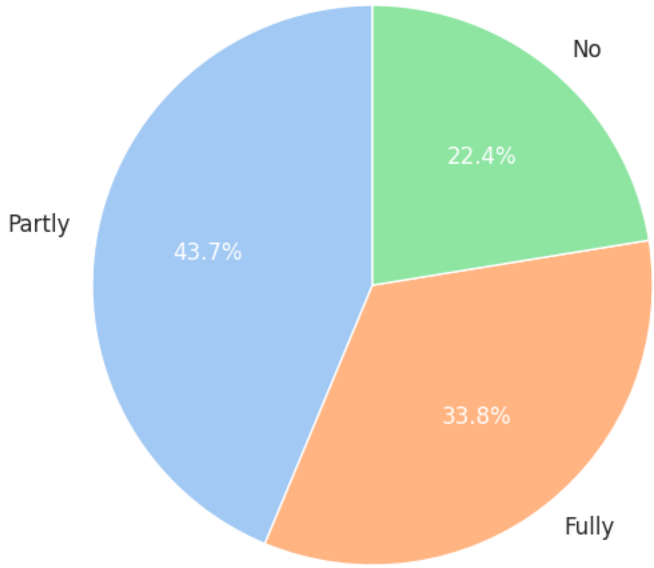

Figure 5.5: Security of the building project during deconstruction (Created by author)

Figure 5.5 illustrates the security of the deconstruction project site during the deconstruction. The majority were partly secure or not secure at all. This will arguably mean a high cost to insure recoverable materials.

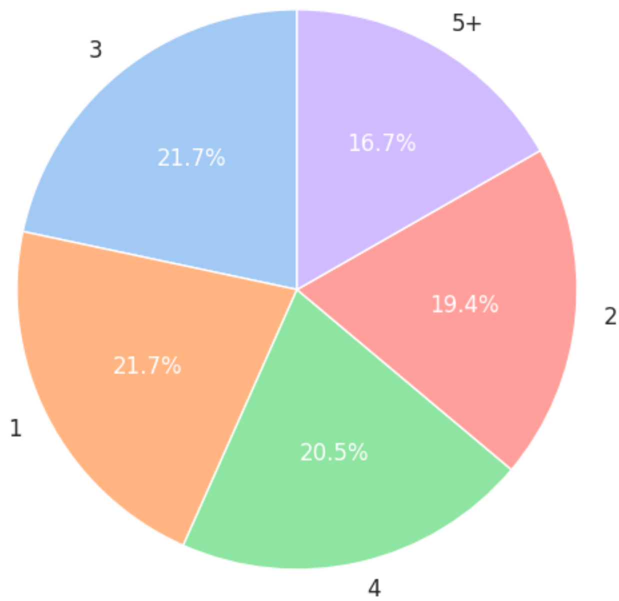

Figure 5.6: Distribution of rooms in the deconstructed projects (Created by author)

Figure 5.6 shows the distribution of rooms in the deconstruction projects. The three-bedroom and one-bedroom apartments were the most frequently deconstructed of all other properties.

5.8 Chapter Summary

The methodology chapter outlines a systematic approach to developing the AI-DPM model framed within a positivist paradigm. This approach is characterised by a realist ontology and an objectivist epistemology, emphasising that knowledge can be gained through unbiased observation.

A deductive theoretical approach was employed to align with the research aim, starting with established hypotheses regarding the identified explanatory variables. A quantitative method of inquiry was used, involving numerical data, statistical analysis, and the development of AI/ML predictive models. A survey strategy targeted deconstruction expert, focusing on buildings at their end-of-life stage as both the unit of analysis and observation. Respondents, including demolition engineers and contractors, were selected through random sampling, with outreach extended via Google Ads and snowballing techniques.

The questionnaire was informed by a thorough literature review, piloted, and received ethical approval. Of 2,831 deconstruction professionals contacted, 301 completed the survey, resulting in 263 valid responses.

Respondents without prior experience in deconstruction projects were filtered out to ensure data quality. Those with relevant experience were encouraged to provide detailed insights about their roles, enhancing the dataset's depth and accuracy. Respondents were instructed to focus their answers on a single deconstruction project, improving the collected data's coherence and relevance.

Throughout the research process, strict ethical standards were maintained, including obtaining informed consent from participants and ensuring the confidentiality of the data collected. As part of the methodology, the research carried out an initial step involving descriptive analysis to understand dataset (see Figure 5.1-Figure 5.6) providing a visual summary of the retrieved data, which is essential for setting the stage for more advanced statistical and AI modelling. The figures offered insights such as professions of respondents, geographical distribution of projects.

This methodological approach not only bolsters the study's validity but also ensures that it makes a significant and reliable contribution to the field of deconstruction. Chapter 6 will present the AI-DPM model development using the collected data.

Chapter Six

6.0 Development of Artificial Intelligence Predictive Deconstructability Model

This chapter covers.

- *Data preprocessing including encoding, missingness, imbalance class.*
- *Model development including training and validation*
- *Experiments, and model results*
- *Model explainability and generalisability*
- *Selection of best AI-DPM Model*

Machine learning, a subset of AI, encompasses unsupervised, supervised, and reinforcement learning. The primary distinction among these types lies in the prior knowledge of the expected model output for a given input (see Chapter 4 for more on AI and machine learning). Given the data's characteristics and the previous chapters' discussion on deconstructability, this study falls under supervised learning, specifically binary classification, as deconstructability is categorised as either deconstructible or non-deconstructible.

The workflow for supervised machine learning is divided into two main stages: training and testing. These stages can be iterative, allowing for continuous model refinement. Figure 6.1 shows this workflow. A training set is utilised to develop the classification model during the training phase. This involves selecting relevant features, choosing an appropriate algorithm and/or tuning hyperparameters to achieve optimal performance. Once the model is trained, it is evaluated using a test set. The test set, which consists of data unseen by the trained model, is essential for assessing the model's performance and generalisability. This evaluation helps identify potential overfitting and ensures the model performs well on unseen/new data. Adjustments can be made to improve the model's accuracy and robustness by iterating between training and testing.

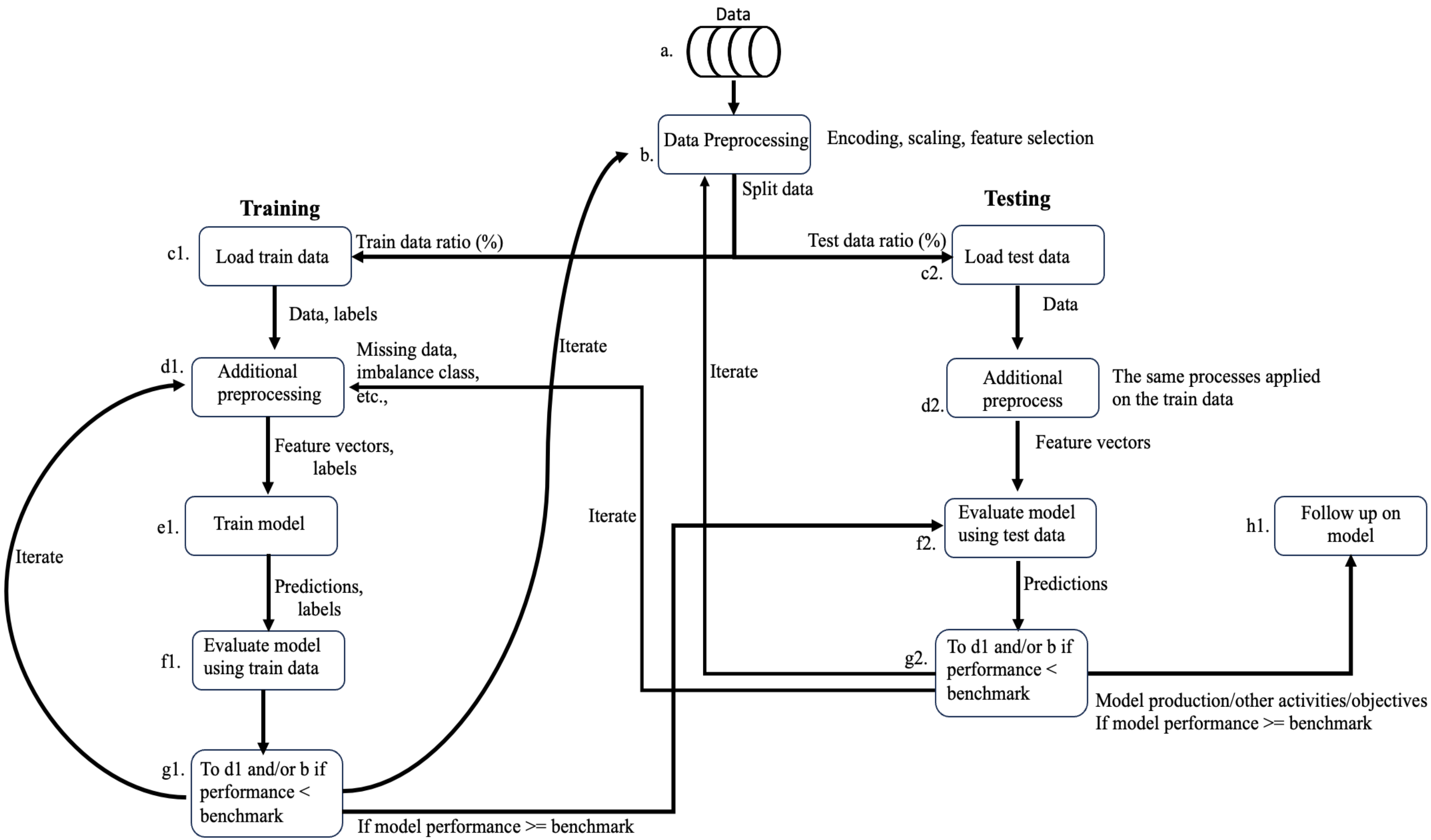

Figure 6.1: Supervised learning workflow *(Created by author)*

6.1 Data preprocess

The data preprocess involves transforming questionnaire survey data into an artificial intelligence and machine learning predictive model-ready state. This preprocess involves handling missing value, scaling, discretisation, and feature engineering (i.e., feature selection, feature extraction/dimensionality reduction) (Obaid et al., 2019). Subsequent sections will discuss data encoding, missing data, and feature selection in detail.

6.1.1 Data Encoding

AI/ML models are mainly designed for numerical inputs; as a result, efficiently encoding categorical features is a significant step in data preprocessing. Data encoding techniques are either target-agnostic or target-based (Pargent et al., 2022). Target agnostic refers to techniques that do not rely on information about the target variable; examples include one-hot encoding, ordinal (Integer), frequency encoding and more. Target-based techniques try to incorporate information about the target values associated with a given level, and examples include leaf, impact, and regularised impact techniques. Readers interested in encoding techniques are referred to (Pargent et al., 2022).

Among the various techniques available, one-hot encoding—a target-agnostic method—has been established as a standard approach for handling categorical variables (Gnat, 2021; Hancock & Khoshgoftaar, 2020). However, it is not without its drawbacks, particularly the issue of the curse of dimensionality, which becomes pronounced with increased cardinality (Tokuyama et al., 2020). High cardinality can lead to very high-dimensional vector representations, which can cause significant memory and computability concerns for machine learning models. In this research, the maximum cardinality of any variable is 5, and there are 96 total variables. Consequently, the resulting dimensionality is manageable and should not lead to excessively high-dimensional representations that pose substantial memory or computational challenges.

6.1.2 Missing Data

Data availability, quality, and completeness are common challenges in real-life AI/ML model development. The same challenge was faced in this study. Data for building deconstruction projects is not readily available, making the survey opt for data from professionals working on past deconstruction projects. The data collected between November 2021 and June 2022 is not free from missing values. 305 missing out of 96* 263, i.e., 1.21% of the total data were discovered missing.

Missing data can cause several issues in supervised learning modelling. Firstly, it reduces the available information, weakening the model's learning power. Secondly, it can bias parameter estimates, leading to inaccurate results. Thirdly, missing data reduces sample representativeness, making findings less generalisable. Lastly, it complicates model implementation, requiring additional preprocessing steps. These issues can jeopardise the model's performance validity and lead to incorrect outcomes.

There are several ways to deal with missing data; they can, however, be classified into two types. The first is completely ignoring the missing data (Silva & Zárate, 2014), and the second is imputing a value to compensate for it. The former is straightforward yet ineffective, notably when a sizeable part of the dataset is missing. Furthermore, if carried out improperly, it may result in skewed compensated values. Only when a tiny quantity of data is absent can the missing value be removed; nevertheless, in most real-life situations, datasets have a significant amount of missing data. However, because it requires several assumptions on the distribution of the dataset, imputation is likewise not an easy task. The ability to reconstruct and impute missing values and the potential to prevent missing recurrence in the future will be made possible by understanding the causes of the high rates of missing values. To understand missing data imputation rates in the academic literature, a thorough analysis of the missing data types is thus necessary. Missing data can be (a) missing completely at random (MCAR), where the missing probability is independent of the value and any other observable values; (b) missing at random (MAR), where the missingness depends on the observed variables; and (c) missing not at random (MNAR), where the missingness depends on both the observed variables and the unobserved variables. This study assumes the data are missing completely at random.

It was discovered from existing academic literature that many imputation techniques were supplied based on statistics and machine learning techniques (Rahman & Davis, 2013; Thomas & Rajabi, 2021). Statistical Imputation is a procedure that replaces missing values with estimated values based on statistical information in the dataset. The most often used statistical approaches in the literature include mean imputation, median imputation, most common value imputation, zero imputation and last value imputation (Jerez et al., 2010). All these imputations are helpful as they are assumed to stand for and have statistical information about the missing value. In addition to statistical imputations, machine learning-inspired imputation methods are based on creating a predictive model to estimate absent values from the information in the dataset.

Different studies have shown the usefulness of ML-based imputation techniques for data imputation. The K-Nearest Neighbour (KNN) (Hudak et al., 2008) imputation fills missingness with the mean value of k nearest neighbours. Multivariate imputation by Chained Equation (MICE) (White et al., 2011) draws from the variable's posterior predictive distribution using a sequential regression model to impute missingness. MICE handle different variable types. Other methods include the clustered-based imputation (Keerin et al., 2012), Decision tree-based imputation (Rahman & Islam, 2013), ensemble-based imputation (Fountas & Kolomvatsos, 2020), deep belief network-based imputation (Du et al., 2018), convolutional neural network-based imputation (Benkraouda et al., 2020; Zhuang et al., 2019) and recurrent neural network (RNN) based imputation (Sangeetha & Kumaran, 2020; Yuan et al., 2018). Of all these ML-based imputation methods, the KNN-based method has continuously been the day's talk for its outstanding performance (Thomas & Rajabi, 2021). Therefore, the KNN imputation is used in this study. We assumed the dataset to be MAR/MCAR.

6.1.3 Imbalance Class

Unequal target class distribution is a common problem typically faced in real-life situations. This challenge mostly poses a difficulty for learning algorithms, as it may make models biased towards a particular target class. Equally, the minority class is usually the critical group; for example, this study's deconstructible (D) class is the focus, yet with the least samples. This is typically the case for many other real-life examples. Therefore, there is a significant concern about overcoming such bias during the model development. It is common knowledge first to try out training on the actual distribution unless there are concerns; that is when techniques to handle imbalanced classes would be necessary. Handling an imbalanced class is mainly achieved by under-sampling, oversampling or mixed sampling (i.e., hybrid).

Under-sampling is the sampling of the majority to create a subset consisting of a small number of the majority to have a corresponding sample as that of the minority samples. Two common ways to achieve these are (i) making the boundaries of the different class samples farther and (ii) focusing on the classification rule based on the borderline samples (Runchi et al., 2023). Examples of techniques built using the under-sampling concepts include the Tomek link.

Conversely, oversampling is the sampling from the minority samples with or without replacement to create a more significant subset of the minority samples to have a balanced sample as that of the majority samples. There has been growing interest in this area, and more advanced methods have been introduced; an example is the Synthetic minority over-sampling technique (SMOTE). SMOTE is an oversampling technique that creates new artificial instances using the knowledge about neighbours surrounding each sample in the minority class. It finds the nearest neighbours of a given minority from the neighbourhood using K-nearest neighbour (KNN) (Chawla et al., 2002). SMOTE is widely used for its efficiency [238], and this has resulted in various variants, including ADASYN (He et al., 2008), KMeans-SMOTE, SVM-SMOTE, Borderline-SMOTE and more (Runchi et al., 2023).

Lastly, hybrid sampling merges the under-sampling and the oversampling ideas. It balances the two class samples by excluding some majority samples and increasing the minority samples simultaneously. Examples include SMOTE-Tomek (Sain & Purnami, 2015), which uses SMOTE and Tomek links to establish new minority samples and Tomek links to remove noise samples. Other examples include SMOTE-ENN (Guan et al., 2021), which uses a weighted, nearest-neighbour rule to identify and remove noise after SMOTE is utilised.

This study employed SMOTE owing to its efficiencies (Runchi et al., 2023) and the relatively small data available in this research. See Figure 6.2 for the class distribution of the training set before and after implementing the SMOTE technique.

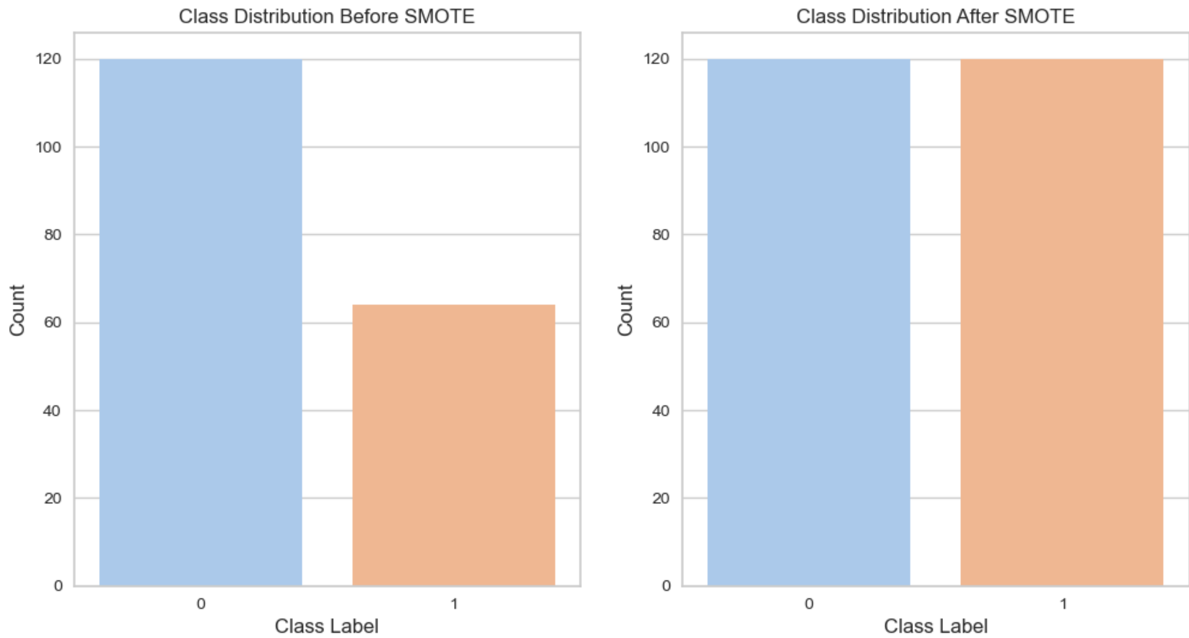

Figure 6.2: Class distribution before and after SMOTE applied on training set (Created by author)

6.2 *Feature Selection*

Conventional and classical supervised learning model's performance arguably depends on the input (i.e., features/variables used in developing the model). Research studies such as (Alaka et al., 2015; Balogun et al., 2021; Egwim et al., 2021,2023; Olu-Ajayi et al., 2022, 2023) have proved the relevance of feature selection and dimensionality reduction in different domains. It selects the most impactful features from the original set of features as the new input features. Thus, not all features impact prediction, making feature selection critical in developing machine-learning predictive models (Reddy et al., 2020).

Feature selection (FS) is a significant step in implementing machine learning algorithms across different domains; it aids in reducing features to a minimum, reducing computational cost, and thus improving the learning performance of the model. Aside from providing efficiency in the model implementation, FS can help eliminate redundant information and enhance data generalisation (Tang et al., 2020). FS is categorised as a filter, wrapper, and embedded method. See Figure 6.3 for the classification.

