Developing an Artificial Intelligence Maturity Model (AIMM)

Applicable to the UK Construction Industry

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A thesis submitted in partial fulfilment of the requirement of the University of the West of England, Bristol for the degree of Doctor of Philosophy,

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DECLARATION

I affirm that this research work is my own and was conducted by me, excluding where due acknowledgement has been made in the text, and that it has not been submitted in part or full for any other award than the degree of Doctor of Philosophy of the University of the West of England. Materials from other sources have been duly acknowledged and referenced in line with ethical standards, and the list of publications made from the thesis has been provided.

Signed: Ummul-yumn Maryam Hamza

Signature:

Date: August 2024

ABSTRACT

In this study, a robust Artificial Intelligence Maturity Model (AIMM-CI) was designed with the capability of evaluating and determining the level of AI technology adoption and implementation in construction companies located in the United Kingdom. The model was built on the foundation of the Peffers framework, extensive literature review, empirical insights, and stakeholder perspectives, thereby making it a tailored model specifically designed for the unique challenges and opportunities present in the UK construction industry. Through a meticulous exploration of the existing AI technologies, both in the construction industry and a comparative study with other industries, the study drew insights from diverse use cases by identifying parallels, contrasts, and unique challenges in relation to AI adoption. More so, both quantitative and qualitative analyses were conducted to capture the perspectives of expert stakeholders directly involved in the UK construction industry. By using this systematic approach, a total of seven (7) themes were identified as the key factors that influence the adoption of AI in the UK construction industry. These seven (7) themes include Data Availability and Usability, Organisational culture, Human Capital Development, Robust Business Case, Legal Regulations, Stakeholder's Support, and Technology and Tools. The seven (7) themes contained a total of 40 success factors: Data availability and usability contained 5 success factors; Organisational culture contained 7; Human capital development contained 6; Stakeholders' support contained 5; Legal regulations contained 4; Robust business care contained 9, and Technology and tools contained 4 success factors. The seven (7) themes and the 40 success factors formed the framework used in designing the AIMM-CI model. The AIMM-CI model comprises seven dimensions; each dimension is intricately linked to the overall maturity of AI adoption. The model provides a systematic approach for construction companies in the UK to evaluate their current state AI adoption, identify areas for improvement, and progress through maturity levels. Therefore, the AIMM-CI is not just a theoretical construct; it is a practical tool that construction companies in the UK can leverage to navigate the complex terrain of AI adoption. It holds profound implications for the UK construction industry, as it offers practical insights and guidance for companies seeking to adopt and mature their AI capabilities. In essence, when organisations strategically address data challenges, cultivate a collaborative and innovative culture, optimise technology readiness, develop robust business cases, manage stakeholders effectively, and navigate legal and ethical dimensions, they position themselves for comprehensive AI maturity.

DEDICATION

This PhD thesis is dedicated to my Rabb, Almighty Allah (S.W.T), the most merciful, the most loving, for making this Doctorate Degree a reality. I earnestly dedicate my research work to my three lovely children, Mayameen Oluwafiresayo Tijani, Muhammad-Mahrus Olayemi Tijani, and Musallim Olakunle Tijani, for their tolerance, unwavering support, and understanding throughout this difficult period. Finally, I also dedicate this with immense happiness to my parents, RT Lt. col. Hamza Onivehu Umar and my amazing mother, Hajiya Amina Atimpo Ibrahim, for their unwavering support, love, and prayers.

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CHAPTER ONE – INTRODUCTION

1.0 Background

The integration of Artificial Intelligence (AI) within industries has revolutionised traditional practices by providing unprecedented opportunities for efficiency, innovation, and competitive advantage (Dwivedi et al., 2021). The increasing evolution of AI has made its adoption imperative for organisations seeking to remain relevant and drive future growth. AI technologies in the construction industry have the capacity to revolutionise project planning, execution, and management, leading to improved productivity, reduced costs, and enhanced safety (Abioye et al., 2021). However, the effective adoption of AI within construction firms remains a complex challenge; this necessitates a structured approach to evaluate and guide the integration of these advanced technologies. The concept of Maturity Models (MM) has proven invaluable in this regard, as it provides a systematic framework to assess the maturity and readiness of organisations in adopting new technologies and processes. Since the inception of the first Maturity Model, the Capability Maturity Model (CMM) by Paulk (2009), there have been several new suggestions for MM by researchers and practitioners across different sectors (De Bruin et al., 2005; Titov et al., 2016). This development has therefore influenced the emergence of numerous maturity models across a broad range of fields such as the Business Intelligence Maturity Model (BIMM) (Skyrius and Skyrius, 2021), the Testing Maturity Model (TMM) (Burnstein et al., 1996), the Safety Culture Maturity Model (SCMM) by Fleming (Ayob et al., 2022) and the Maturity Model for Data-Driven Manufacturing (M2DDM) (Weber et al., 2017) among others. According to Van Steenbergen et al. (2010) maturity models are tools used to measure and assess the quality of processes and capabilities in an organisation. Within the construction industry, MMs have also been adopted across various divisions and processes in the construction business (Serpell et al., 2015; Wang et al., 2018). For instance, Farrokh and Mansur (2013) introduced the Organisational Project Management Maturity Model (OPM3) which assesses project management strengths and weaknesses; and enables organisations to improve their project management maturity (Korbel and Benedict, 2007). Similarly, Wang and Wang (2009) came up with Construction Supply Chain Maturity Model (CSCMM) which facilitates an incremental and lasting improvement in performance and inter-organisational relationships. Also, the Building Information Modelling Maturity Model (BIM3) has featured prominently within construction literature as a vital tool for simplifying complex projects, and improving cost performance while managing challenging projects (Taxén & Lilliesköld, 2008). However, despite this enormous body of literature on Maturity Models in the construction sector, there is currently no literature on Artificial Intelligence (AI) Maturity Model, which could provide an effective and scalable guide for UK construction organisations seeking to implement AI-driven technologies.