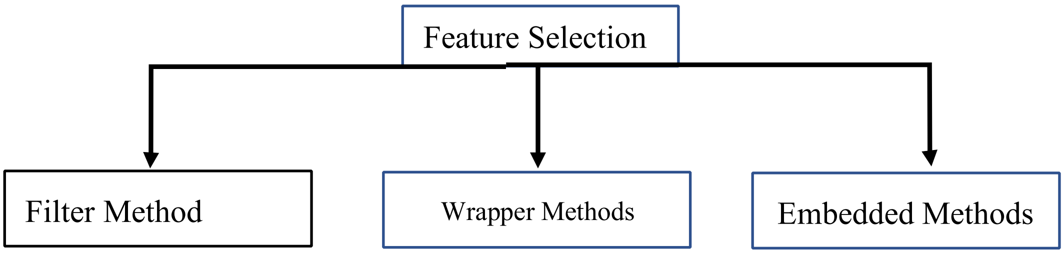

Figure 6.3: Feature Selection Classification

The filter method uses the statistical characteristics of the dataset, providing feature ranking as output and selecting features regardless of the model. Examples of the many standard filter methods can be seen in the research by (Jović et al., 2015). Though filter methods are easily employed due to their low cost for computation, the wrapper method is better because of their search strategy on a modelling algorithm (Jović et al., 2015). Furthermore, wrapper methods are designed to evaluate individual feature subsets using learning algorithms (Figure 6.4, showing the architectural design of the wrapper FS method).

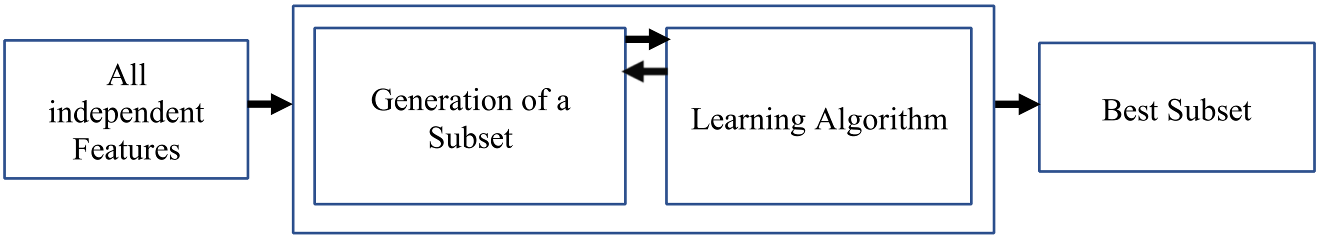

Figure 6.4: Wrapper Feature Selection

As a plus to the two methods, i.e., filter and wrapper FS methods, embedded FS methods select features during the algorithm modelling implementation. This method enjoins performance and computational cost advantages from the filter and wrapper method. An interested reader of the embedded method is referred to (Lei, 2005).

Overall, all FS methods have their strengths and weaknesses and thus would have a different impact on the machine learning model's performance. Inferring from this, this study utilised eight FS techniques (3 filter methods, 3 wrapper methods and 2 embedded methods).

Filter methods

1. Chi-square (CHIS) is a filter method used to test the independence between two events. It evaluates the degree of association between two categorical variables by measuring the deviation from the expected frequency,

assuming that the feature is independent of the class label (Liu & Setiono, 1995).

2. Analysis of Variance (ANOVA): This type of univariate filter-based technique utilises variance to detect the separability of each feature between classes (Ding & Li, 2015).
3. Mutual Information (MI): Mutual Information (MI) is a filter method that evaluates the dependence between two variables. MI quantifies the amount of information one random variable contains about another (Bennasar et al., 2015).

Wrapper Methods

4. Recursive feature elimination (RFE): RFE is a wrapper-style feature selection method. It recursively eliminates 0-n features in each iteration, selecting the optimal number of features for each model (Mustaqeem et al., 2017). The best-performing subset of features is chosen based on the cross-validation score. Herein, the random forest was carried out as RFE.
5. Forward Feature Selector (SFS): Forward selection is an iterative technique that begins with no features. Initially, the feature with the best performance is added. Then, the next most significant feature that improves performance in combination with the previously added feature is selected. This process continues until adding a new feature no longer enhances the classifier's performance (Aboudi & Benhlima, 2016; Mustaqeem et al., 2017). Herein, a random forest classifier was employed.
6. Backward Feature selection (BFS): In backward elimination, the algorithm starts with all the features available and discards the most insignificant feature from the model recursively. This elimination process is repeated until features are removed, which does not enhance the model's performance (Chandrashekar & Sahin, 2014; El Aboudi & Benhlima, 2016). A logistic regression classifier was utilised as BFS.

Embedded Methods

7. Embedded Random Forest: The Random Forest algorithm was used as an embedded feature selection method. The significance of each feature is calculated by performing random permutations of the features in the out-of-bag (OOB) set and measuring the increase in misclassification compared to the default state of the OOB set (Liu et al., 2019).

8. Embedded LightGBM (ELGBM): LightGBM classifier was utilised as an embedded feature selection method in this research due to its efficiency (Tang et al., 2020). ELGBM assigns global importance to the features in this research by averaging their importance across all trees (base learners). The contribution value of each feature is then calculated and compared against a threshold. Features with contribution values lower than the set threshold are subsequently eliminated.

The top 45 features and their raw scores for the 8 FS techniques are shown in Figures 6.5 to 6.12. The figures display features arranged by their scores for each FS technique, with the bars indicating the importance scores assigned to each feature by the respective technique. Figures 6.5 to 6.7 present three filter FS techniques. Figures 6.8 to 6.10 present three wrapper FS techniques, and 6.11 to 6.12 present embedded FS. Table 6.1 provides a comprehensive list of the features chosen to develop the AI-DPM. Features were selected based on their counts and included if their count satisfied at least 3/4 of the eight methods, meaning if a variable had a count of 6 or more, it was selected (see Table 6.1). This decision aligns with the FS ensemble, which combines several FS outputs through aggregation/thresholding (Veronica and Amparo 2019).

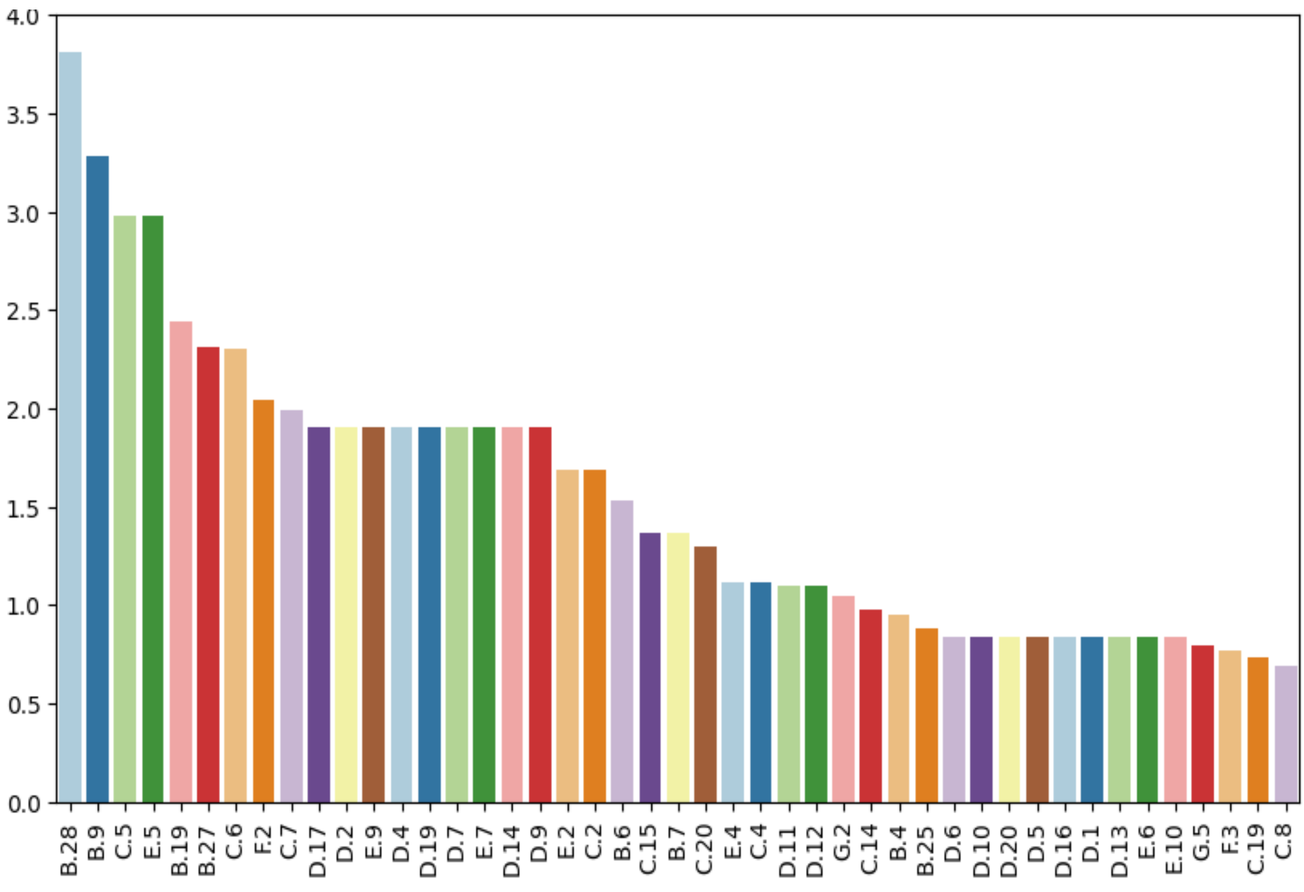

Figure 6.5: Charts of scores assigned by Chi-square (Created by author)

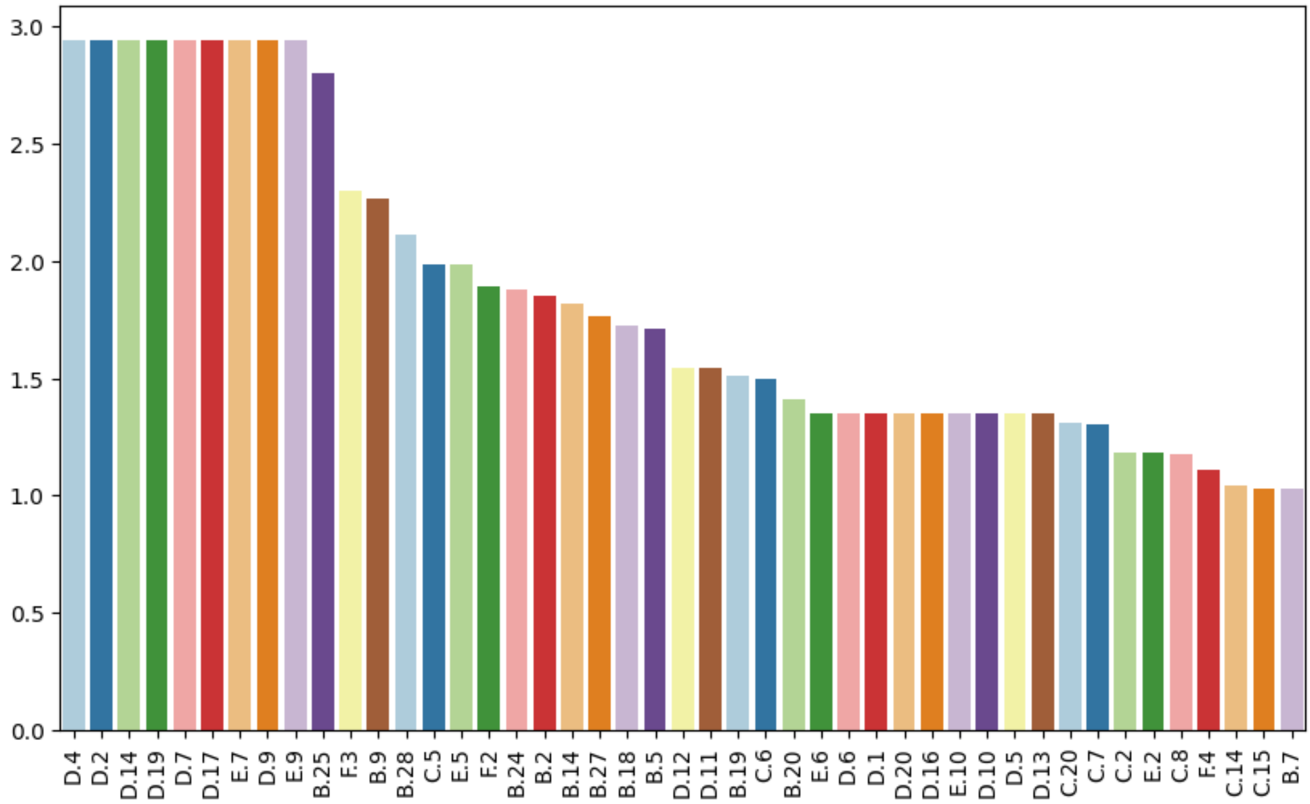

Figure 6.6: Charts of scores assigned by ANOVA (Created by author).

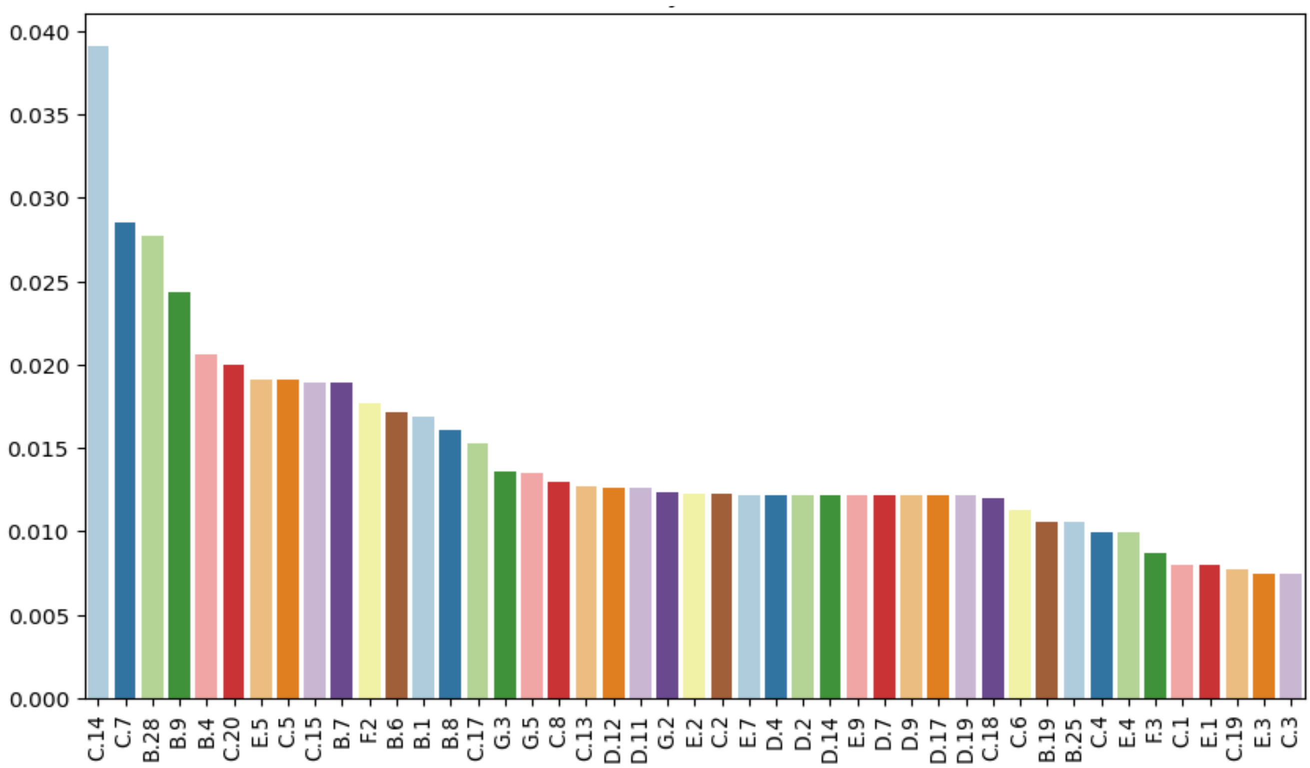

Figure 6.7: Charts of scores assigned by Mutual information (Created by author).

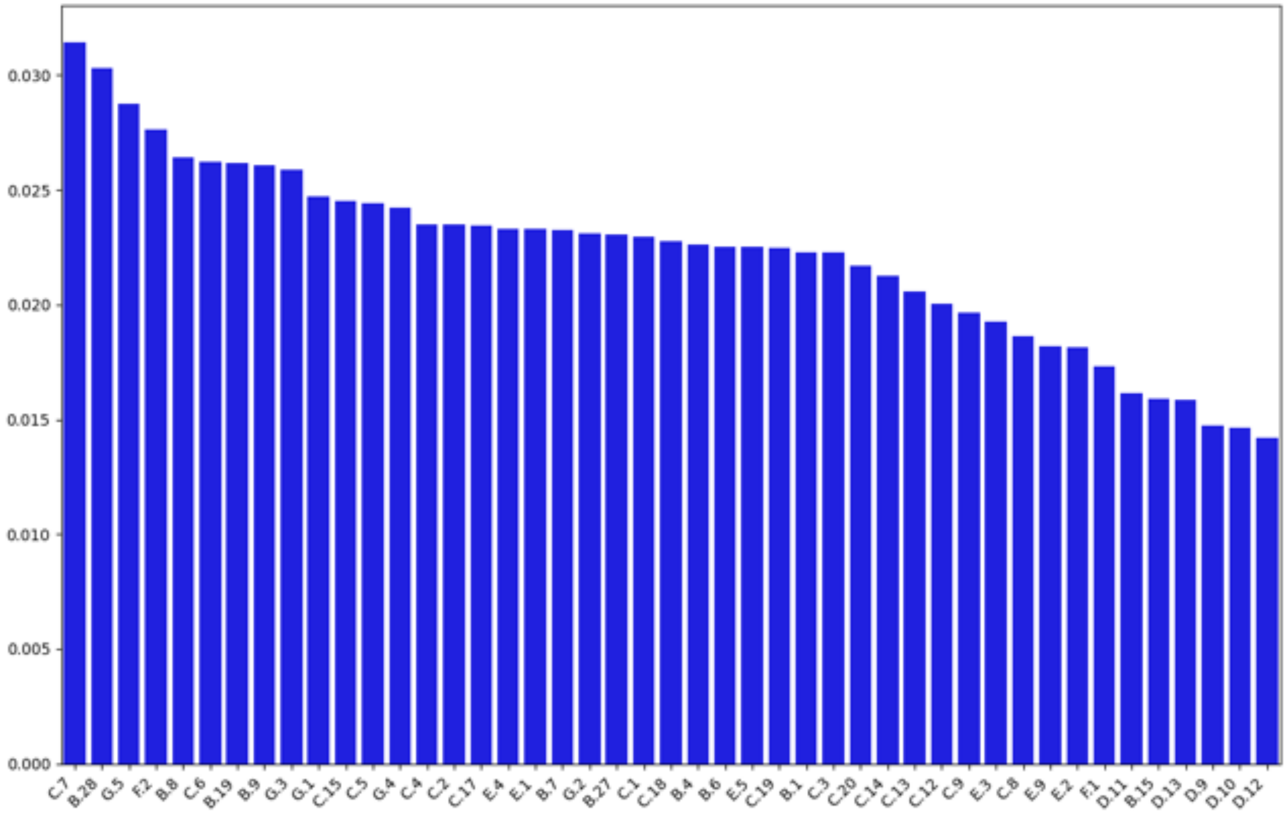

Figure 6.8: Charts of scores assigned by Recursive feature elimination using Random Forest (Created by author)

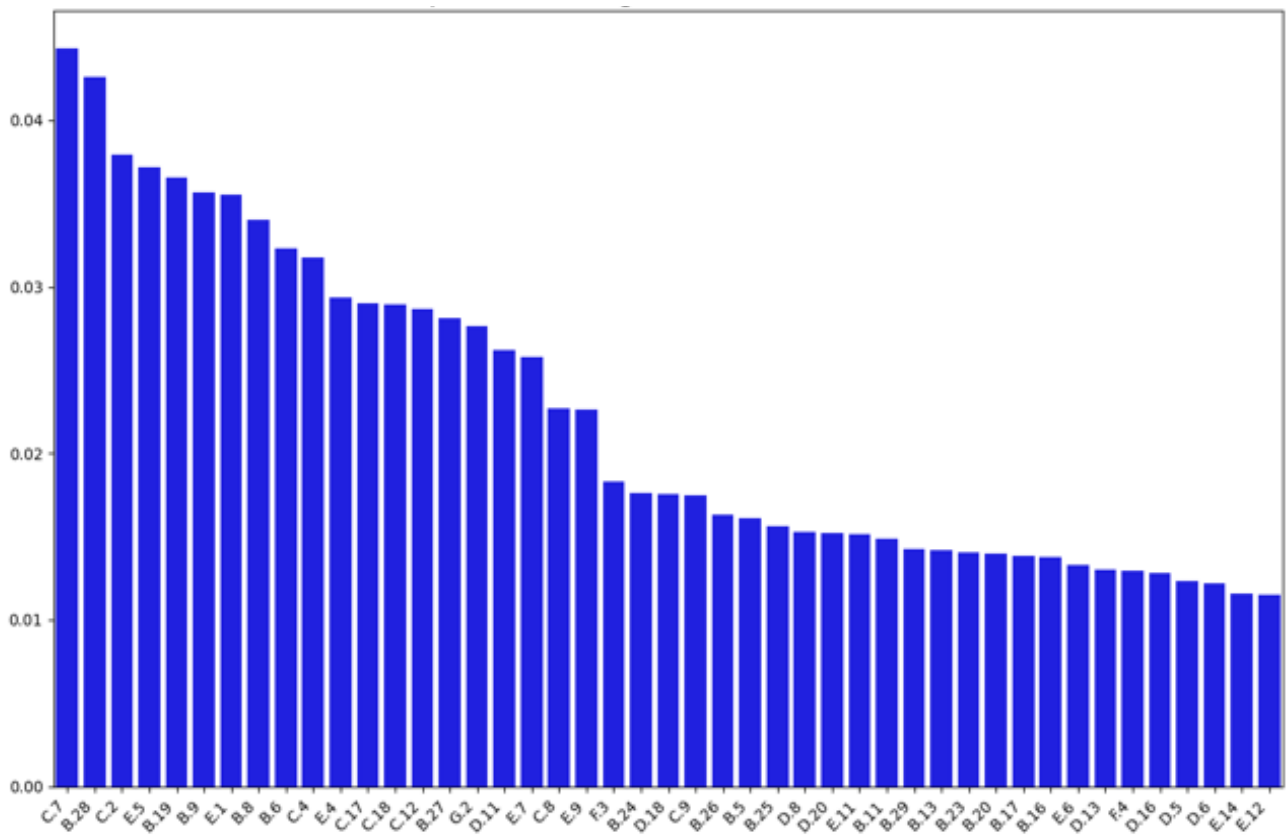

Figure 6.9: Charts of scores assigned by Forward Feature elimination using Random Forest (Created by author).

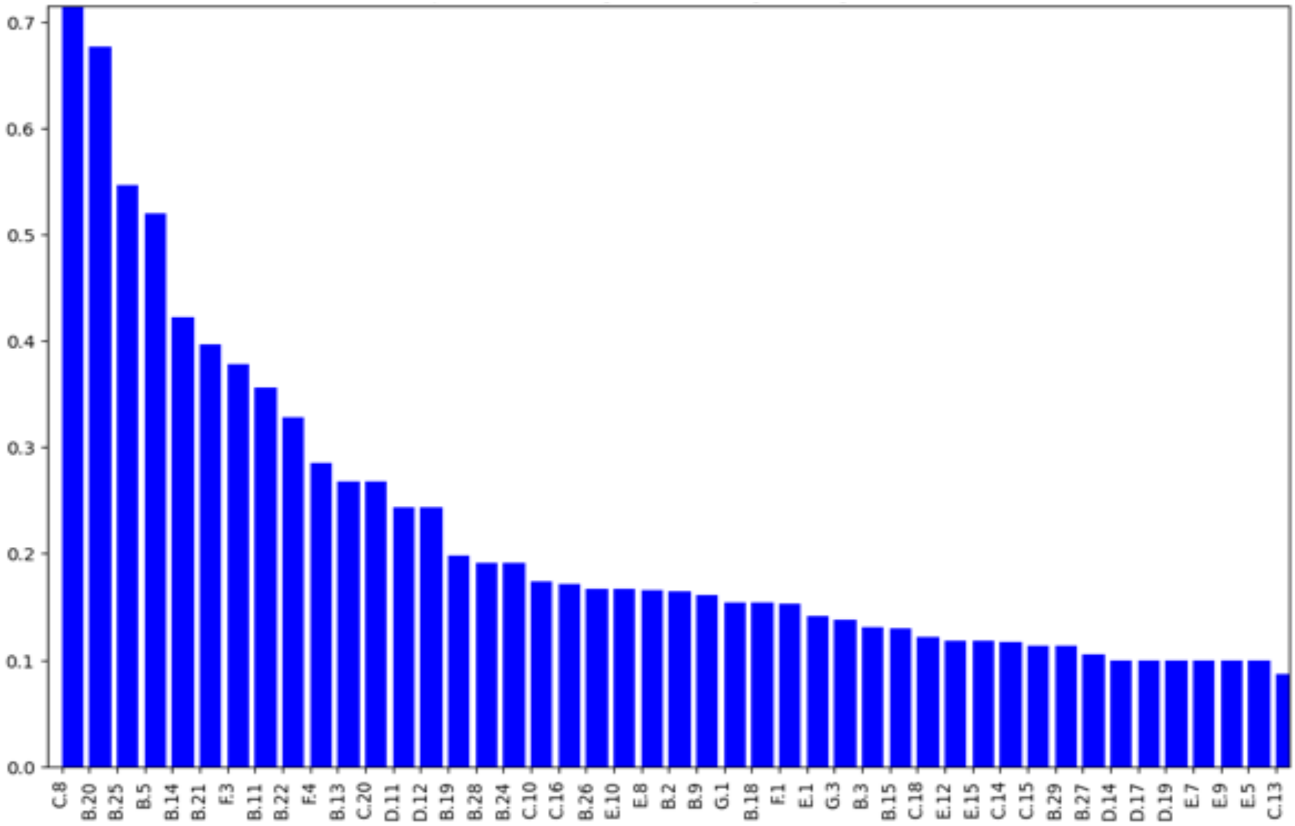

Figure 6.10: Charts of scores assigned by Backward feature elimination (Created by author)

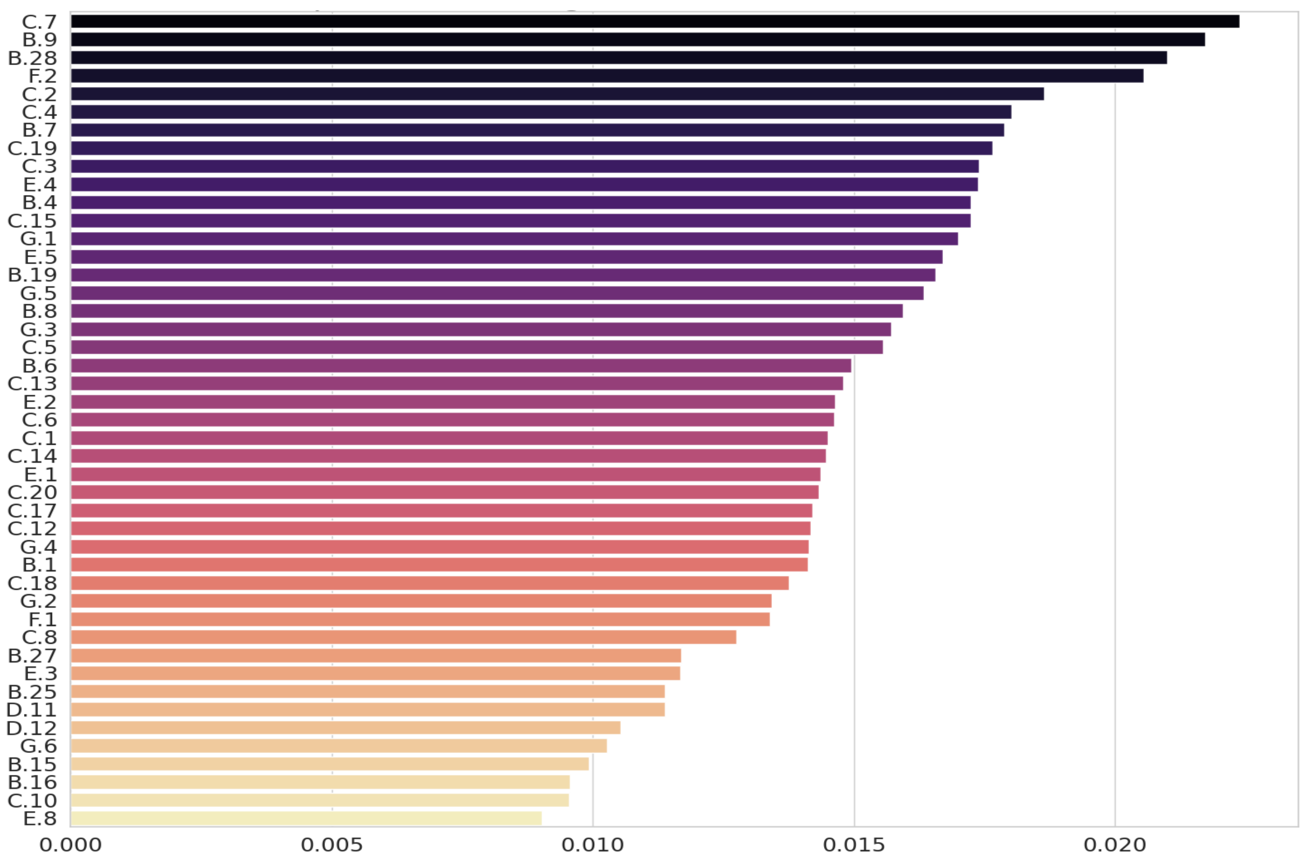

Figure 6.11: Charts of scores assigned by Embedded FS using Random Forest (Created by author).

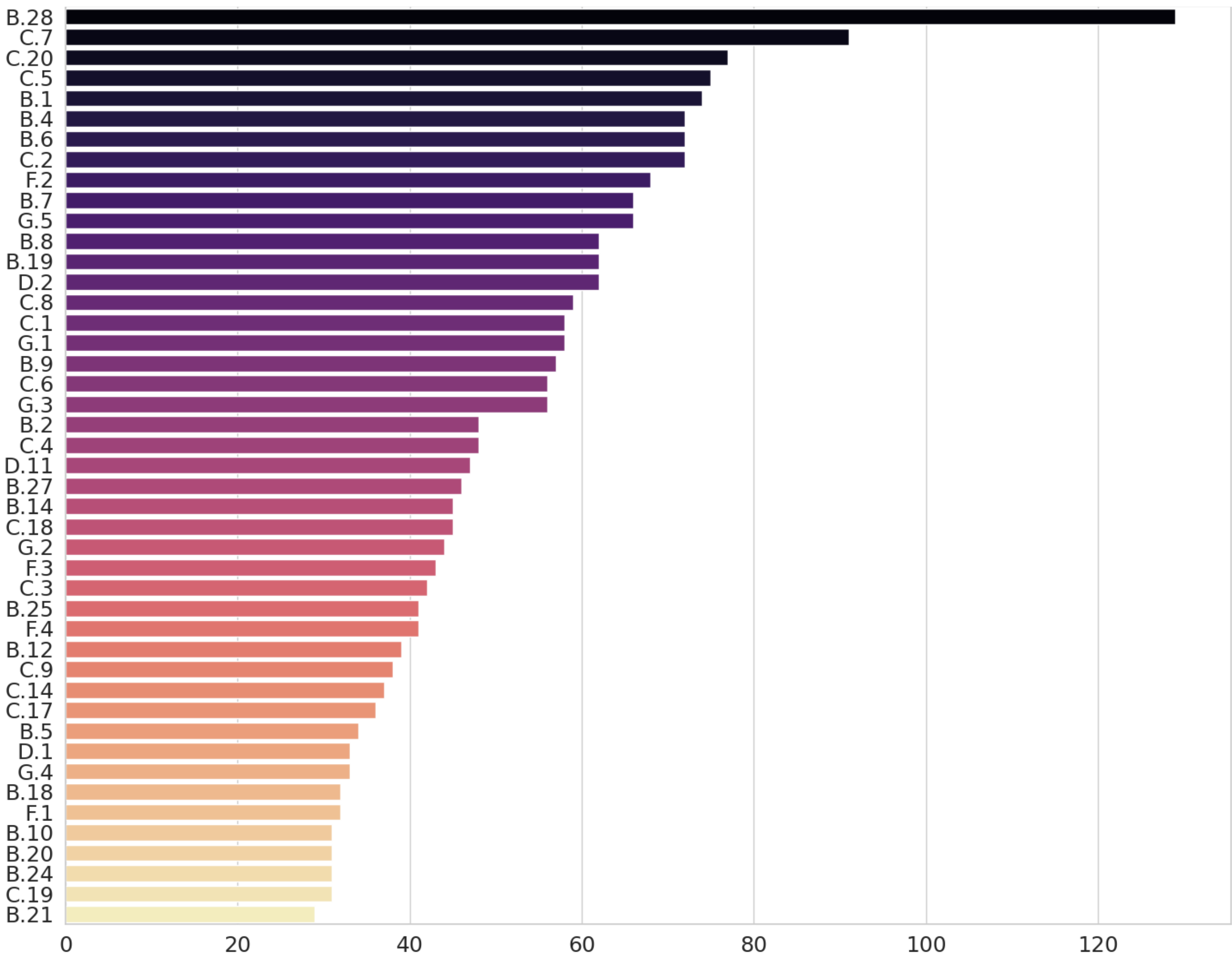

Figure 6.12: Charts of scores assigned by Embedded FS using LightGBM (Created by author)

Table 6.1: Feature selection methods, variables, and selection decision *(Created by author)*

Variable	CHIS	ANOVA	MI	RFE	FFS	BFS	ERF	ELGBM	Count	Decision
B.1			X	X			X	X	4	
B.2		X			X	X		X	4	
B.3					X				1	
B.4	X		X	X				X	4	
B.5		X			X	X		X	4	
B.6	X		X	X	X		X	X	6	Selected
B.7	X	X	X	X			X	X	6	Selected
B.8			X	X	X		X	X	5	
B.9	X	X	X	X		X	X	X	7	Selected
B.10								X	1	
B.11					X	X			2	
B.12								X	1	
B.13					X	X			2	
B.14		X				X		X	3	
B.15				X		X	X		3	
B.16				X	X		X		3	
B.17									0	
B.18		X			X	X		X	4	
B.19	X	X	X	X		X	X	X	7	Selected
B.20		X				X		X	3	
B.21						X		X	2	
B.22					X	X			2	
B.23					X	X			2	
B.24		X			X	X		X	4	
B.25	X	X	X	X	X	X	X	X	8	Selected

Variable	CHIS	ANOVA	MI	RFE	FFS	BFS	ERF	ELGBM	Count	Decision
B.26					X	X			2	
B.27	X	X		X		X	X	X	6	Selected
B.28	X	X	X	X	X	X	X	X	8	Selected
B.29					X				1	
B.30									0	
C.1			X	X	X		X	X	5	
C.2	X	X	X	X			X	X	6	Selected
C.3			X	X			X	X	4	
C.4	X		X	X			X	X	5	
C.5	X	X	X	X	X		X	X	7	Selected
C.6	X	X	X	X			X	X	6	Selected
C.7	X	X	X	X			X	X	6	Selected
C.8	X	X	X	X	X	X	X	X	8	Selected
C.9					X			X	2	
C.10				X	X	X	X		4	
C.11					X				1	
C.12				X	X		X		3	
C.13			X	X	X		X		4	
C.14	X	X	X	X	X	X	X	X	8	Selected
C.15	X	X	X	X		X	X		6	Selected
C.16						X			1	
C.17			X	X			X	X	4	
C.18			X	X		X	X	X	5	
C.19	X		X	X	X		X	X	6	Selected
C.20	X	X	X	X	X	X	X	X	8	Selected
D.1	X	X			X			X	4	

Variable	CHIS	ANOVA	MI	RFE	FFS	BFS	ERF	ELGBM	Count	Decision
D.2	X	X	X					X	4	
D.3									0	
D.4	X	X	X		X				4	
D.5	X	X			X				3	
D.6	X	X							2	
D.7	X	X	X						3	
D.8									0	
D.9	X	X	X						3	
D.10	X	X			X				3	
D.11	X	X	X	X		X	X	X	7	Selected
D.12	X	X	X	X		X	X		6	Selected
D.13	X	X			X				3	
D.14	X	X	X			X			4	
D.15									0	
D.16	X	X							2	
D.17	X	X	X			X			4	
D.18					X	X			2	
D.19	X	X	X			X			4	
D.20	X	X							2	
E.1			X	X		X	X		4	
E.2	X	X	X	X			X		5	
E.3			X	X			X		3	
E.4	X		X	X	X		X		5	
E.5	X	X	X	X	X		X		8	Selected
E.6	X	X			X	X			4	
E.7	X	X	X			X			4	

Variable	CHIS	ANOVA	MI	RFE	FFS	BFS	ERF	ELGBM	Count	Decision
E.8				X		X	X		3	
E.9	X	X	X			X			4	
E.10	X	X			X	X			4	
E.11						X			1	
E.12					X	X			2	
E.13					X				1	
E.14									0	
E.15						X			1	
F.1				X		X	X	X	4	
F.2	X	X	X	X	X		X	X	7	Selected
F.3	X	X	X		X	X		X	6	Selected
F.4		X				X		X	3	
F.5					X				1	
G.1				X	X	X	X	X	5	
G.2	X		X	X			X	X	5	
G.3			X	X	X	X	X	X	6	Selected
G.4				X			X	X	3	
G.5	X		X	X			X	X	5	
G.6				X	X		X		3	
Total	45	45	45	45	45	45	45	45		22

22 variables were identified as having a count of 6 or more (Table 6.1), which is ¾ of the total of 8. This threshold was chosen to balance the strengths and weaknesses of the eight feature selection methods (Shen et al., 2012; Veronica and Amaparo 2019). These selected variables will be used to develop the AI-predictive model for deconstructability. Furthermore, all variables will be tested to allow for various experiments. This approach aims to achieve optimal model performance and identify the most impactful variables influencing the deconstructability of buildings.

6.3 Machine Learning Modelling

6.3.1 Classification Learning Algorithms

Choosing a machine learning algorithm for predictive modelling is paramount due to the absence of a universally superior model that suits all problems (Olu-Ajayi et al., 2022b, 2022a, 2023; Wusu et al., 2022). This research aims to develop a predictive model with the highest possible accuracy for estimating the deconstructability of a building. While accuracy is a pivotal criterion for model selection, the interpretability of the chosen model is equally crucial (Rakhshan et al., 2021a, 2021c). This holds weight in the context of this study, which strives to offer a comprehensible AI-DPM model accessible to diverse stakeholders in the deconstruction space. Notably, these stakeholders may need more proficiency to navigate complex AI models. The insistence on interpretability is strategic, fostering effective utilisation of the model by stakeholders. This emphasis on accessibility is indispensable for the selected predictive model to fulfil its intended purpose.

Consequently, opting for interpretable models to train the predictive deconstructability model seems reasonable. However, it is essential to acknowledge that while interpretable models offer transparency, they may not consistently deliver high accuracy (Rakhshan et al., 2021a, 2021c). This limitation arises from their inherent rigidity, often adhering to predetermined functional forms for the relationship between predictors and the response, as observed in parametric models. On the contrary, highly flexible models tend to provide accurate predictions. Nonetheless, this flexibility introduces challenges, including a loss of interpretability, increased variance, and the risk of overfitting, ultimately leading to a lack of generalisation of unseen data. Hence, when selecting a method for predictive modelling, careful consideration of the trade-off is crucial.