According to Lee et al. (2017), AI is a computing method that allows machines and computers to imitate human cognitive functions. Some of the major subfields of AI, as shown in Figure 1. include Natural Language Processing (NLP), Machine Learning (ML), Computer Vision, Knowledge-based Systems, and Robotics (Henstock, 2019; Walczak, 2019; Tixier et al., 2016). In the new global economy, these subfields of AI applications have been responsible for the snowball increase in efficiency and profit performance in businesses across several industries like financial services, information technology (IT), and manufacturing sectors among others (Tarhan et al., 2016). These industries have introduced various AI applications that have totally transformed business processes and re-defined market competitions. For instance, AI has been attributed to the deployment of autonomous vehicles i.e., self-driving cars, unmanned drones, flying taxi-cabs, self-parking vehicles and cruise controls in the transportation industry. Similarly, robotic surgeons, patient monitoring, and virtual nursing assistants are also new AI-driven innovations in the healthcare sector. In the financial service sector, AI for compliance and fraud detection, digital banks, Robo-advisors, and AI for credit scoring are among recent advances in AI that are revolutionizing the global business environment (Sabharwal, 2018).

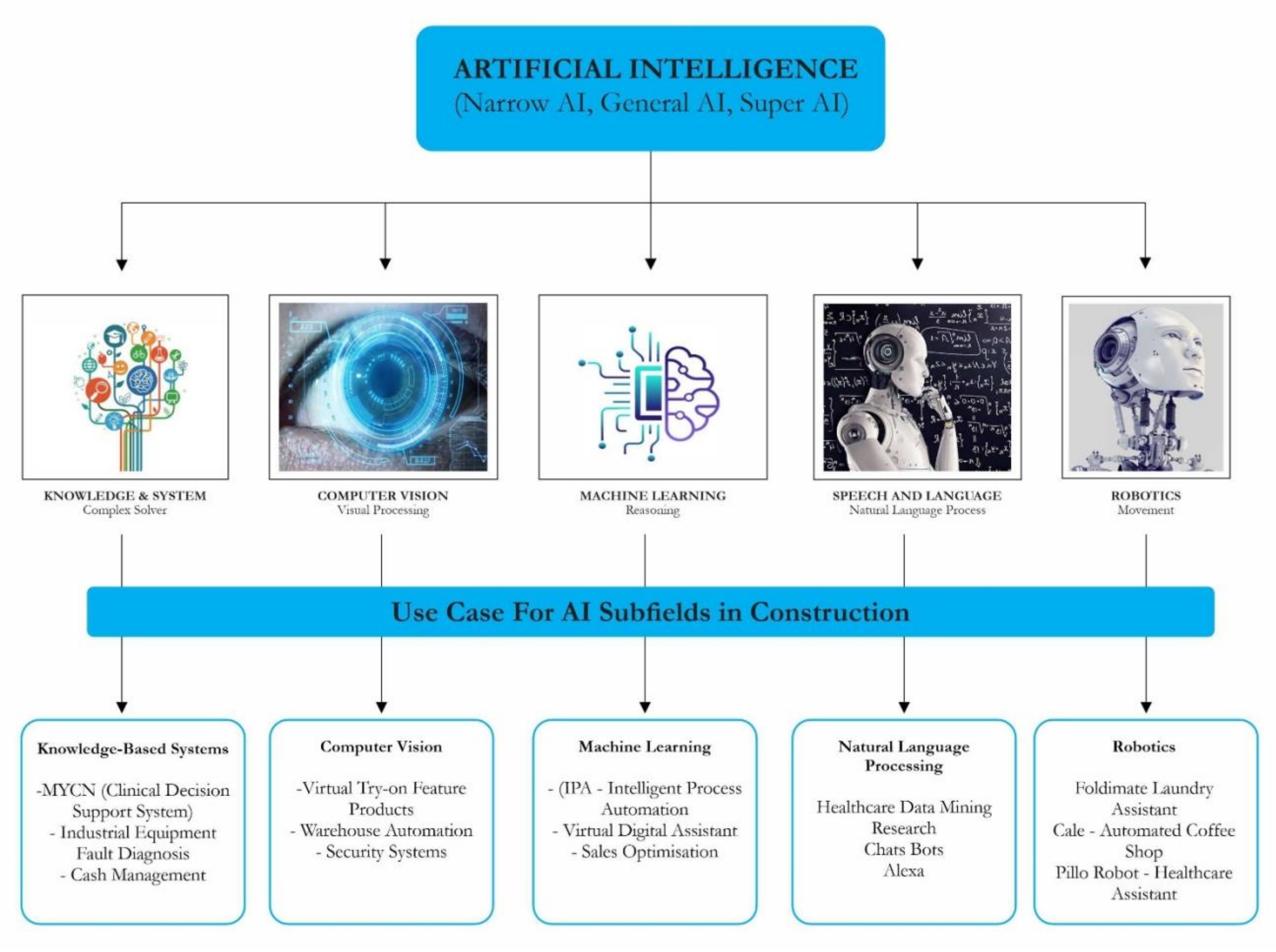


Figure 2.1 Subfields of Artificial Intelligence

The performance of AI technologies in the aforementioned sectors have prompted scholars and policymakers alike to call for more uptake of AI-based technologies, especially within the UK construction industry. According to the report of McKinsey (2020), emerging technologies, such as AI, have the capability to revolutionise and provide transformative solutions to tackle the age-long challenges within the construction industry. Such challenges include poor-quality performance, stagnant productivity, shortage of skilled labour, high numbers of on-site accidents, project cost, and time overrun, among others (Azhar, 2011; Keenan & Rostami., 2021). However, despite the huge potential benefits and opportunities achievable with AI within construction project practices and processes (i.e., enhanced project planning and improved safety and risk management), a critical review of the existing literature has revealed a surprising neglect of the need for a practical, competency-based guide, in the form of a Maturity Model to encourage the adoption and incremental implementation of AI within the UK construction industry.

1.1 Potential Challenges and Limitations of AI in The Construction Industry

AI systems rely heavily on data for training and making accurate predictions. In the construction industry, data often comes from various sources, including architects, engineers, contractors, and suppliers. However, the challenge lies in the inconsistency and fragmentation of data. Each stakeholder may use different software and data formats, leading to interoperability issues and data silos. More so, the successful implementation of AI in construction requires a careful integration strategy to minimize disruption and gain acceptance from the workforce. Construction projects often involve numerous stakeholders, each with their own set of responsibilities and workflows. Hence, introducing AI technologies aims to complement existing processes rather than replace them entirely. Furthermore, the dynamic and unpredictable nature of construction projects poses a significant challenge for AI systems, which may struggle to account for the multitude of variables and dependencies involved. Weather conditions, regulatory changes, and unexpected site conditions can all impact the progress and outcomes of a construction project. Besides, the initial costs associated with implementing AI technologies in construction can be a significant barrier, especially for smaller organisations operating on tight budgets (Abioye et al., 2021; Rampini and Cecconi, 2022; Regona et al., 2022). Given the above highlighted challenges associated with implementing AI in the construction sector, little wonder that scholars are intensifying the call for better standardization of AI competencies as a guide for modelling the maturity of AI expertise in the industry (Chen et al., 2022; Wang et al., 2018).

However, beyond existing criticisms of maturity models (MM) across diverse literature - i.e. its lack of theoretical basis (Lahrmann et al., 2011) and inadequate empirical validation (Lasrado et al., 2015) - Studies such as Röglinger et al. (2012); Brooks et al. (2015) have commended the use of MM in providing organisations with a well-documented guideline informing a progressive method to encourage and promote continuous improvement. Furthermore, with AI expected to contribute up to $13trillion in economic activity by 2030 and the global construction industry propelled by AI adoption also projected to grow at 33.79% cumulative average growth rate (CAGR) [worth $2,486.78 million] (McKinsey, 2017). Thus, evolving an AI-maturity model that will not only boast digital competencies within the UK construction sector but also propel the British Government's digital construction strategy – remains a vital pathway to the future of the industry. In addition, such an AI-competency Maturity model will help set-out an incremental measurement guide for digital competencies and AI applications within the UK construction industry and thus, provide parameters for evaluating AI capabilities within construction organisations. Based on the above background, this study sets out to investigate and propose an "AI maturity model for the UK construction industry", with an overarching goal of providing a viable digital competency road map for the adoption of AI by construction businesses.

1.2 Justification of study

The critical essence of conducting this research is to develop an AI-Maturity Model for the UK construction industry, to provide a suitable digital road map for the adoption of AI by construction businesses. The goal of this study is in consonance with the recent UK government policy strategy on fast-tracking the adoption of digital technologies within the construction sector. Over the last couple of decades, the construction sector has been known to have so much apathy towards digital innovation (Bilal et al., 2016). However, recent trends in the sector have suggested that more organisations are beginning to appreciate technology-based construction approaches and are inclining towards digital construction (Kusimo et al., 2019). For instance, the use of BIM, Big Data Analytics for predicting project cost & time overrun, waste analytics, including Internet of things (IoT) for progress reporting and waste management among others (Abioye et al., 2021). These increasing influx of emerging technologies within the construction sector has ushered in a new dawn for AI applications in construction and the need for proper mechanisms for articulating best practices.

Additionally, the construction industry is considered one of the leading contributors to the global economy, contributing about US$10.6 trillion to the global economy (Ahmad and El-Sayegh, 2021). Experts believe that AI adoption in the construction sector can boost productivity by as much as 50% through real-time analysis of data (Mckinsey, 2017). Intelligent systems are also believed to hold massive potential for eliminating monotonous tasks, reducing error, and increasing operational effectiveness and efficiency. Currently, the UK government has invested £ 18 million to foster the adoption of AI in construction, while the US and Chinese government have also recently increased their spending on the implementation of AI in construction by 69.9% and 62.2% to reach an equivalent of US$ 129.3 million and US$ 94.1 million respectively, with potential to increase exponentially over the next few years (Mckinsey, 2017). These investments in AI are in a bid to exploit the capabilities of AI to enhance business growth and drive market competition within the industry. On this basis, it becomes important to begin to consider AI competency-based maturity models for scaling the application of AI in construction businesses. As such, an AI-Maturity model for the construction sector is urgently needed to understand the incremental measurement of digital applications within the industry and provide parameters for evaluating the digital capabilities of construction organisations. It is on this premise that this study emerged.