Moreover, it's a widely accepted practice to explore a wide range of machine learning models. Although specific models may appear more suitable in theory or practical applications for specific tasks, the author's current understanding of these models does not reliably predict their performance in advance. The "no-free-lunch" theorems (Wolpert, 1996) further emphasise that no single machine learning model consistently outperforms all others across diverse scenarios. Therefore, when addressing complex problems like the one in this study, it is advisable to experiment with multiple algorithms to ascertain the most effective one.

Building on the previous discussions, the use of various machine learning algorithms such as Gradient Boosting, KNN, Naive Bayes, MLP, Random Forest, SVM (Linear, Poly, and Radial kernels), Logistic Regression, AdaBoost, Discriminant Analysis, and Decision Tree is justified by the diverse strengths and unique capabilities each algorithm brings to the table. Each algorithm handles data differently and has specific characteristics that suit certain problems. For instance, Gradient Boosting and AdaBoost are powerful ensemble methods that combine the strengths of multiple weak learners to enhance prediction accuracy, making them particularly effective for complex datasets with non-linear relationships. Similarly, Random Forest, another ensemble method, provides robust predictions by averaging the results of multiple decision trees, reducing overfitting and improving generalisation.

On the other hand, algorithms like K-Nearest Neighbours (KNN) and Support Vector Machines (SVM) are valuable for their simplicity and effectiveness in classification tasks. KNN is particularly useful for problems where the decision boundary is irregular and the dataset is manageable, as it makes predictions based on the closest training examples in the feature space. With its different kernel functions (Linear, Poly, Radial), SVM is highly versatile and capable of handling linear and non-linear classification tasks, providing flexibility in modelling complex relationships. Meanwhile, Naive Bayes, with its strong independence assumptions, is computationally efficient and performs well in high-dimensional spaces, making it suitable.

Algorithms like Logistic Regression and Discriminant Analysis are widely used for their interpretability and effectiveness in binary classification tasks. Logistic Regression is straightforward and interpretable, providing probabilistic outputs and insights into the influence of each feature. Discriminant Analysis, which includes Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA), is valuable for its ability to model the class distributions and make predictions based on the likelihood. Lastly, Decision Trees and Multi-Layer Perceptron (MLPs) are powerful tools for capturing complex interactions in the data. Decision Trees are easy to interpret and visualise. At the same time, MLPs, as a type of neural network, can learn intricate patterns through their multiple layers and non-linear activation functions.

Overall, twelve classification algorithms, including Gradient Boosting, KNN, Naive Bayes, MLP, Random Forest, SVM (Linear, Poly, and Radial kernels), Logistic Regression, AdaBoost, Discriminant Analysis, and Decision Tree, were used in this research. They are explained briefly below.

1. Logistic regression

Logistic regression measures the relationship between the categorical dependent variable and one or more independent variables by estimating probabilities using a logistic distribution. In logistic regression, the functional form of *p*(*X*) is.

$$p(X) = p(Y = 1|X = x) = \frac{e^{\beta_0+\beta_1 x_1+\cdots+\beta_p x_p}}{1 + e^{\beta_0+\beta_1 x_1+\cdots+\beta_p x_p}}$$

Where:

$x_1, \ldots\ x_p$ represent the independent features.

$\beta_0, \ldots\ \beta_p$ represent the logistic regression coefficients and these coefficients are computed using the approach of maximising likelihood:

$$\iota(\beta) = \sum_{i=1}^{N} \left[y_i \beta^T x_i - \ln(1 + e^{\beta^T x_i})\right]$$

Where:

y_i represents the observed value of the ith observation alongside its independent features, denoted as x. *p*(*X*) predicts the probability based on values in x. Subsequently, these probabilities are transformed into binary outcomes using a threshold of 0.5.

2. Discriminant analysis

Discriminant analysis operates on the premise that different data classes are generated from distinct Gaussian distributions. This analysis can be either linear or quadratic approaches (as referenced). In the linear form, Bayes' theorem is utilised to derive probability estimates. Specifically, for a scenario with "m" classes and an input vector "x" containing independent features, the probability of the output class is expressed as follows:

$$p_m(X) = P(Y = m|X = x) = \frac{\pi_m f_m(x)}{\sum_{i=1}^{M} \pi_i f_i(x)}$$

Where:

π_m represent the prior probability (0.5 in this study)

$f_m(x)$ represent density function of X, assuming a Gaussian distribution, π_m can be computed as:

$$p_m(X) = P(Y = m|X = x) = \frac{\pi_m \frac{1}{\sigma_m\sqrt{2\pi}} e^{\left(-\frac{1}{2\sigma^2 m}(x-\mu_m)^2\right)}}{\sum_{i=1}^{M} \pi_i \frac{1}{\sigma_i\sqrt{2\pi}} e^{\left(-\frac{1}{2\sigma^2 i}(x-\mu_i)^2\right)}}$$

Where:

μ_m & σ_m represent mean and the variance of the observations in the mth class.

3. K-nearest neighbours

K-nearest neighbour often called KNN is a non-parametric approach to categorising data into various groups. The KNN classifier can be seen attributing a weight of 1/k to the K nearest neighbours, while assigning zero weight to all others. For a given positive integer "k" and test observation "x", the KNN classifier identifies k data points in the dataset that are in proximity to "x". The estimated conditional probability of "x" belonging to class "k" is then computed as:

$$p_k(X) = P(Y = k \,|X = x) = \frac{1}{k}\sum_{i \in N_k} I(y_i = k)$$

4. Naïve Bayes classification

Naïve Bayes (NB) utilises Bayes theorem to classify data. NB classifier determines that an output belongs to a specific class if the probability linked to the variable prediction exceeds 0.5. this classifier operates under the assumption that the features (represented as the input vector "x" in this case) are independent, considering a particular class. Given an input vector "x", the NB classification calculates the probability of the output variable belonging to class "m" as:

$$P(Y = m|x) = \frac{P(Y = m)P(x|Y = m)}{P(x)} = \frac{P(Y = m)\prod_{i=1}^{N} P(x_i|Y = m)}{P(x)}$$

5. Support vector machine (SVM)

SVM is a non-probabilistic classifier. The internal structure of the model depends on the kernel function, which is linear, polynomial, Gaussian, Laplace, and sigmoid. SVM can prevent overfitting problems during training and validation by the theory of structural risk minimisation. The approximate functions in the SVM model are:

$f(x) = \omega\varphi(x) + b$

Where:

$\varphi(x)$ represent high dimensional feature space mapped by the input space x.

b represents minimized empirical parameters measured by the regularised error function.

$R_{SVMs}(C)=C * \frac{1}{n}\sum_{i=1}^{n} L(d_i, y_i) + \frac{1}{2}\|\omega\|^2$

Where:

$C * \frac{1}{n}\sum_{i=1}^{n} L(d_i, y_i)$ is estimated by the function $L_\varepsilon(d, y)$:

$$L_\varepsilon(d, y) = \begin{cases} |d - y| - \varepsilon |d - y| \geq \varepsilon \\ 0 \; otherwise \end{cases}$$

Where:

$\frac{1}{2}\|\omega\|^2$ represent regularisation term; C represents the empirical parameter used to control the error and the regularisation term; ε represent tube size nearly equal to approximate accuracy during training.

$\varepsilon_i \; and \; \varepsilon_i^*$ are introduced, to estimate parameters W and d,

$R_{SVMs}(W, \varepsilon^{(*)}) = \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\varepsilon_i + \varepsilon_i^*)$

With Lagrange multipliers & optimal constrained introduced, the following decisions functions.

$$f(x, a_i, a_i^*) = \sum_{i=1}^{n}(a_i - a_i^*)K(x_i, x_j) + b$$

Where:

$K(x_i, x_j)$ represents the kernel function; equal to the inner product of two vectors x_i,x_j in the feature space.

$K(x_i, x_j) = \mu(x_i)^* - \mu(x_j)$.

6. Decision tree

A decision tree is a non-parametric technique. The technique generates a tree-like graph based on the input data. The response can be predicted by following the decision in the tree from the start node to the end node. Each node is associated with a test condition, and each branch represents the outcome of the test.

7. Adaptive Boosting

Adaptive boosting, often called AdaBoost, was initially introduced by Freud and Schapire in 2012 to tackle a classification task. Since its inception, AdaBoost has become a widely used ensemble model in classification challenges. The fundamental concept involves an iterative process where numerous weak classifiers are generated using the training dataset, which is then combined based on a specific strategy.

The process begins with creating a weak classifier using a training dataset where all samples have equal weights. However, the weights of misclassified samples in the training set are increased (or "boosted"). In the subsequent round, a new weak classifier is built using this updated weighted training data in the following round. This procedure is repeated, yielding multiple weak classifiers. Each classifier is assigned a score based on its corresponding classification error.

A final robust classifier is formed by employing a specific rule to combine all the weak classifiers. This adaptive approach enhances the overall classification performance by iteratively focusing on the previously misclassified samples, creating a more robust model.

Considering a typical binary classification task, with a training set represented as

$$\Theta = \{(X_1 y_1), \dots, (X_p y_p)\}$$

Where:

$X_i, i = 1,2, \dots p$ represent the independent features.

$y_i \in \{+1, -1\}$ represent the label of the classes (i.e., ND vs D)

The weights of the samples w_i are initialised as:

$$d_0 = \{w_1, \dots, w_p\}$$

$$w_i = \frac{1}{p} \,; i = 1,2, \dots, p$$

Where:

d_0 represent the initial weight distribution vector for the training data. Then, an iterative process is called to figure out the best classifier. Representing the current iteration number as t and the total iteration number as T, train a weak classifier l_t from the Θ (i.e., training data) using the distribution d_t.

$$l_t(X) = \varphi(\Theta, d_t)$$

Where:

$\varphi(.)$ represents a certain standalone learning algorithm. Theoretically, any standalone algorithm (e.g., SVM, KNN, DT, LR and more) can be used. The classifier error computation is calculated using.

$$e_t = \sum_{i=1}^{p} w_{t,i} \mathbb{I}\left(l_t(X_t) \neq y_i\right)$$

Where:

$\mathbb{I}(\cdot)$ means it will return 1 for correctly classified sample & 0 for misclassified.

The weight of the weak classifier l_t can be computed as:

$$\alpha_t = \frac{1}{2} \log \frac{1 - e_t}{e_t}$$

The distribution of weights is updated accordingly:

$$d_{t+1}(i) = \frac{d_t(i) \exp\left(-\alpha_t y_i l_t(X_i)\right)}{Z_t}$$

Where:

Z_t represent normalised factor & can be computed as:

$$Z_t = \sum_{i=1}^{p} w_{t,i} \exp\left(-\alpha_t y_i l_t(X_i)\right)$$

From the most recent equation, if a sample is wrongly classified, its weight will increase in the following training round. Otherwise, the weight will decrease. This ensures the misclassified get more attention in subsequent learning round l_{t+1}.

Following the T times iterations, weak classifiers are obtained. Consequently, the strong classifier can be produced by a simple combination rule, i.e., weighted majority voting,

$$L(X) = sign\left\{\sum_{t=1}^{T} \alpha_t l_t(X)\right\}$$

8. Gradient Boosting

Gradient boosting is a boosting algorithm and an example of ensemble models (e.g., Adaboost, Xgboost, random forest, among others) combining weak learners, typically decision trees, to create a robust predictive model. It operates by iteratively adding models that correct errors of the mixed ensemble, optimising for a given loss function. Initially, a simple model is fit to the data, and subsequent models are trained on the residual errors of the prior models. This process uses gradient descent to minimise the loss function, progressively refining the model's predictions. Regularisation techniques, such as shrinkage (learning rate) and tree depth, prevent overfitting and enhance generalisation. The flexibility and effectiveness of Gradient Boosting make it a powerful tool for classification tasks. Interested readers are advised to check (Bentéjac et al., 2021).

9. Random forest

Random forest consists of an ensemble of simple tree predictors, each capable of producing a response when represented with a set of input variable values. The training algorithm generates random forests by bootstrap aggregating or bagging. After training the prediction of a vector x can be achieved by averaging the predictions from all the individual's decision trees (B) using equation. For the current study, 100 decision trees are used based on a sensitivity study.

$$\hat{y} = \frac{1}{B}\sum_{b=1}^{B} f_b(x)$$

Where:

f_b represents individual decision trees.

10. Artificial neural network (ANN)

ANN is an Artificial Intelligence (AI) technique that follows the principle of biological neural networks to solve the complex nonlinear problem between input-affecting factors and output variables. Usually, it contains an input layer, which contains the input parameters that affect the output values, one (or several) hidden layer (s) and an output layer, representing the simulated outcomes. Each layer contains neurons, which are connected by the activation function. The weighted sum of input factors is applied to a nonlinear activation function to generate output values. The equations are listed below.

Weighted sum: $y = f(\sum_{i=1}^{n} w_i x_i - \theta)$

Where:

w_i is the weight of each input factor,

x_i is the input factor,

θ is the threshold value for activation, and

f(x) represents the activation function,

We chose logarithmic sigmoid and tangent sigmoid functions for this study.

Logarithmic sigmoid function: $\log sig(n) = \frac{1}{1-\exp(-n)}$

Tangent sigmoid function: $\tan sig(n) = \frac{2}{1+\exp(-2n)} - 1$

6.3.2 ML Model Development

This research aims to investigate various machine learning models and determine the most suitable one, especially in terms of its ability to generalise well when applied to future unseen deconstructability data. The research will utilise K-fold cross-validation (KfCV); see section 6.4 for more information on kfCV. This approach was chosen to ensure a robust and reliable method for selecting the best machine-learning model based on performance.

The ML models and their performance metrics were implemented using Python programming language. ML libraries such as Scikit-learn, Pandas, and Seaborn, among others, were used. The development of the ML models was carried out using Google Colab python integrated development environment. Additionally, each model used its default configurations without hyperparameter tuning.

6.4 ML Model Evaluation

6.4.1 Metrics

Evaluating the performance of predictive models is essential throughout the machine learning development process. It is typical for the machine learning process only sometimes to yield an optimal model with the expected performance, highlighting the need for a thorough evaluation to assess the predictive effectiveness of the developed deconstructability machine learning model. Predictions fall into four categories in scenarios like the binary classification addressed in this study, where the model categorises buildings into deconstructible (1) or non-deconstructible (0) classes.

To evaluate whether the chosen classifier accurately predicts and assigns buildings to their respective classes, criteria such as true negatives (TN) and true positives (TP) are utilised, as shown in the confusion matrix (Table 1). This matrix provides further insights into misclassification rates, including instances where a deconstructible building is incorrectly labelled as non-deconstructible (false negative or FN) or vice versa (false positive or FP). It's important to clarify that the rows in Table 1 represent actual values, while the columns represent predicted values. This distinction helps comprehensively assess the model's performance and understand its predictive capabilities.

Table 6.2. Confusion matrix (Created by author)

		Prediction	
		Negative (Not deconstructible)	Positive (Deconstructible)
Actual	Negative (Not deconstructible)	True Negative	False Positive
	Positive (Deconstructible)	False Negative	True positive

Table 6.2 shows various metrics, including accuracy score, precision, recall, F1 score, ROC curve, and AUROC (Area Under Receiver Operating Characteristic Curve), which can be calculated.

For instance, the accuracy score reflects the proportion of correct predictions made overall and can be derived directly from the confusion matrix. Mathematically, it is calculated as the sum of true positive (TP) and true negative (TN) predictions divided by the total number of predictions:

1. Accuracy score = $\frac{True\ Negatives + True\ Positives}{\text{Number of predictions}}$

Precision measures the proportion of true positive predictions among all positive predictions:

2. Precision = $\frac{True\ Positives}{\text{True positives + False positives}}$

Recall, also known as sensitivity or true positive rate, quantifies the proportion of actual positives that were correctly identified:

3. Recall = $\frac{True\ Positives}{True\ positives + False\ Negatives}$

The F1 score is the harmonic mean of precision and recall, providing a balanced measure between the two:

4. F1= 2 * $\frac{Precision * Recall}{Precision + Recall}$

5. ROC curve (Receiver Operating Characteristic curve) is a graphical plot illustrating the performance of a binary classifier across various threshold settings. It depicts the trade-off between true positive rate (TPR) and false positive rate (FPR). The diagonal dotted line in the middle represents the ROC curve, which is expected to be as far away as possible from the diagonal line.

6. AUROC (Area Under the Receiver Operating Characteristic Curve) quantifies the overall performance of a binary classifier, providing a single scalar value summarising the ROC curve. A higher AUROC value indicates better classifier performance. A perfect AUROC should have a score of 1, whereas a random classifier will have a score of 0.5.

6.4.2 Out-of-sample testing

The resampling technique is commonly used to evaluate a predictive machine learning model and estimate how well it will generalise on test data. It may provide some assurances on how accurately a predictive model will perform in practice. Multiple strategies exist to do this, such as cross-validation, a resampling strategy that uses different dataset segments to train and test a model on different iterations. The simplest is two rounds of cross-validation, which involves partitioning data into subsets, training on one subset, validating the model on the other subset, and vice versa. Multiple rounds of cross-validation are performed using different partitions to reduce variability, and the validation results are averaged over the rounds to estimate the model's predictive performance. There are various types of cross-validation.

K-fold cross-validation

In K-fold cross-validation (KfCV), the original dataset is randomly divided into K folds, each containing roughly equal observations. One of the K folds is set aside as the testing set, while the remaining k-1 folds are used for training the machine learning model. The model's performance is then assessed using the held out set, repeating this process k times, with each fold serving as the validation set. Performance metrics are recorded for each fold, and the model's overall performance is evaluated by averaging across the k folds. The average performance metric from each iteration estimates the model's generalisation performance when fitted to all available data. In general, k remains an unfixed parameter. Typical values are k =3, k =5, and k =10; the most used value in applied machine learning is k =5. The popular choice of k =5 is due to various published studies that found it to provide a good trade-off of low computational cost and low bias in estimating a model’s performance (Fushiki, 2011; Jung, 2018; Normawati & Ismi, 2019; Nti et al., 2021). The disadvantage of this method is that the training algorithm must be rerun from scratch k times, which means it takes k times computation time to evaluate. Figure 6.13 shows a 10-fold cross-validation. The reader can look up Figure 7.13 to see how the 5fold cv validation was used in this research.

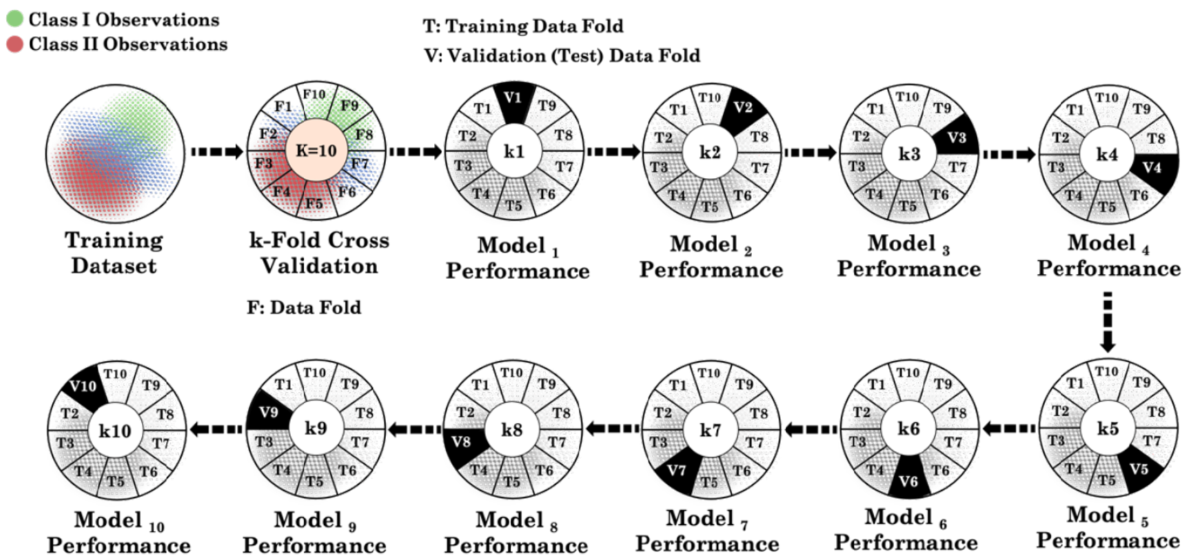

Figure 6.13: K-fold Cross Validation (Created by author)

6.5 *Experiments*

Two dataset groups were used to develop the two predictive models from which the most efficient (generalisable) and explainable will be chosen as the final AI-DPM. Group 1 uses all 96 variables; Group 2 uses the 22 variables obtained through the FS methods.