1.3 Aim and Objectives

The overall aim of this study is to develop a robust Artificial Intelligence Maturity Model (AIMM) that would evaluate and determine the level of AI-technology adoption and implementation in UK construction organisations, with the goal of enhancing AI integration, improving operational efficiencies, and driving innovation within the industry.

To achieve the above aim, the following objectives have been identified for this study.

1. To examine the various existing AI-based technologies implemented within the construction industry by comparing them with a few other use cases in other business sectors.
2. To identify challenges and success factors for the implementation of AI in the UK construction sector.
3. To investigate the perspectives of expert stakeholders regarding best practices for AI implementation in the construction sector.
4. To identify progressive determinant factors for AI implementation within the industry.
5. To design and develop an effective AI-maturity model based on best practices of AI applications for the UK construction industry.

1.4 Research Questions

In achieving the aim and objectives of the study, the following set of research questions would be fulfilled:

1. What are the current practices and tools used to implement AI across industries?
2. How can AI adoption by construction organisations be benchmarked?
3. What are the key process indicators for each level grid of AI applications in construction?

4. Can past and current best practices of AI applications help to evaluate and assess a well-documented guideline?

1.5 Unit of Study

The unit of study describes the object of the research. As such, depending on the focus of the research, the unit of analysis could be individuals, teams, projects, or organisations. Since the purpose of this study is to develop a holistic AIMM that would assess and evaluate the level of AI-technology application in UK construction organisations using construction experts' perspectives, the unit of study is the individual. Hence, the focus of analysis in this study will also be on individual experts with experiences in the application of AI within the UK construction industry.

1.6 Research Contribution

This research will contribute to the body of knowledge in the following ways:

1.6.1. Contribution to Theory

This research will contribute massively to the literature on maturity models and technology acceptance within construction organisations by proposing a robust AI Maturity Model for the UK construction industry. The study will expand the knowledge on the integration of user/expert opinion on technology adoption and competency measurements. As such, the study will be a rich addition to the construction literature within the UK environment.

1.6.2. Contribution of Study to Industry Practice

The construction industry is a diverse field that includes businesses of various sizes, expertise levels, and operational scopes, from planning to on-site delivery. While existing studies have investigated maturity models for specific aspects of the industry, such as BIM, supply chain management, risk management, and safety (Zhao et al., 2013; Nývlt & Prušková, 2017), a comprehensive AI maturity model tailored to the unique needs of construction firms remains unexplored. This study aims to fill this gap by developing an Artificial Intelligence Maturity Model (AIMM) specifically designed for UK construction firms. The AIMM model will significantly contribute to the industry by providing a structured framework to evaluate and enhance AI adoption and implementation across construction firms, regardless of their size and specialization. This model will provide a holistic understanding of AI integration, including strategic planning, operational execution, and technological deployment. The identification of the current maturity levels of AI adoption will enable construction companies to pinpoint areas for improvement and develop targeted strategies to advance their AI capabilities.

One of the key contributions of this study is the development of a comprehensive AI maturity model that incorporates best practices and guidelines tailored to the construction industry. This model will serve as a practical tool for construction firms to assess their AI readiness and maturity, enabling them to benchmark their progress against industry standards. The AIMM will provide clear metrics and criteria for evaluating AI adoption, facilitating a systematic approach to enhancing AI capabilities within construction organisations. Furthermore, the AIMM will address the specific challenges and opportunities associated with AI implementation in the construction industry. Construction projects are inherently complex which involves multiple stakeholders, intricate processes, and diverse data sources. The proposed model will guide firms in navigating these complexities by highlighting critical success factors and potential pitfalls in AI adoption. By leveraging the insights from the AIMM, construction firms can optimize their AI strategies to achieve greater efficiency, productivity, and innovation.

The contribution of this study extends beyond theoretical advancements to practical implications for industry practice. The AIMM will provide construction firms with a roadmap for AI adoption, outlining actionable steps to enhance their AI capabilities. This roadmap will include best practices for data management, algorithm selection, integration with existing systems, and workforce training. By following the guidelines provided by the AIMM, construction firms can ensure a smooth and effective transition to AI-driven processes and technologies. Additionally, the AIMM will support construction firms in making informed investment decisions related to AI technologies. The model will offer insights into the cost-benefit analysis of AI adoption, helping firms allocate resources efficiently and prioritize AI initiatives that align with their strategic goals. By understanding the potential return on investment and long-term benefits of AI implementation, construction firms can make strategic decisions that drive sustainable growth and competitive advantage. Besides, the diversity of the construction industry, with its wide range of project types and operational scales, necessitates a flexible and adaptable AI maturity model. The proposed AIMM will be designed to accommodate the varying needs and contexts of different construction firms. Whether a small contractor or a large multinational corporation, construction firms can customize the model to suit their specific requirements and objectives. This flexibility ensures that the AIMM remains relevant and valuable to a broad spectrum of industry stakeholders.

1.7 Scope of Study

The focus of this study is on developing a robust AI-Maturity Model, which will be useable by construction practitioners to scale up the level of AI implementation in construction organisations. As such, the scope of this study is the UK construction organisations. Hence, attention will be placed on stakeholders within the UK construction sector. Participants for the research will also be from the UK Organisations regardless of their size within the construction industry. However, only construction organisations that have implemented AI technologies or approaches are considered in this study. Similarly, whilst the activities of the construction industry are divided into two, which are building construction and infrastructural facilities, this project scope is limited to building construction projects.

Thesis Outline and Structure

In a bid to address the research questions outlined in section 1.4, the research structure is shown in Figure 1.2.

Figure 2.2 Structure of the Thesis

Chapter Summary

The chapter provides an overview of the current state of Artificial Intelligence (AI) and maturity models within the construction industry. The chapter discusses the persistent impediments related to the use of AI in the construction sector, while also providing an analysis of its possible impact on the global economy. This chapter explores the existing knowledge gaps and provides a rationale for carrying out the study. The primary objective is to explore the maturity model concepts, identify challenges and success factors in the construction industry, and investigate expert perspectives to identify progressive determinant factors. This is necessary due to the intricate nature of the construction industry.

2 CHAPTER TWO – AI LITERATURE REVIEW

The second chapter examines, assesses, and discusses the literature supporting AI deployment in the construction sector in order to gain a better understanding of AI, its types, sub-fields, and applications. Section 2.1. engages in defining AI and its characteristics whilst section 2.2. discussed the different types of AI i.e., Artificial narrow intelligence, Artificial general intelligence, and Artificial super intelligence. Section 2.3. explores the different subfields of AI and its current applications. In section 2.4. the review of AI applications specific to the construction industry is examined. Section 2.5. goes on to explore recent trends of AI applications within the construction industry as well as its prospective potential. Section 2.6. analyses the various challenges encountered in the deployment of AI in construction. Section 2.7. examines the ethical implications of AI applications in the construction industry. Finally, through gathering the expert stakeholder perspectives, Section 2.9. delves deeply into and underlies determinant critical success factors for benchmarking and assessing AI implementation in construction.

2.1 Definition of Artificial Intelligence and its Characteristics

Alan Turing's intelligence test was a watershed moment in AI because it went beyond earlier theological and mathematical assumptions about the possibility of sentient machines, where AI was viewed as a way for robots to replicate human intellect (Wilks, 2019). Since its inception in the 1950s, AI has progressed to today's modern applications, with Lee et al. (2017) defining AI as "a broad term encompassing computing approaches that train robots and computers to emulate human cognitive processes such as reasoning, visual processing, voice and language processing, and emotional intelligence." Likewise, Huang and Rust (2021) defines AI as the study of how to make robots accomplish tasks that people do better at the moment. The AI subsets used to achieve these cognitive capabilities include Natural Language Processing (NLP) for speech and language processing, Machine Learning (ML) for reasoning, Computer Vision for visual processing applications, Knowledge-based Systems for complex problem-solving solutions, and Robotics for automation (Henstock, 2019). Thus, Figure 2.1 displays some of AI's most key technological strands, demonstrating its conceptual interpretation.