The researcher experimented with a dataset split into training and testing sets to evaluate the performance of various machine-learning models. Though other splitting ratios, including 50:50, 60:40, 70:30, and 80:20, among others, have been used in studies, it is known that there is no such thing as a best-split ratio (Nguyen et al., 2021; Tao et al. 2020). As a result, the dataset in this research was partitioned into 75% for training and 25% for testing following studies such as (Ahmed et al., 2023; Bhosale & Patnaik, 2023). The training set underwent further preprocessing using the Synthetic Minority Over-sampling Technique (SMOTE) to address class imbalance, ensuring a balanced representation of classes for model training using the twelve models in section 6.3.1.

Using the 75% training data with SMOTE applied, we employed 5-fold Cross-Validation (CV) to assess each model’s performance rigorously. Metrics discussed in section 6.4.1 were calculated/used to evaluate the predictive capabilities of each model. During each CV iteration, the models were trained on the balanced training subset and tested on a test set to provide robust and unbiased performance estimates. This step was crucial to ensure the oversampling process did not artificially inflate the models' performance metrics. By testing on the untouched 25%, we assessed how well the models could generalise to real-world data distributions, thereby providing a realistic measure of their effectiveness.

Figure 6.14 gives the AI-based predictive deconstructability model development and validation workflow.

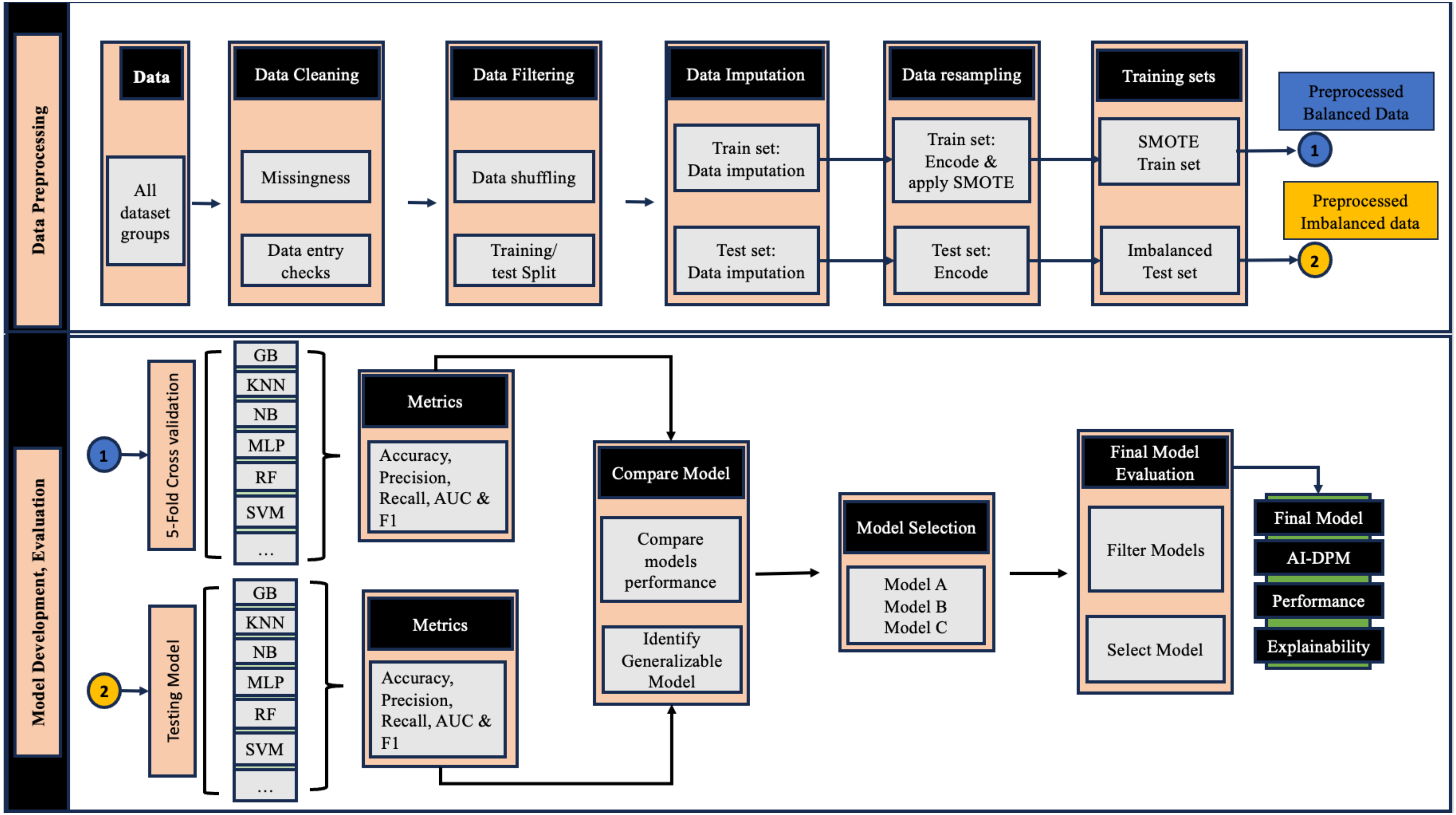

Figure 6.14: Workflow for AI-Deconstructability Predictive Mode (Created by author)

Table 6.3 illustrates how various classification algorithms are performed across three distinct sets of features: utilising all features, features derived from EFA, and features selected through the FS technique. The confusion matrices, first through 5-fold cross-validation (CV) on 75% of the total dataset, balanced using SMOTE and then tested on the remaining 25% of untouched data, were presented in Table 6.3. Predicted values (P) represented rows in each confusion matrix, and the columns indicated the actual values (A). The categories within matrices were labelled "D" (Deconstructible) and "ND" (Non-Deconstructible), representing two possible classes predicted by the model.

Analysing the confusion matrices provides valuable insights into the model's performance metrics, such as accuracy, precision, recall, and F1 score for each feature set. For example, in the first confusion matrix utilising all features, there were fewer correctly predicted instances (true positives and true negatives), with counts of 26 and 16, respectively. In contrast, the matrices for the reduced feature sets (features from FS) showed higher counts of correctly predicted instances (i.e., 22 and 27 for FS features). Despite using fewer features in the FS sets, this indicates that the models maintain high-performance levels, suggesting efficient feature reduction without significant loss of critical information.

Furthermore, analysing the distribution of false positives and false negatives across the two matrices can highlight how the FS impacts model performance. Overall, Table 6.3 provides a comprehensive comparison, illustrating that while all features might offer the best raw accuracy, carefully selected feature subsets, through FS techniques, can achieve comparable performance with potentially improved interpretability and reduced computational cost.

Table 6.3: Confusion Matrix for the developed AI Models for balanced (SMOTE) and Imbalance data (Validation)

	All Features						Features from FS					
Model	5-Fold CV (Balance data)			Testing (Imbalance data)			5-Fold CV (Balance data)			Validation (Imbalance data)		
Gradient Boosting (GB)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	97	35	ND	16	17	ND	87	45	ND	22	11
	D	47	85	D	7	26	D	45	87	D	6	27
K Nearest neighbour (KNN)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	36	96	ND	11	22	ND	39	93	ND	4	29
	D	10	122	D	3	30	D	9	123	D	0	33
Naive Bayes (NB)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	92	40	ND	26	7	ND	90	42	ND	23	10
	D	38	94	D	12	21	D	42	90	D	4	29
Artificial Neural Network (MLP)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	95	37	ND	27	6	ND	98	34	ND	23	10
	D	43	89	D	7	26	D	40	92	D	7	26
Random Forest (RF)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	101	31	ND	26	7	ND	108	24	ND	19	14
	D	43	89	D	9	24	D	45	87	D	8	25
Support vector Machine with Linear kernel (SVM-L)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	74	58	ND	22	11	ND	90	42	ND	19	14
	D	50	82	D	8	25	D	44	88	D	8	25

	All Features						Features from FS					
Support vector Machine with polynomial kernel (SVM-P)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	95	37	ND	23	10	ND	96	36	ND	12	21
	D	38	94	D	5	28	D	25	107	D	3	30
Support vector Machine with Radial kernel (SVM-R)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	111	21	ND	31	2	ND	112	20	ND	29	4
	D	52	80	D	11	22	D	51	81	D	12	21
Logistic regression (LR)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	82	50	ND	21	12	ND	96	36	ND	21	12
	D	47	85	D	8	25	D	42	90	D	8	25
AdaBoost (AB)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	86	46	ND	21	12	ND	93	39	ND	18	15
	D	45	87	D	12	21	D	44	88	D	6	27
Discriminant Analysis (DA)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	60	72	ND	27	6	ND	96	36	ND	15	18
	D	54	78	D	16	17	D	42	90	D	9	24
Decision Tree (DT)	P/A	ND	D	P/A	ND	D	P/A	ND	D	P/A	ND	D
	ND	80	52	ND	21	12	ND	86	46	ND	16	17
	D	49	83	D	9	24	D	52	80	D	12	21

Tables 6.4 and 6.5 offer a comprehensive comparison of model performance across various evaluation metrics—Accuracy (Acc), Precision (Pre), F1 score (F1), Recall (Rec), and Area Under the Curve (AUC)—for different classification algorithms. These metrics were calculated through 5-fold cross-validation and then tested on the untouched, imbalanced data (25% of the total dataset). Tables 6.4 and 6.5 correspond to the metrics calculated for the different feature sets: all features and features selected through the FS technique, respectively.

Each table compares the metrics obtained from the cross-validation phase with those from the testing phase. This comparison helps assess whether the model's performance on the training data indicates its generalisability to unseen data. If the performance metrics from cross-validation exceed those from testing, it suggests potential overfitting, where the model learns to memorise the training data instead of learning underlying patterns. This scenario is highlighted in the tables with yellow colouring. Conversely, suppose the performance metrics from testing are comparable or better than those from cross-validation. In that case, the model is balanced and can generalise well to new, unseen data. This situation is depicted with green colouring on the tables.

For example, Table 6.4 highlights instances of potential overfitting, where the model's performance during cross-validation surpasses that of testing. In Table 6.4, the random forest achieved an accuracy of 0.7194 during cross-validation, but it decreased to 0.6813 during testing, indicating potential overfitting. Conversely, models like Gaussian Naive Bayes (NB), Logistic regression (LR) and Artificial neural network (MLP) demonstrate consistent performance across both phases, suggesting robust generalisation capabilities.

Table 6.4: Accuracy, Precision, Recall, F1 score and AUC score for All features (Created by author)

Model	Acc	Acc_V	Pre	Pre_V	Rec	Rec_V	F1	F1_V	AUC	AUC_V
GB	0.6894	0.6352	0.7063	0.6611	0.6493	0.7911	0.6723	0.6755	0.7458	0.6575
KNN	0.5988	0.622	0.5624	0.5856	0.9247	0.9044	0.6971	0.6985	0.7304	0.787
NB	0.7044	0.7121	0.711	0.745	0.7128	0.6276	0.7087	0.6705	0.7621	0.7489
MLP	0.6554	0.7714	0.6916	0.7533	0.6435	0.6673	0.6304	0.7402	0.7309	0.8669
RF	0.7194	0.6813	0.7471	0.8083	0.6479	0.7625	0.6925	0.7196	0.7876	0.8545
SVM L	0.5909	0.7099	0.5874	0.6754	0.6295	0.7292	0.5973	0.7002	0.6097	0.8026
SVM P	0.716	0.7714	0.7192	0.7333	0.7147	0.8425	0.7129	0.7761	0.7925	0.8852
SVM R	0.7235	0.8022	0.7991	0.9	0.6114	0.6451	0.6848	0.7417	0.7865	0.8439
LR	0.6325	0.6956	0.6251	0.6635	0.6517	0.7406	0.6312	0.6976	0.6728	0.8329
AB	0.6553	0.6363	0.652	0.6476	0.6657	0.6229	0.6543	0.6239	0.6913	0.6446
DA	0.5227	0.6637	0.5182	0.72	0.6008	0.5098	0.5501	0.5928	0.5346	0.6465
DT	0.5908	0.7143	0.6026	0.7073	0.6553	0.7803	0.6431	0.6609	0.6023	0.6667

Table 6.5: Accuracy, Precision, Recall, F1 score and AUC score for features derived through FS techniques (created by author)

Model	Acc	Acc_V	Pre	Pre_V	Rec	Rec_V	F1	F1_V	AUC	Auc_V
GB	0.6592	0.6659	0.6589	0.7089	0.6829	0.7565	0.6415	0.7246	0.7373	0.8099
KNN	0.6139	0.5615	0.5694	0.5346	0.9311	1	0.7058	0.6891	0.7731	0.6442
NB	0.6814	0.789	0.6987	0.736	0.6842	0.881	0.6836	0.7999	0.7486	0.7879
MLP	0.7311	0.7418	0.73	0.7795	0.7245	0.8137	0.7085	0.744	0.7656	0.8182
RF	0.7045	0.7857	0.7793	0.6969	0.6654	0.7565	0.6975	0.7143	0.8081	0.8163
SVM L	0.6742	0.667	0.6783	0.6754	0.6687	0.7565	0.6689	0.6893	0.7075	0.7245
SVM P	0.7689	0.6374	0.7535	0.591	0.8131	0.9044	0.7767	0.7075	0.8361	0.831
SVM R	0.7311	0.7549	0.8069	0.8833	0.6191	0.6613	0.697	0.724	0.8177	0.8586
LR	0.7045	0.6956	0.7181	0.6912	0.6867	0.7565	0.693	0.7073	0.7537	0.7815
AB	0.6858	0.6813	0.6927	0.7006	0.6715	0.8137	0.6768	0.7229	0.7431	0.7521
DA	0.7046	0.5901	0.7284	0.5817	0.6869	0.7378	0.694	0.6305	0.7374	0.6111
DT	0.6557	0.6209	0.626	0.6611	0.6472	0.6724	0.6332	0.7132	0.6515	0.6667

6.7 *Selection of the best AI-DPM*

Based on the performance metrics in Tables 6.4 and 6.5, the best machine-learning models can be identified by examining their AUC, accuracy, precision, recall, and F1 scores. Notably, the research aims to select models that do not exhibit signs of overfitting.

From Table 6.4, Support Vector Machine with Polynomial Kernel (SVM P) stands out with consistently high-performance metrics across cross-validation and testing phases. It achieves an AUC of 0.7925 and 0.8852, an accuracy of 0.716 and 0.7714, and a balanced precision, recall, and F1 score, indicating a robust and generalisable model. Artificial Intelligence with multi (MLP) also performs well with an AUC of 0.7309 and 0.8669, accuracy of 0.6554 and 0.7714 on cross-validation and testing, and balanced precision, recall, and F1 scores, showcasing strong generalisation. Lastly, the Support Vector Machine with radial kernel (SVM R) model is notable for its stable performance with an AUC of 0.7865 and 0.8439, accuracy of 0.7235 and 0.8022, and other metrics suggesting reliable performance on both balanced and imbalanced datasets.

From Table 6.5, MLP continues to excel with an AUC of 0.7656 and 0.8182, accuracy of 0.7311and 0.7418, and high precision, recall, and F1 scores. This consistent performance across various feature sets makes it a top contender. The naive Bayes (NB) model also performs well with an AUC of 0.7486 and 0.7879, an accuracy of 0.6814 and 0.789, and balanced metrics, indicating it handles different feature sets effectively. Lastly, Gradient Boosting (GB) maintains strong performance with an AUC of 0.7373 and 0.8099, accuracy of 0.6592 and 0.6659, and other balanced metrics, making it a reliable choice.

Overall, the top two models were based on their consistent and robust performance across all metrics; the top models were SVM with Polynomial Kernel (SVM P) for all features and Artificial intelligence with multilayer perceptron (MLP) using FS techniques. These models demonstrated generalisation capabilities without overfitting, making them suitable candidates for deployment. Table 6.6 presents the metrics (generated from the test set) of the top models and the features used.

Table 6.6: Top two model's performance

Model	Features used	Accuracy	Precision	Recall	F1	AUC
SVM P	All features	0.7714	0.7333	0.8425	0.7761	0.8852
MLP	Features from FS Techniques	0.7418	0.7795	0.8137	0.744	0.8182

From the two best, the SVM with a polynomial kernel stands out as a robust choice due to its well-rounded performance across multiple evaluation criteria. With an AUC of 88%, the model demonstrates excellent capability in distinguishing between the deconstructability classes, indicating a high overall effectiveness in prediction. Additionally, the SVM's F1 score of 77% reflects a good balance between precision and recall, which is crucial for scenarios where false positives and false negatives carry significant consequences. The recall rate of 84% suggests that the model is particularly adept at identifying the true positive cases (deconstructability class), reducing the risk of missing critical instances. However, the precision of 73% indicates there is some trade-off, with a moderate rate of false positives. Nevertheless, an accuracy of 77% shows that the model performs reliably across the entire dataset, making it a dependable choice for general use.

The SVM model was served and deployed as a web application for deconstruction professional validation. To use, the list of the checklist/features established needs to be provided either as an Excel or CSV file. Upon loading the data, users (i.e., deconstruction professionals and non-professionals) can click on the modelling, and the AI-DPM will be invoked, generating a deconstructability prediction. The user story for the AI-DPM model developed and deployed is presented in section C of this thesis’s appendix.

6.8 Model Explainability

The increasing use of advanced and complex AI algorithms has made explaining AI models essential. The European Union (EU) and the General Data Protection Regulation (GDPR) mandates that algorithms making significant decisions about users must provide explanations (Bibal et al., 2021; Brożek et al., 2024; Sovrano et al., 2021). Individuals have the right to understand these decisions, which can be achieved by clarifying the logic behind black box models (Brożek et al., 2024).

Due to its comprehensiveness and importance, there are many interpretations of explainability, but this research adopts the one by the AI group of experts (AI-EG) (AI, 2019). According to AI-EG, explainability involves providing information on how AI model decision-making works, the final decision, reasons for the conclusion, the data features used in the model or decision, and the combination of data features. Most importantly, AI-EG emphasises that explanations should be tailored to the expertise of the concerned stakeholders (e.g., academicians and professionals) and highly dependent on the context (Bibal et al., 2021; Hamon et al., 2022; Sovrano et al., 2021).

Trustworthy explanations foster user trust, help identify model failures and support AI deployment across domains (Hamon et al., 2022). AI/ML models, like decision trees, naturally provide transparent decision-making processes. Meanwhile, there have been efforts to explain complex and less transparent AI models, including artificial neural networks and random forests.

6.9 Chapter Summary

This chapter explored supervised machine learning for binary classification of deconstructability. Data preprocessing involving tasks such as handling missing values using KNN data imputation, one-hot encoding and eight FS techniques from the three different FS types (i.e., filter, wrapper and embedded) were used collectively to arrive at 22 features. These features were ranked high by the different FS techniques whose count across the FS techniques exceeds 2/3, i.e., features with a count over 6 out of 8. These 22 features formed a feature set used in developing AI-DPM. While all the 96 features retrieved from the literature formed another feature set. The two feature sets were each divided into 75% for training and 25% for testing and were used in developing AI-DPM.

The training data underwent SMOTE and one-hot encoding, while the test data was only one-hot encoded. Preprocessing was performed separately on the training and test sets after the split to prevent data leakage and overly optimistic performance (overfitting). Over ten classification predictive models, including KNN, RF, AB, LR, NB, DT, and GB, were developed for each dataset group. 5-fold cross-validation was utilised for the training dataset across the three feature sets to have a robust evaluation of the models developed.

The models developed using the training data set and cross-validation across the two feature sets for all the AI algorithms were tested using the 25% unseen data (test and unbalanced pre-processed data) to assess the models' generalisability. From this assessment, the top three models based on performance across all metrics were SVM-with-Polynomial Kernel (SVM-P) for all features and multilayer-perceptron (MLP) using features from FS techniques. These models demonstrated generalisation capabilities without overfitting, making them suitable candidates for deployment. However, the objective was to decide on the best-regarding generalisability and interpretability. This led to SVM with a polynomial kernel emerging as the best among the two models. SVM-P was selected best due to its balanced performance across various evaluation metrics. It achieves an AUC of 88%, demonstrating strong capability in distinguishing between different deconstructability classes, indicating high predictive effectiveness. It has an accuracy of 77%, proving it is a reliable choice suitable for AI-DPM. Chapter seven discusses the findings, contribution, limitations, and future research.