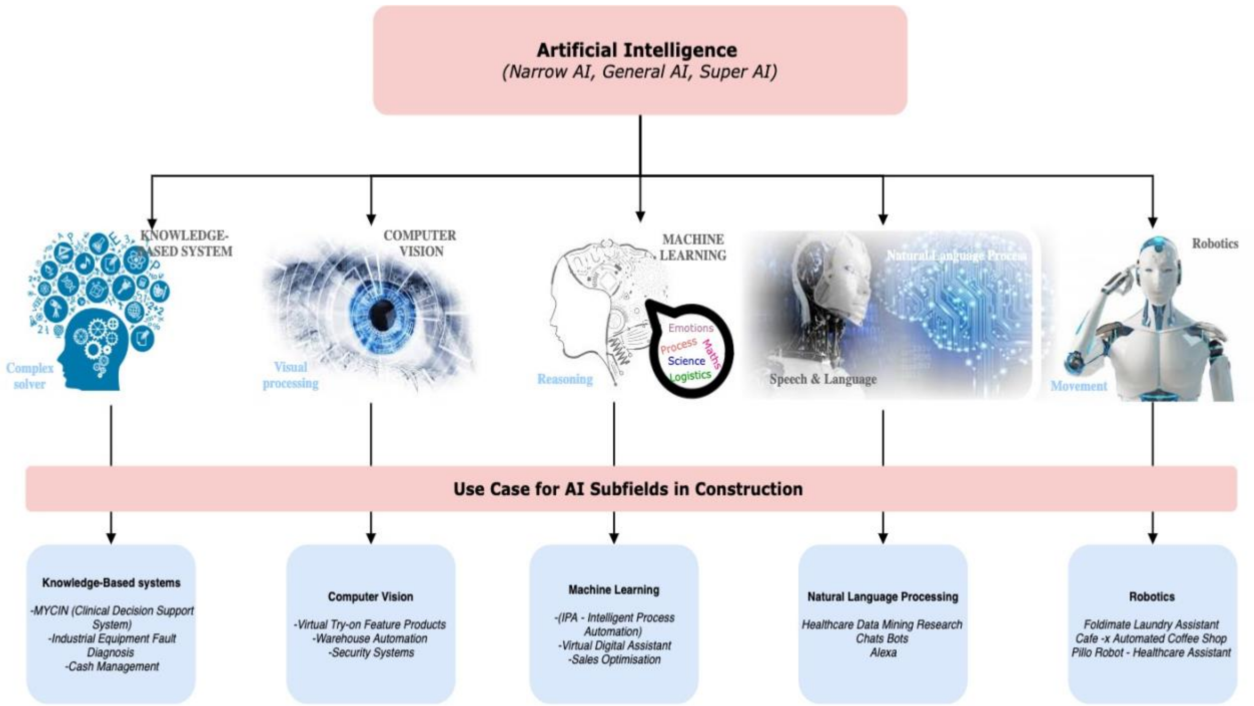


Figure 2.1 subfields and examples of Artificial Intelligence

The application of these AI subfields to various business processes has resulted in a snowball growth in efficiency and profitability in firms across a variety of industries, where Hatami et al. (2019), lauded AI's use in the construction industry to automate processes and enable state-of-the-art design and manufacturing. Thus, McKinsey (2018) compared the building materials and construction industry to other industries and discovered that ten of those industries are further along in their current AI adoption than the building materials and construction industry, implying that AI spending will increase at a faster rate over the next three years.

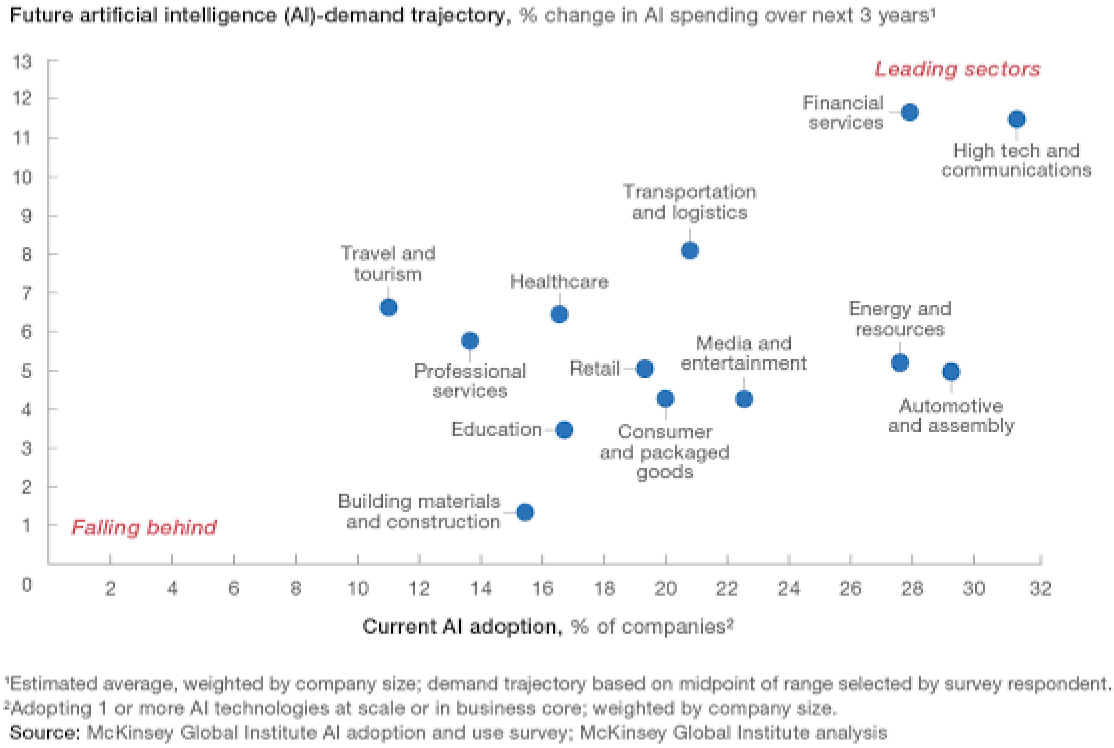


Figure 2.2 Sectors leading AI adoption (Source: Mckinsey and Company, 2018)

Abioye et al. (2021) have also highlighted that, despite the benefits of utilising AI and other digital technologies in construction, such as managing cost overruns, creating better designs through generative design, risk mitigation, safety, overcoming labour shortages, and managing the construction life cycle. Alaloul et al. (2020) indicate that there is still a relative gap in AI adoption in construction due to cultural barriers, high initial implementation costs, security concerns, a shortage of skilled personnel, and a shortage of computing capacity. As a result, the construction industry's adoption of AI is likely to remain low.

2.2 Types of Artificial Intelligence

According to Williams (2020), Artificial General Intelligence (AGI) refers to the hypothetical intelligence of a computer programme capable of grasping any intellectual work or learning that an individual performs. It is a prominent stance in science fiction and futurology, as well as a primary focus of AI research. Thus, Mikhaylovskiy (2020) attributes it to strong AI and full AI, with some academic sources reserving the term "strong AI" for computer systems capable of sentience, self-consciousness, and awareness. The Church-Turing thesis implies that algorithmic replication of the human brain is theoretically possible. Singularity models are being used by emerging artificial general intelligence firms to generalize the capabilities of AI algorithms and update AI systems. Scientists are working on a range of initiatives targeted at expanding the capabilities of AI algorithms, and they feel that hybrid artificial intelligence, which incorporates neural networks and rule-based systems, is the way to go. Additionally, some researchers and professional experts anticipate that pure neural network–based models will eventually achieve reasoning capabilities. Everitt et al. (2018), on the other hand, critiqued AGI's safety and emphasised the difficulties associated with value definition, dependability, security, and societal ramifications. In general, it is considered that today's AI is at least a few decades away from AGI.