Chapter Seven

7.0 Discussion and Conclusion

This chapter covers

- *Summary of findings and conclusion*
- *Contributions to academic knowledge and industrial practices*
- *Research Limitations*
- *Future work*

The aim of this research is to develop an AI-based predictive Deconstructability model for buildings, which can be used as a potential tool for assessing the deconstructability of buildings quickly and accurately. Predicting the deconstructability of a building can contribute to preventing demolition, as clients/owners already have informed knowledge about the state of the building and decisions around the end-of-life options best suited for the building. This thesis defined deconstructability as a binary-class problem that includes deconstructible and non-deconstructible.

The correct classification of buildings for deconstruction/as deconstructible is a way of preventing demolition and encouraging reuse. The result improves the confidence to deconstruct buildings more and to avoid the waste that comes with complete demolition. However, the physical examination and thorough audit usually required before deconstruction is not ruled out; the AI-DPM only provide a quick assessment before the in-depth analysis. As a result, buildings assumed to be written off for demolition may be given another chance if they eventually get correctly predicted as deconstructible.

In this thesis, there are two impact scenarios in the case of misclassification of a building's deconstructability. First, it could result in an increased cost (i.e., misclassification of the non-deconstructible building as deconstructible) and may result in the client spending unnecessarily to carry out a thorough audit, which may be time-consuming or expensive. However, this scenario may be managed, as a report will provide at least the building owner/client with a BREEAM sustainability credit/badge.

The second scenario could result in writing off a building deconstructible as non-deconstructible. This could have a significant negative impact, increasing the complete demolition rate. However, thorough audits may manage these impacts, especially for locations where it is a legal requirement, such as the London Circular Economy statement. However, in cases where the audit is voluntary, there may be no acceptable compensation. From that point of view, the correct classification of the building as deconstructible outweighs the proper classification as non-deconstructible.

The scale of deconstructability was set with rigid boundaries. These boundaries were set based on the professional's (respondents) first-hand experience. They provided scores in percentage indicating the deconstructability, with higher percentages indicating greater deconstructability and lower scores for otherwise. These scores were then transformed into a binary classification: 'deconstructible' for projects scoring above 60% and 'not deconstructible' for those scoring below 60%. Also, this boundary was considered based on documented observations in building deconstruction research such as Akinade et al., 2015, Basta et al., 2020, among others.

7.1 *Summary of Findings and Conclusions*

7.1.1 Objective One: To identify explanatory variables from all perspectives (i.e., social, economic, technical, environmental, schedule, legal) influencing building deconstructability through a systematic literature review.

To address the objective of identifying explanatory variables influencing building deconstructability through a systematic literature review, it is crucial to consider variables from multiple perspectives: social, economic, technical, environmental, schedule, and legal. An extensive examination of existing literature has identified several vital variables influencing deconstructability.

From a social perspective, community awareness and stakeholder engagement play pivotal roles. The level of public knowledge regarding the benefits of deconstruction can drive the adoption of deconstructible designs. Moreover, the involvement and cooperation of various stakeholders, including property owners, construction professionals, and local governments, are essential for successfully implementing deconstructability practices. Therefore, social acceptance and support for sustainable building practices are crucial explanatory variables.

Economically, the variables associated with deconstruction cost and its benefit were discovered to be significant. This includes fees for deconstruction, potential savings from salvaging materials, and market demand for reclaimed materials. Economic incentives, such as tax or subsidies for deconstruction, can also influence the decision-making process. The overall economic viability and potential profitability of deconstructible projects are essential.

Technically, the design and construction methods are significant determinants of a building's deconstructability. Factors such as the choice of materials, construction techniques, and modular or prefabricated components can facilitate or complicate the deconstruction process. Technological advancements in tools and machinery used for deconstruction also play a role. Furthermore, technical knowledge and expertise among construction professionals about deconstructible design principles are necessary for effective implementation.

Environmental considerations include the potential for reducing waste and minimising environmental impact through deconstruction. The ability to recycle and reuse building materials contributes to sustainability goals. Environmental regulations and standards, such as those related to waste management and resource conservation, influence the adoption of deconstructible practices. Moreover, environmental impact assessments and lifecycle analyses help understand the broader implications of deconstruction on ecosystems and resource depletion.

Scheduling aspects consider the time required for deconstruction compared to demolition. Deconstruction is often perceived to be more time-consuming due to the careful dismantling process. However, efficient scheduling and planning can mitigate time-related concerns.

Legal aspects encompass the regulatory framework governing deconstruction practices. Building codes, zoning laws, and permits required for deconstruction activities are critical legal variables. Compliance with these regulations ensures that deconstruction projects are carried out within legal boundaries.

In conclusion, a multifaceted approach considering the social, economic, technical, environmental, schedule, and legal perspectives is essential for understanding and enhancing deconstructability. The identified explanatory variables highlighted the complexity of deconstruction. Addressing these variables comprehensively, stakeholders can promote more sustainable and efficient deconstructible building designs, ultimately contributing to environmental conservation and resource management. The systematic literature review underscores the need for an integrated strategy incorporating diverse perspectives to advance deconstructability.

7.1.2 Objective two: To develop a deconstructability construct-based conceptual framework to aid data collection

Developing a deconstructability construct-based conceptual framework to aid data collection involves systematically identifying and defining key constructs that influence deconstructability. This framework is a foundation for structured data collection, analysis, and interpretation, ensuring that all relevant variables are considered. The goal was to create a comprehensive and practical tool to guide researchers/practitioners in assessing and improving building deconstructability.

The first step in developing this framework was identifying the primary constructs influencing deconstructability. These constructs were categorised into several dimensions: social, economic, technical, environmental, schedule, and legal, following the TELOS framework, extended to incorporate the social dimension. Each dimension encompasses a specific variable that needs to be considered. For instance, social constructs included community awareness/attitude and stakeholder engagement, while economic constructs covered cost-benefit analysis and market demand for reclaimed materials. Technical constructs involved building information such as mechanical joinery, design and construction methods, and environmental constructs focused on waste reduction and recycling potential.

Once the key constructs were identified, the next step was to establish measurable indicators. For example, "community awareness" was measured by indicators such as public knowledge about deconstruction benefits and the extent of stakeholder participation in deconstruction projects. Similarly, "economic viability" was measured by indicators like deconstruction costs, potential savings from material salvage, and availability of economic incentives.

To ensure the framework's effectiveness, it was essential to validate the constructs and their indicators through empirical research. This involves collecting data from surveys.

In conclusion, the deconstructability conceptual framework for deconstructability provided an organised and systematic approach to the collection and analysis of data, enabling a comprehensive assessment of deconstructability. By clearly defining/measuring key constructs across multiple dimensions, the framework aided in identifying areas for improvement and developing strategies to enhance deconstructability. This systematic approach advances academic research and provides practical insights for industry professionals, contributing to more sustainable and efficient building practices.

7.1.3 Objective three: To investigate the explanatory variables helpful in developing and selecting the best AI model with an explainability and generalisability for deconstructability prediction useful for BIM, non-BIM, DfD and non-DfD buildings.

To investigate the explanatory variables helpful in developing an explainable and generalisable AI for a deconstructability predictive model applicable to BIM (Building Information Modelling), non-BIM, DfD (Design for Deconstruction), and non-DfD buildings, a comprehensive approach such as identifying and using a range of variables that influence deconstructability across different building contexts was undertaken. The goal was to create an AI model that predicts deconstructability accurately and provides insights into the variables driving its predictions, ensuring transparency and generalisability.

The first step was to identify explanatory variables that influence building deconstructability. These variables are categorised into several dimensions: social, economic, technical, environmental, schedule, and legal. For instance, social variables include stakeholder engagement and community awareness, while economic variables involve cost-benefit analyses and market demand for reclaimed materials. Technical variables involved construction methods, material types, and the presence of modular components, while environmental variables focused on waste reduction potential and recycling capabilities. Schedule-related variables considered the time required for deconstruction, and legal variables covered regulatory frameworks and compliance requirements.

For BIM-based buildings, additional variables related to the digital representation of the building were considered. These included the level of detail (LOD) in BIM models, the presence of as-built BIM data, and the integration of deconstruction-specific information. For non-BIM buildings, the presence of traditional construction documentation and any available digital data was utilised. In the context of DfD buildings, the variables emphasised design features that facilitate easy disassembly, such as standardised components, connections for easy removal, and documentation of deconstruction sequences. Non-DfD buildings required a focus on retrofit potential and adaptability of existing structures for deconstruction.

Collecting and preprocessing data related to these variables to develop a predictive AI model was crucial. This involves gathering data from a survey (provided by experts) representing deconstructed buildings. The collected data were pre-processed into usable form for AI model training. Feature selection techniques were employed to extract relevant features from raw data, and a data augmentation method (SMOTE) was applied to address imbalances in the dataset.

Explainability and generalisability were critical aspects of the AI model. Explainability ensures that deconstruction professionals and every potential user can understand and trust the AI's predictions. This was achieved by employing techniques like SHAP (Shapley Additive explanations) to explain the best AI predictive model for AI-DPM. Generalisability ensures that the AI- models perform well across different building types and contexts. This was achieved by training on datasets that include/represent various building scenarios, including BIM and non-BIM, DfD and non-DfD buildings. Cross-validation techniques and robust performance metrics were employed to evaluate the model's generalisability.

In conclusion, investigating explanatory variables for developing an explainable and generalisable AI model for deconstructability involves thoroughly analysing the established variables. Focusing on explainability and generalisability, the resulting AI model (SVM with polynomial kernel) using all the 96 established variables provided the most accurate predictions. Furthermore, the performance of SVM with the polynomial kernel using all 96 variables over an MLP using features extracted from the FS showed and validated that all the established variables were significant and valuable in deconstructability prediction. This also supports the claim that many perspectives must be incorporated for a realistic and practical deconstructability prediction. In this research, variables B.1 to G.7 (see Appendix B for their definitions) need to be checked for building of all sorts nearing or at the end of their useful lives for their deconstructability prediction/assessments. The findings in this research suggest the relevance of all the established variables, and the robust AI algorithm development and validation approach not only advances academic study but also offers guides for deconstruction professionals, providing a guide for future research looking into the use of AI/ML for prediction.

7.2 Contributions to Knowledge

7.2.1 Contribution of study to academic knowledge

One of the most significant contributions of the research into AI for deconstructability is its demonstration of how advanced AI techniques can be effectively utilised to develop predictive models for building deconstructability. This research has successfully shown variables encompassing different dimensions, such as social, economic, technical, environmental, schedule, and legal, can be leveraged with sophisticated AI tools to create accurate and generalisable models for predicting the deconstructability of buildings. The ability to analyse these variables quickly using advanced AI techniques represented advancement over traditional methods, often requiring extensive manual effort and time.

The research introduced numerous explanatory variables to the deconstructability literature using survey questionnaires from experts regarding past deconstructed projects. This comprehensive approach has emphasised the importance of integrating diverse variables to capture the multifaceted nature of deconstructability. The study has shown that combining technical variables, such as material properties and construction techniques, with social variables, like stakeholder engagement and regulatory compliance, leads to more robust and insightful predictive models. This methodological innovation underscores the necessity of a holistic perspective in developing AI models for deconstructability.

Additionally, the research has provided valuable insights into the suitability of different AI tools for developing deconstructability predictive models. It has established methods like LR, DT, and KNN may not be well-suited for integrating variables. In contrast, methods such as Random Forests (RF), Multi-layered perceptron (MLP), and Support Vector Machines (SVM) can effectively handle the complexity of such data. This revelation enriches the existing body of knowledge and guides future research towards utilising more robust and appropriate AI techniques. By exposing the field to these advanced tools, the study encourages other researchers to explore beyond commonly used methods, potentially leading to significant improvements in predictive modelling for deconstructability and other areas of construction research. This shift towards more sophisticated AI methodologies promises to enhance the generalisability and explainability of predictive models, ultimately supporting more sustainable and efficient building practices.

7.2.2 Contribution of study to practice/deconstruction industry

The research has made three significant contributions to the deconstruction industry. First is the capability to identify variables influencing deconstructability early in the planning and design stages. This early identification is possible due to the integration of various academic and industrial literature. By incorporating these variables, the conceptual framework developed in this research enhances early predictive capabilities, allowing construction professionals to make informed decisions that facilitate deconstructability from the outset.

The second significant contribution is the versatility of the AI models, predicting deconstructability for different building types, including those designed with Building Information Modelling (BIM), Design for Deconstruction (DfD), and traditional construction methods. Unlike previous models that may have focused predominantly on specific building types, the developed AI models apply to BIM buildings and non-BIM structures. This is particularly important for the construction industry, which comprises a diverse mix of building projects non-DfD and non-BIM. Including comprehensive variables ensures the models are robust and adaptable, offering practical insights and predictions relevant to a broad spectrum of deconstruction projects.

The third contribution is the systematic literature review (i.e., chapter four) focused on the AI/ML applications for deconstruction. It provides an overview of what is already in existence (i.e., the AI application areas and the subfields employed) and some challenges from the existing literature affecting AI for deconstruction; suggestions on possible deconstruction yet to be exploited using AI were highlighted. The researcher believes this will help and serve as a starting point for deconstruction practitioners and academics in supporting the AI skill force without deconstruction domain expertise to understand areas where AI can be used for deconstruction activities. Also, it will help deconstruction practitioners just starting on AI adoption to note subfields and methods that are relevant/feasible for deconstruction activities. This study is a valuable resource for researchers and industry practitioners, offering insights into relevant AI uses and ongoing research within deconstruction.

7.3 Overview of Key Findings

This research developed an AI-based Deconstructability Predictive Model (AI-DPM) to quickly assess whether a building is suitable for deconstruction rather than demolition, advancing sustainability in construction. The model's binary classification structure—deconstructible or non-deconstructible—streamlines decision-making by assigning a precise categorisation to buildings based on a threshold score. Crucially, this model integrates diverse variables spanning social, economic, technical, environmental, scheduling, and legal dimensions, creating a multifaceted approach to predict deconstructability. The study demonstrated the model's applicability across BIM, non-BIM, DfD, and non-DfD buildings, filling a notable gap in current deconstructability assessment literature.

7.3.1 Interpretation of Findings and Theoretical Implications

1. Confirmations of Known Influences on Deconstructability

Consistent with existing literature, this research reaffirms that economic and technical factors primarily influence deconstructability. For instance, deconstruction costs, salvage value, and modular construction methods have previously been highlighted as core factors (e.g., Akinade et al., 2015). This alignment strengthens the reliability of the model's approach, indicating that these variables continue to be relevant and can be effectively leveraged by AI.

2. The Role of Multi-Dimensional Variables in Deconstructability

This research confirms that deconstructability is influenced by various variables, each contributing uniquely to deconstructability outcomes. Integrating variables beyond the technical and economic—such as social concerns like stakeholder engagement and environmental concerns like waste minimisation—reflects an essential shift from traditional views in deconstructability studies. While prior research has emphasised technical concerns (e.g., Akinade et al., 2015; Guy, 2006) and economic concerns (e.g., Tatiya et al., 2018), this research expands the framework, supporting theories on sustainability and resilience by underscoring the complex interdependencies between non-technical and technical concerns like social, environment, schedule and economic (e.g., Akinade et al., 2017), aligning with frameworks like the TELOS.

3. Binary Classification and Threshold Limitations

The binary classification of deconstructability (i.e., deconstructible vs. non-deconstructible) effectively translates complex data into actionable insights for deconstruction professionals. The decision to use a 60% threshold aligns with prior studies. Still, this research indicates that relying on a rigid threshold may overlook nuanced cases that do not fit neatly within either category. For instance, certain buildings could exhibit features that suggest “partial deconstructability,” where some elements are suited for reuse while others are not, highlighting the need for granularity in classification.

A more sophisticated multi-class model could better capture the continuum of deconstructability. However, the binary system offers significant advantages in terms of simplicity and usability, especially for industry professionals who may prefer clear yes-or-no over ambiguous scoring. This approach highlights a tension between practical applicability and theoretical precision, suggesting that future models may need to balance clarity and detail by incorporating "intermediate" classes or probabilities for more realistic predictions.

4. *Insights on AI Models: SVM with Polynomial Kernel*

The success of the SVM model with a polynomial kernel over simpler models (e.g., Logistic Regression, Decision Trees) demonstrates the importance of advanced AI techniques in handling multi-dimensional deconstructability data, as shown by inconsistencies in results across simpler algorithms like KNN. The SVM model’s superior performance confirms that advanced AI can more effectively capture non-linear relationships between variables.

5. *Feature selection; not applicable to all predictive modelling scenario*

The research finds that support vector machines with the polynomial kernel (SVM-P) using all features and Artificial neural networks with multilayer perceptron (MLP) using the features deducted from the FS techniques are the two high-performing models. Among the two, the SVM-P shows the highest predictive capabilities because of its higher accuracy and AUC, even as it uses all features. These findings made it known that, though researchers have proved the use of FS for enhancing predictive capabilities in AI predictive models, their uses and advantages may depend on the problem and scenario; as such, their uses may not apply to all kinds of issues/scenario where AI predictive model is used. Additionally, the predictive modelling performance of SVM-P suggests and supports the idea that deconstructability is a multifaceted concept. This is evidenced by the fact that the highest performance was achieved when all the diverse set of variables was used

6. *Explainability as a Vital Component for Industry Acceptance*

The study emphasises that explainability—achieved here with SHAP (Shapley Additive explanations)—is crucial for real-world adoption, especially as many stakeholders may lack AI expertise. By clarifying how the model makes predictions, SHAP enables users to understand which factors influence outcomes, adding a layer of transparency often lacking in AI applications.

This emphasis on explainability aligns with the interpretability-accuracy trade-off in AI, where complex models often excel at prediction but struggle to provide clear insights into how decisions are made. The model gains trustworthiness by prioritising interpretability—a significant advantage for industry adoption—though it might sacrifice some predictive nuance. This insight has broader implications, suggesting that AI models in deconstruction should prioritise transparency as much as accuracy, particularly when decisions impact sustainability and long-term resource management.

7.3.2 Implications of Findings

- *Policy Implications for Encouraging Sustainable Deconstruction*

This research suggests that deconstructability could inform policy frameworks such as BREEAM certifications and circular economy standards (e.g., London circular statement) and push for broader regulatory adoption. Such frameworks could incentivise projects incorporating deconstruction planning, potentially increasing deconstruction implementation. This research can further support pre-redevelopment and pre-demolition audits in line with the Sustainable Development Goals (SDGs) and Site Waste Management Plan (SWMP).

7.4 Limitations

In developing AI predictive models, numerous methods and considerations are available, often drawn from empirical findings in research. No single approach universally applies to all scenarios. This supports the No Free Lunch Theorem notion that no algorithm is universally superior. Nevertheless, this research demonstrates that strategically selecting a diverse range of methods and algorithms within an end-to-end modelling framework can potentially create a robust solution adaptable to multiple challenges within a specific domain—such as predicting building deconstructability in this research. However, this approach has drawbacks, including vulnerability to SMOTE overfitting. Some limitations identified include:

When the data available for training an AI model is limited, the model's ability to learn/generalise effectively is severely hindered. This scarcity of data can result in numerous issues, such as overfitting, where the model performs exceptionally poorly on unseen data (test/validation). Small datasets often need more diversity and representativeness for the model to capture the underlying trends within the data. Consequently, the model's predictions of new data can be unreliable and inaccurate. Additionally, small datasets can lead to increased variance in the model's performance, making it difficult to achieve consistent results. To mitigate these issues, techniques such as synthetic data generation and transfer learning can be employed. However, these solutions are not always feasible or sufficient, emphasising the critical need for large, high-quality datasets in developing reliable and effective AI predictive models.

In addressing missing data, there is no one-way-fits-all solution. Researchers often develop their approaches based on literature reviews, experiments and the domain/problem. In this research, the researcher employed machine learning data imputation, specifically KNN, assuming missing data were entirely at random (MAR/MCAR). However, implementing KNN for missing data imputation can take time and effort.

When dealing with an imbalanced class, caution is necessary when employing data resampling techniques such as SMOTE. SMOTE application can result in overly optimistic performance for the developed AI model. The experiments indicated that SMOTE makes the AI predictive models developed prone to overfitting. The research is constrained by a clear recommendation regarding the SMOTE threshold to mitigate overfitting.

Furthermore, more extensive validation of AI-DPM lies in their practical deployment and validation within real-time deconstruction projects by deconstruction experts. While AI-DPM were developed and tested using past deconstruction project data, their effectiveness for current and real-time deconstruction needs to be investigated.

Lastly, this research gathered data through survey questionnaires relying on expert opinions. While experts offer valuable insights, their responses may introduce bias. This could limit the model's objectivity. Additionally, the data focused exclusively on residential apartment buildings, excluding other building types that might exhibit different deconstructability characteristics. This limited scope could result in the loss of significant insights. Non-residential buildings (e.g., office buildings, schools, or industrial facilities) often have distinct structural, regulatory, and economic factors influencing their deconstructability. For future research, incorporating a wider variety of residential and non-residential building types would enhance the model's generalisability and allow it to reflect the broader diversity in sustainability needs across the building sector.

7.4 Future work

Several promising avenues for future work can be identified based on the limitations and findings of this research. An important direction for future research is the comprehensive validation of AI-DPM through expert evaluations and practical implementations. Collaborating with industry professionals and conducting pilot projects on actual deconstruction sites will provide valuable feedback and highlight practical challenges and opportunities for improvement. This hands-on approach can uncover nuances and context-specific difficulties that might not be evident through theoretical modelling alone. Furthermore, involving a multidisciplinary team, including environmental scientists, architects, and policymakers, can enrich the validation process and ensure that the models align with sustainability goals and regulatory frameworks.

Using more extensive (more samples) and varied sources of datasets (such as documents, images, videos, plans and others) for AI-DPM development will enhance the models used by deconstruction experts and other potential users, including waste management consultants and building owners. This will help to test and refine the models' robustness across diverse building types and geographical regions.

Lastly, exploring the integration of AI-DPM with other emerging technologies, such as reality-capturing technologies and the Internet of Things (IoT), can open new frontiers in building deconstructability. They can facilitate real-time data collection, aiding monitoring of structural health/material conditions and facilitating real-time predictive modelling. By using these technologies, future research can create more holistic and resilient deconstructability frameworks that predict and actively manage the lifecycle of buildings, promoting a circular economy in the construction industry.

7.5 Chapter Summary

The chapter presented significant insights drawn from the study findings. The best-performing AI-DPM demonstrates that integrating diverse variables is crucial for the prediction of building deconstructability. This indicated the robustness and validity of AI-DPM models. Moreover, the high-level performance achieved by many AI-DPMs underscores the possibility of developing a single, comprehensive model applicable to deconstruction projects of all sizes, including non-design for deconstruction and non-BIM.

The research has contributed some significant variables to the AI-DPM and deconstruction research area and established the need to incorporate and look at deconstructability from diverse perspectives, including social, economic, technical, schedule, environmental, and legal. The research has established that SVM and MLP are high-performing models with good generalisability capabilities. The research has also shown the efficiency of feature selection and how they were not the best solution in all AI/ML predictive model development.

The chief limitation of the research is the use of a questionnaire, small sample size and oversampling techniques to augment and balance the class in the 263 data retrieved from the questionnaire survey representing deconstruction projects. Future research should investigate the possibility of getting more data, including video, images, and documents, to develop AI-DPM. They should also seek to carry out large-scale AI-DPM validation through expert evaluation/practical implementations. Collaborating with industry professionals and conducting pilot projects on actual deconstruction sites will provide valuable feedback and highlight practical challenges and opportunities for improvement. This hands-on approach can uncover nuances and context-specific factors that might not be evident through theoretical modelling.

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Appendix

Appendix A: Online Survey

The process of data collection in this study is illustrated in Figure A1.

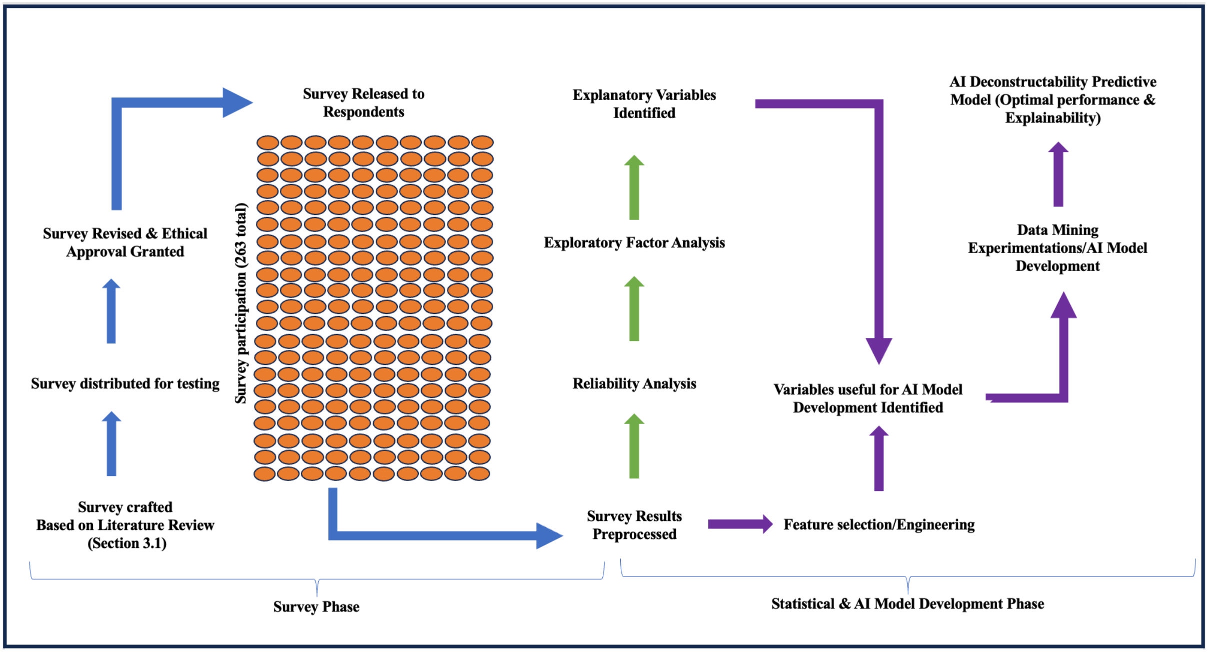

Figure A1. Process of the Multi-method Quantitative Research Approach

Respondent Information Sheet:

You are invited to complete an online survey as part of a PhD Research undertaken by Habeeb Balogun, a Business Analytics student at Business School, University of Hertfordshire, UK.

Please read the following information carefully before deciding whether to take part. Please ask if there is anything unclear or if you would like more information.

You are eligible to take part in this study if you are 18 or over.

The Study

The study aims to develop an artificial intelligence-based deconstructability predictive model able to predict if a building is a good candidate for deconstruction. The model will create pre-deconstruction audit knowledge, aid faster decision-making on whether a building is suitable for deconstruction or not, and increase wider implementation of deconstruction during and after the design stage thus increasing a sustainable environment and economy.

What does taking part involve?
If you agree to take part in this study, you will be asked to complete an online survey/questionnaire. This survey/questionnaire will ask about impactful factors influencing the deconstructability of an existing building and it will take you approximately [8] minutes to complete.

Do I have to take part?
No. It is up to you to decide whether to take part. You are free to withdraw from the study at any time and without giving a reason. If you choose not to take part, you do not need to do anything further.

Are there any benefits or risks for me if I take part?
You may not directly benefit from this research; however, we hope that your participation in the study may give you asses to test how the model works when its ready for end users. There are no expected risks for participants. Any data that you provide will be treated as confidential and the questionnaire is anonymous.
All data from the study will be stored securely on my university One Drive cloud storage system which only I have access to and will be deleted once I am done developing the artificial intelligence predictive model.

What will happen to the findings of this study?
The findings will be used to train, test and validate the artificial intelligence deconstructability model.

Has this study received ethical approval?
This study has been approved by the University of Hertfordshire Social Sciences, Arts and Humanities, Ethics Committee with Delegated Authority (SSAH ECDA). The Ethics Protocol number for this study is cBUS/PGR/UH/05259.

If you would like to receive more information and for any other queries about this project you can contact me by email (h.balogun@herts.ac.uk) or my director of studies, Professor Hafiz Alaka (h.alaka@herts.ac.uk)

Although we hope this is not the case, if you have any complaints or concerns about any aspect of the way you have been approached or treated during this study, please write to the University's Secretary and Registrar at the following address:

Secretary and Registrar
University of Hertfordshire
College Lane
Hatfield, Hertfordshire
AL10 9AB
United Kingdom

Ethical approval

The proof of ethical approval from the University of Hertfordshire, UK

University of Hertfordshire UH

SOCIAL SCIENCES, ARTS AND HUMANITIES ECDA

ETHICS APPROVAL NOTIFICATION

TO	**Habeeb Balogun**
CC	**Dr. Hafiz Alaka**
FROM	**Dr Ian Willcock, Social Sciences, Arts and Humanities ECDA, Chairman**
DATE	**30/09/2021**

Protocol number: cBUS/PGR/UH/05259

Title of study: Deconstructability prediction using artificial intelligence model

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

Conditions of approval specific to your study:

Ethics approval has been granted subject to the following points:

- A UH-approved online survey system must be used to administer the survey. The student is recommended to use Online Survey because of security issues with other sources. For those in the Hertfordshire Business School, supervisors should request an OS account on behalf of their students through CASE (CASE-Technology@herts.ac.uk).Contact Que Mirza for an account for either Online Survey or Qualtrics q.mirza@herts.ac.uk

  Please use a UH approved online survey system –
  See FAQ:
  https://www.studynet1.herts.ac.uk/ptl/common/ethics.nsf/Frequently+Asked+Questions/B8C3196F1E5BF9BB8025837F003E58C3

- The provision of information to participants and the collection of explicit consent must all be managed within the survey rather than using the EC6 and EC3.

- All data should be retained until the completion of the PhD.

Table A1. List of Online survey questions

Question Number	Question	Question type	Options
Section A			
A1.1	I confirm that I have read and understood the respondent information sheet	Multiple Choice: Single Answer	Yes / No
A1.2	I understand that all personal information will remain confidential and that all efforts will be made to ensure I cannot be identified (except as might be required by law).	Multiple Choice: Single Answer	Yes / No
A1.3	I agree that data gathered in this study may be stored securely and anonymously and may be used for solely for this research	Multiple Choice: Single Answer	Yes / No
A1.4	I understand that my participation is voluntary and that I am free to withdraw at any time without giving a reason.	Multiple Choice: Single Answer	Yes / No
A1.5	I agree to take part in this study	Multiple Choice: Single Answer	Yes / No
A1.6	I have worked/participated/engaged on/in a building end-of-life project where disassembly/deconstruction was considered/done?	Multiple Choice: Single Answer	Yes / No
NOTE: If your response to A1.6 is no, then you are not fit to respond to the subsequent questions. Thank you and Goodbye.			
A1.7	If response to A1.6 is yes, what option was agreed upon/implemented	Multiple Choice: Single Answer	Deconstruction / Refurbishment / Renovation / Demolition / Abandon or Do nothing
Respondents Information			
A1.8	What of the following services do you offer?	Multiple Choice: Multiple Answers	Demolition / Deconstruction / Refurbishment / Redevelopment / Others
A1.9	How would you best describe your profession/role?	Multiple Choice: Single Answer	Client / Developer / Demolition Contractor or Engineer / Architect / Other
A1.10	How many years of experience do you have in Demolition/Deconstruction/waste management field?	Multiple Choice: Single Answer	1 / 2 / 3 / 4 / 5+
NOTE: Where the respondent has worked on multiple deconstruction/demolition project, s/he should please provide answers based on just one project. However, respondents can complete this questionnaire multiple times; in each case, all answers should be based on a specific project.			

Question Number	Question	Question type	Options
A1.11	I confirm that all/subsequent response is exclusively focused on a single deconstruction project?	Multiple Choice: Single Answer	Yes / No
A1.12	To what extent was the building deconstructed or can the building be deconstructed to?	Multiple Choice: Single Answer	Full deconstruction / Partial demolition / Full Demolition
A.1.13	On a scale of 0 -100, can you describe how deconstructible the building was?	Multiple Choice: Single Answer	< 25% / 25-50% / 50-99% / 100%
Section B			
B.1	Where was/is the building deconstruction project located?	Multiple Choice: Single Answer	USA / UK / France / China / Others
B.2	What was/is the building type?	Multiple Choice: Single Answer	Residential / Non-residential
B.3	What was/is the construction method of the building?	Multiple Choice: Single Answer	Prefabricated / Traditional
B.4	What year was/is the building built?	Multiple Choice: Single Answer	pre-1990 / pre-1930 / pre-1950 / pre-1978 / post-1978
B.5	Was/is the building Occupied	Multiple Choice: Single Answer	Yes / No
B.6	Number of stories/floors	Multiple Choice: Single Answer	1 / 1½ / 2 / 3 / More
B.7	Numbers of rooms	Multiple Choice: Single Answer	1 / 2 / 3 / 4 / 5+
B.8	Number of bathrooms/toilets	Multiple Choice: Single Answer	1 / 2 / 3 / 4 / Others
B.9	Was/is the structure secured to prevent unwanted entry?	Multiple Choice: Single Answer	Fully / Partly / No
B.10	Was/is there room around the structure to serve as staging area?	Multiple Choice: Single Answer	Yes / No
B.11	Was/is there exterior trash?	Multiple Choice: Single Answer	No trash / Piles of Trash
B.12	Was/is there interior trash?	Multiple Choice: Single Answer	No trash / Piles of Trash
B.13	Were there restricted movement in and out of the building?	Multiple Choice: Single Answer	Yes / No
B.14	Were hazards present on-site?	Multiple Choice: Single Answer	Yes / No
B.15	What was/is the state of the building?	Multiple Choice: Single Answer	Collapse / Partial collapse / Healthy
B.16	Was/is the structural elements connection accessible/separable?	Multiple Choice: Single Answer	Yes / No
B.17	Was/is there good road network to the building?	Multiple Choice: Single Answer	Yes / No
B.18	What was/is the roof type?	Multiple Choice: Single Answer	Flat / Pitched
B.19	What was/is the foundation type?	Multiple Choice: Single Answer	Monolithic concrete / Concrete block / Combination / Unknown / Others
B.20	Was/is there any recycling facility closer?	Multiple Choice: Single Answer	Yes / No
B.21	Was/is there major cracking of brick/wood rotting?	Multiple Choice: Single Answer	Yes / No

Question Number	Question	Question type	Options
B.22	Was/is there broken or missing windows?	Multiple Choice: Single Answer	Yes / No
B.23	Was/is there missing bricks and siding	Multiple Choice: Single Answer	Yes / No
B.24	Was/is there roof damage	Multiple Choice: Single Answer	Yes / No
B.25	Were there major fire damages?	Multiple Choice: Single Answer	Yes / No
B.26	Were there major water damages?	Multiple Choice: Single Answer	Yes / No
B.27	What hazardous materials were identified?	Multiple Choice: Single Answer	Asbestos / Mercury / Lead / Others
B.28	What is the estimated quantity of hazardous materials identified?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
B.29	Do you have access to information about the building? (design plans and/or inventory)	Multiple Choice: Single Answer	Yes / No
B.30	Has a detailed disassembly plan been developed?	Multiple Choice: Single Answer	Yes / No
Section C			
C.1	What was/is the percent of Brick Siding?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
C.2	What was/is the percent of Wood Siding?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
C.3	What was/is the percent of Stone Siding?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
C.4	What was/is the percent of Vinyl/Synthetic Siding?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
C.5	What was/is the percent of Aluminium Siding?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
C.6	What was/is the percent of other siding?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
C.7	What was/is the number of rooms with wood flooring?	Multiple Choice: Single Answer	1 / 2 / 3 / 4 / 5+
C.8	Was/is there dimensional ceiling or floor joists observed?	Multiple Choice: Single Answer	Yes / No / Unknown
C.9	Was/is there dimensional lumber larger than 4x4?	Multiple Choice: Single Answer	Yes / No / Unknown
C.10	What was/is the percent of Wall plasters?	Multiple Choice: Single Answer	< 25% / 25-50% / 50-99% / 100%
C.11	What was/is the percent of drywall?	Multiple Choice: Single Answer	< 25% / 25-50% / 50-99% / 100%
C.12	What was/is the number of rooms with crown moulding?	Multiple Choice: Single Answer	1 / 2 / 3 / 4 / 5+
C.13	What was/is the number of rooms with casing around doors & windows?	Multiple Choice: Single Answer	1 / 2 / 3 / 4 / 5+
C.14	What was/is the number of rooms with baseboard moulding?	Multiple Choice: Single Answer	1 / 2 / 3 / 4 / 5+
C.15	What was/is the number of rooms with chair railing moulding?	Multiple Choice: Single Answer	1 / 2 / 3 / 4 / 5+
C.16	Was/is there basement?	Multiple Choice: Single Answer	Yes / No / Unknown

Question Number	Question	Question type	Options
C.17	What kind of the composite materials (in large quantity) are still/was in place?	Multiple Choice: Single Answer	Fibre reinforced polymer / Ceramic / Steel reinforced concrete / Composite wood beam / Others
C.18	What percentage of the total building component can be/was reused?	Multiple Choice: Single Answer	< 25% / 25-50% / 50-99% / 100%
C.19	What percentage of the total building component can be/was recycled?	Multiple Choice: Single Answer	< 25% / 25-50% / 50-99% / 100%
C.20	What percentage of the total building component will be/was sent to landfill?	Multiple Choice: Single Answer	< 25% / 25-50% / 50-99% / 100%
Section D			
D.1	Was/is there a fireplace mantel	Multiple Choice: Single Answer	Yes / No / Unknown
D.2	Was/is there a stair treads/railing	Multiple Choice: Single Answer	Yes / No / Unknown
D.3	Was/is there other architectural woodworks	Multiple Choice: Single Answer	Yes / No / Unknown
D.4	Was/is there stained/leaded glass	Multiple Choice: Single Answer	Yes / No / Unknown
D.5	Was/is there solid wood doors	Multiple Choice: Single Answer	Yes / No / Unknown
D.6	Was/is there wood framed windows	Multiple Choice: Single Answer	Yes / No / Unknown
D.7	Was/is there built-in wood cabinetry	Multiple Choice: Single Answer	Yes / No / Unknown
D.8	Was/is there decorative architectural wrought iron	Multiple Choice: Single Answer	Yes / No / Unknown
D.9	Was/is there lighting fixtures	Multiple Choice: Single Answer	Yes / No / Unknown
D.10	Was/is/are there radiators	Multiple Choice: Single Answer	Yes / No / Unknown
D.11	Was/is/are there sinks	Multiple Choice: Single Answer	Yes / No / Unknown
D.12	Was/is/are there claw foot tub	Multiple Choice: Single Answer	Yes / No / Unknown
D.13	Was/are there old appliances (oven, refrigerator)	Multiple Choice: Single Answer	Yes / No / Unknown
D.14	Was/is there iron gates/fencing	Multiple Choice: Single Answer	Yes / No / Unknown
D.15	Was/is there metal roofing	Multiple Choice: Single Answer	Yes / No / Unknown
D.16	Was/are there countertops	Multiple Choice: Single Answer	Yes / No / Unknown
D.17	Was/is there door hardware	Multiple Choice: Single Answer	Yes / No / Unknown
D.18	Was/are there other old/rare steels	Multiple Choice: Single Answer	Yes / No / Unknown
D.19	Are you aware of any architectural salvage yards?	Multiple Choice: Single Answer	Yes / No / Unknown