2.2.1 Artificial Narrow Intelligence

Artificial narrow intelligence, sometimes referred to as "Weak AI," is a type of AI that is dependent on the execution of defined and programmed tasks. Similarly, Singh (2019) stated that this sort of AI can perform accurate tasks and accounts for a sizable portion of currently operational AI systems. This technology enables high-functioning systems to perform tasks that are similar to, if not identical to, human abilities. Examples include digital voice assistance (i.e., Siri, Alexa) that responds instantly to everyday human inquiries, autonomous vehicles programmed to operate without a human driver, and other robots capable of performing specific tasks such as delivery bots, drones, and medical surgical robots. In comparison to AGI, Miailhe and Hodes (2017) defined it as a weak AI capable of doing routine activities, whereas AGI is primarily concerned with intellectual tasks. Since the ANI is restricted to the situations for which they have been programmed, they exhibit a certain amount of intelligence in that domain, but lack the comprehensiveness, complexity, and associations in judgement that humans possess. It is believed that ANI systems are capable of processing data and executing tasks at a rate far quicker than humans, allowing robots to optimise overall productivity, efficiency, and quality of life. Additionally, ANI systems may leverage AI to assist in making data-driven decisions while factoring in efficiency and efficacy. Undoubtedly, the Narrow AI has also liberated humans from many monotonous, repetitive, and menial tasks and improved human lives significantly by increasing everyday efficiency.

2.2.2 Artificial Super Intelligence

In a wide range of disciplines, Barrett and Baum (2017) have defined artificial super intelligence (ASI) as AI with capabilities that are much larger than human capabilities. Depending on its design, ASI could have highly helpful or catastrophic effects if it is built where expert disagreement is a defining feature of the ASI issue. Pueyo (2018) has featured that experts disagree on whether ASI will be built, when it will be built, what designs it will use, and what impact it will have. The opacity of the underlying ASI issue, as well as the general challenge of anticipating future technology, is reflected in the degree of expert disagreement. This contrasts with other significant global challenges, such as climate change, where there is widespread expert consensus on the issue's fundamental dimensions. Thus, expert consensus does not ensure that the issue will be resolved, but it does provide guidance for decision-making. Considering the challenges of AI super intelligence, Alcoforado (2020) have urged on control mechanisms and research collaboration to promote the utility of ASI.