Question Number	Question	Question type	Options
D.20	Were there any other architectural components present in the building with historic/commercial value?	Multiple Choice: Single Answer	Yes / No / Unknown
Section E			
E.1	What was/is the percent of Claddings reusable/recyclable?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
E.2	What was/is the percent of Connections reusable/recyclable?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
E.3	What was/is the percent of Frameworks reusable/recyclable?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
E.4	What was/is the percent of Glazing reusable/recyclable?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
E.5	What was/is the percent of Insulation reusable/recyclable?	Multiple Choice: Single Answer	1 (little) / 2 / 3 / 4 / 5 (lots)
E.6	How expensive is/was it to hire deconstruction worker in your region	Multiple Choice: Single Answer	Cheap / Expensive / Not sure
E.7	How expensive is/was the tipping/disposal fee for dumping waste in landfill in your region?	Multiple Choice: Single Answer	Cheap / Expensive / Not sure
E.8	How expensive is/was it to get deconstruction/disassembly permit from the government/local authority?	Multiple Choice: Single Answer	Cheap / Expensive / Not sure
E.9	How expensive is/was it to get a trained toxic/hazardous material handler in your region?	Multiple Choice: Single Answer	Cheap / Expensive / Not sure
E.10	How expensive is/was it to get specialised equipment/tools?	Multiple Choice: Single Answer	Cheap / Expensive / Not sure
E.11	Are you aware of any stockists of reclaimed components or elements?	Multiple Choice: Single Answer	Yes / No
E.12	Are there any restrictions or limitations on the availability of certain materials due to environmental regulations or building codes?	Multiple Choice: Single Answer	Yes / No
E.13	Would you consider reclaiming components from a project if you knew there was good demand for them, and they were commercially viable?	Multiple Choice: Single Answer	Yes / No
E.14	Are you in the position to supply spare parts or to provide a reconditioning service on demand or to undertake reconditioning as a core service?	Multiple Choice: Single Answer	Yes / No
E.15	Were tests available to assess the condition/life expectancy of materials (both in-situ and ex-situ)?	Multiple Choice: Single Answer	Yes / No
Section F			

Question Number	Question	Question type	Options
F.1	Which stakeholders would you say have the significant influence on your deconstruction activities	Multiple Choice: Single Answer	Building owner / Contractor / Client / Government / Others
F.2	What would you say was/is the main motivation for the deconstruction?	Multiple Choice: Single Answer	Sustainability badge / Economic gain / Job creation / Social responsibility / Others
F.3	Does the government policy encourage deconstruction in the region?	Multiple Choice: Single Answer	Yes / No
F.4	Does the public attitude encourage deconstruction in the region?	Multiple Choice: Single Answer	Yes / No
F.5	Do you believe that the benefits of material reuse are well-understood by the public?	Multiple Choice: Single Answer	Yes / No / Not sure
Section G			
G.1	What was/is the estimated time it took or the estimated time it will take to for jobsite preparation?	Multiple Choice: Single Answer	Few hours / A Day / Few days / Weeks / Others
G.2	What was/is the estimated time it took or the estimated time it will take to get permit to deconstruction permit?	Multiple Choice: Single Answer	Few hours / A Day / Few days / Weeks / Others
G.3	What was/is the estimated time it took or the estimated time it will take to deconstruct the building?	Multiple Choice: Single Answer	Few hours / Days / Weeks / Months / Others
G.4	What was/is the estimated time it took or the estimated time it will take to assess the building for deconstruction?	Multiple Choice: Single Answer	Few hours / A Day / Few days / Weeks / Others
G.5	What was/is the estimated time it took or the estimated time it will take to sort the recovered building components?	Multiple Choice: Single Answer	Few hours / Days / Weeks / Months / Others
G.6	What time of the year was/is the disassembly/deconstruction (done or proposed to be done)?	Multiple Choice: Single Answer	Rainy / Non-Rainy / Not sure
G.7	We would like to keep in touch with you about this survey. If you would be willing to be contacted, please provide contact information (Phone number or email)	Free Text	

Appendix B: Definitions

Embodied carbon:
provides a measure of the greenhouse gas emissions associated with the extraction, processing, fabrication and transportation of the materials and products used in buildings.

Operational carbon:
provides a measure of the greenhouse gas emissions associated with the in-use operation of a building. This usually includes carbon emissions associated with heating, hot water, cooling, ventilation, and lighting,

Circular economy:
The concept of a closed-loop system of consumption that aims to eliminate waste through the continual use of resources through reuse, sharing, repair, refurbishment, remanufacturing, and recycling, minimising the use of resource inputs and the creation of waste, pollution, and carbon emissions.

Pre-consumer recycling:
The reprocessing of waste materials that arise during the process of manufacturing products. to be used in new production.

Post-consumer recycling:
The reprocessing of waste materials that have been collected after they have spent a period. of time in use.

Design for disassembly (DfD):
A design principle that calls for the end-of-life options of how the product, components and materials can be deconstructed.

Appendix C: Screenshots of the AI-DPM Developed and Served as a Web application

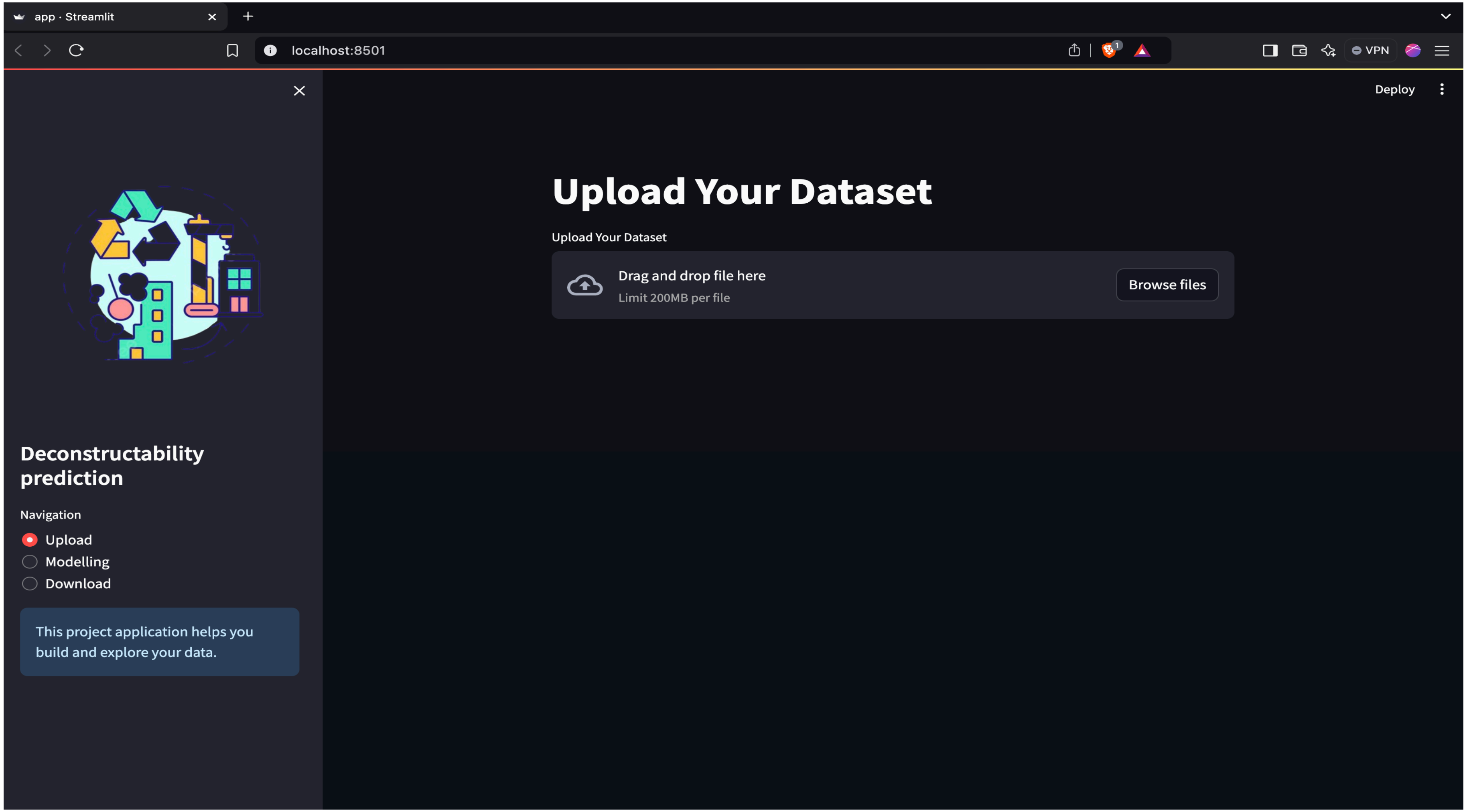

Figure C1: The starting page where user uploads an Excel or CSV file of the deconstruction data (Screenshot from the deployed AI-DPM model)

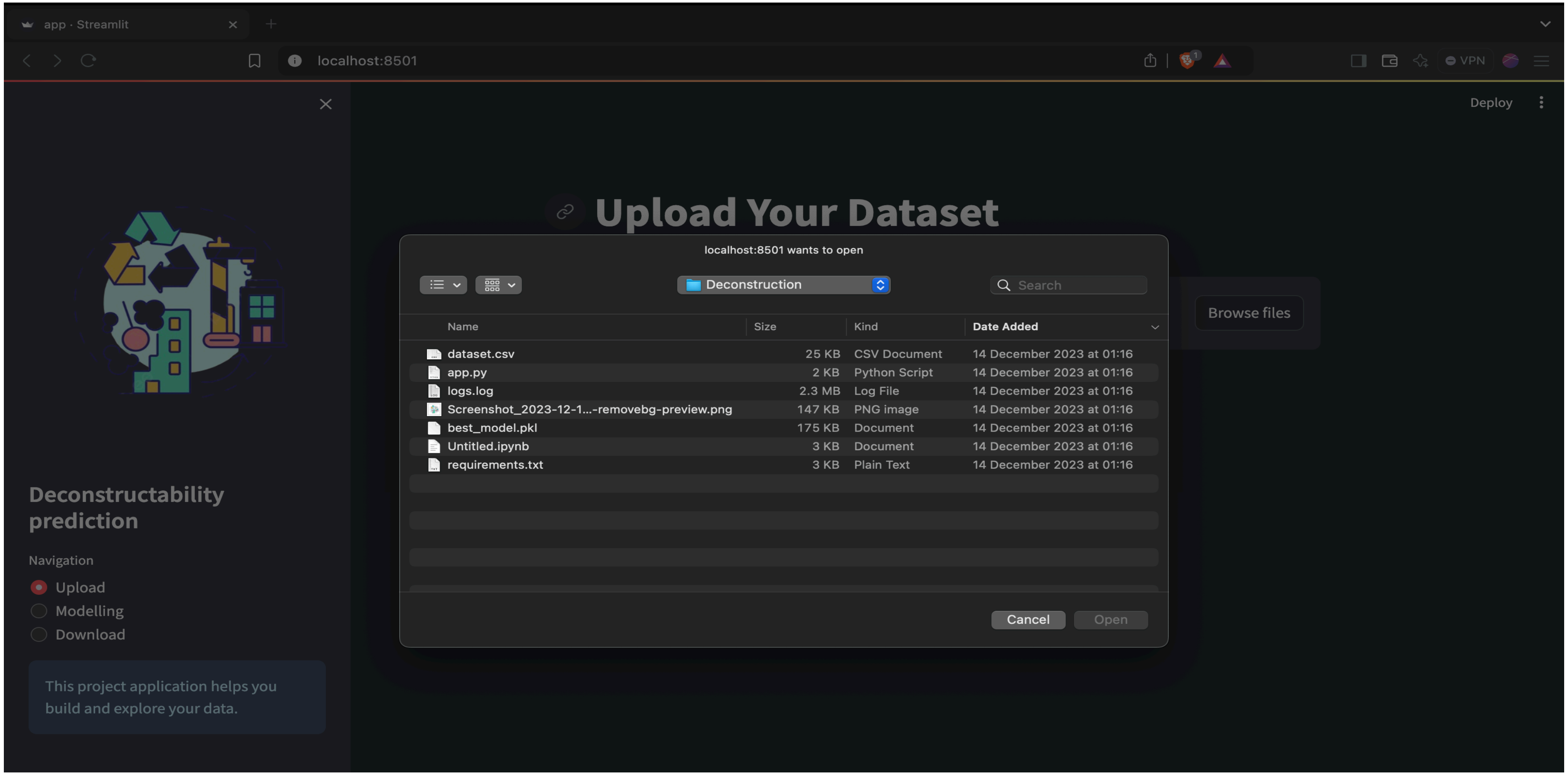

Figure C2: User trying to locate the file directories where the data reside, ready to try AI-DPM (Screenshot from the deployed AI-DPM model)

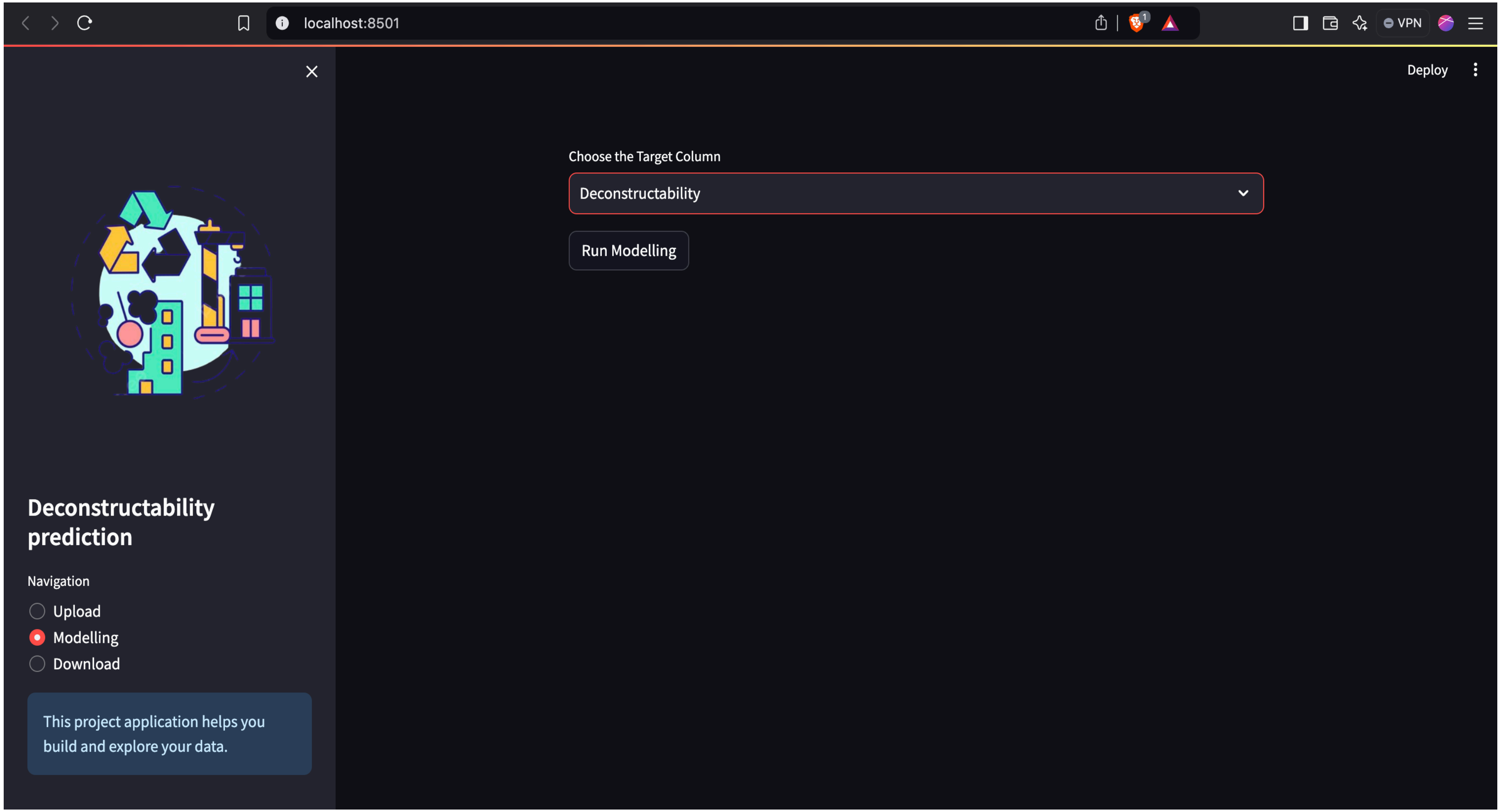

Figure C3: User clicks on Modelling, and selects deconstructability scores for the AI-DPM engine to output prediction (Screenshot from the deployed AI-DPM model)

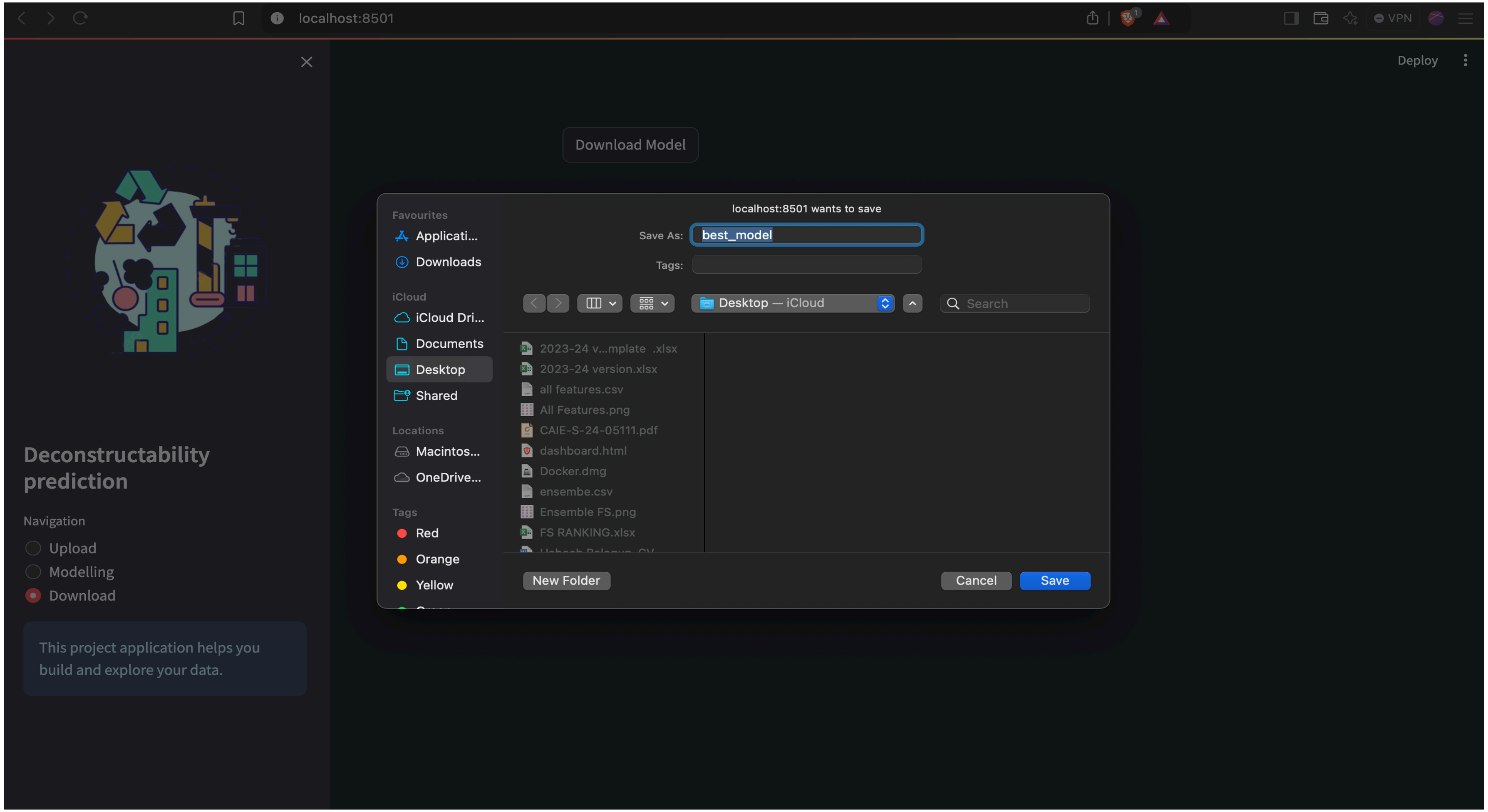

Figure C4: Once the AI-DPM outputs the prediction, User have the choice to save the prediction as a report, like audit report (Screenshot from the deployed AI-DPM model)