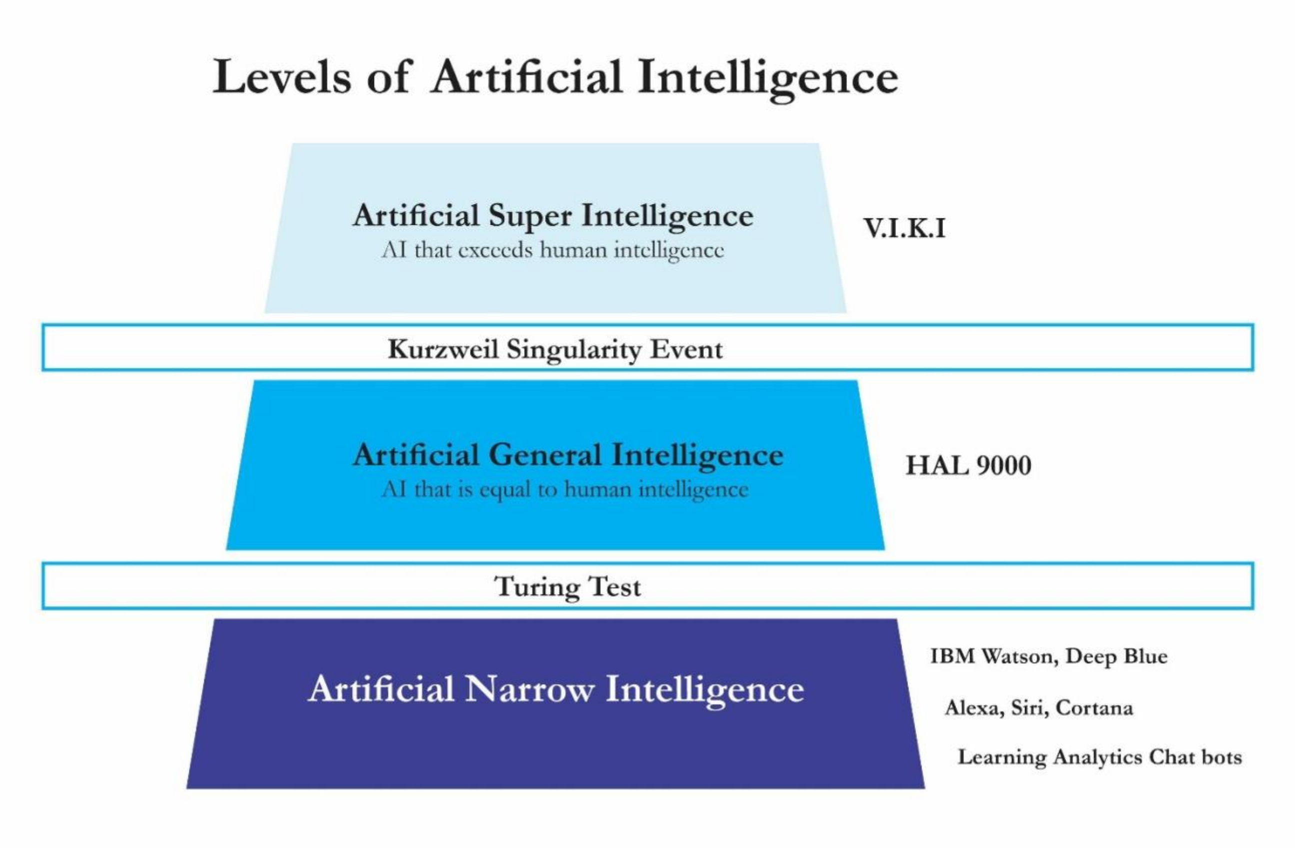


Figure 2.3 Types of Artificial Intelligence (Source: Steve-Wheeler, 2022)

As shown in Figure 2.3, the research also examines the various subfields of AI, and their impact on the construction industry.

2.3 Subfield of Artificial Intelligence

2.3.1 Machine learning

This branch of AI technology is one of the fundamental and fastest growing fields, with broad deployment across multiple industries. Lee et al. (2017) have signified that the principle of machine learning focuses on the process of programming and its ability to learn using computer programmes, and to function on the basis of the experience gained. This technique is applicable through different methods which include supervised, unsupervised, deep learning, and reinforcement. The review by Mahesh (2020) elaborated that machine learning relies on distinctive algorithms to solve data problems in relation to supervised, unsupervised, reinforcement learning, neural network, and instance-based learning.

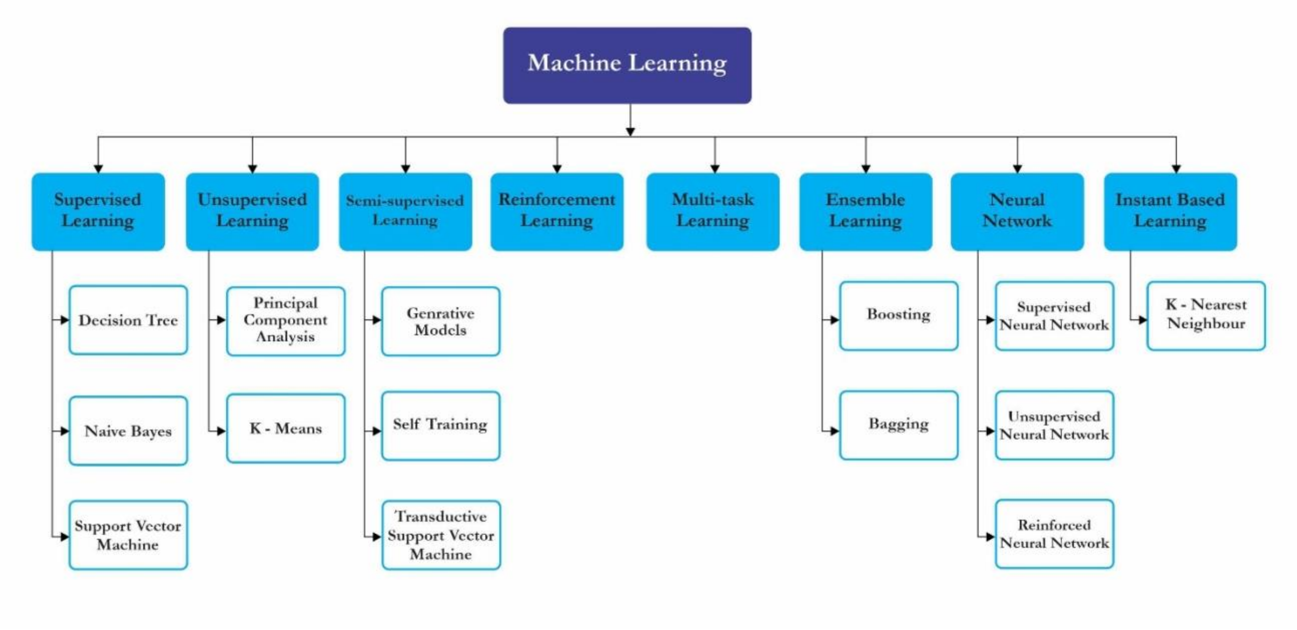


Figure 2.4 Machine Learning Strands (Source: Mahesh, 2018)

However, this application encompasses a set of implementation uses, some of which are intended to provide a prescriptive and predictive purpose. In fact, the implementation of this strategy has a positive effect on an organisation's efficiency and cost-effectiveness. Studies within the construction industry have used this technology in the supply chain and logistics, health and safety in construction (Sanni-Anibire et al., 2021). For example, a study by Tixier et al. (2016) used two machine learning (ML) models namely Random Forest (RF) and Stochastic Gradient Tree Boosting (SGTB), to predict injury, energy type and body part with a high skill. Also, Valpeters et al. (2018) studied the use of machine learning methods for predicting injuries in the construction industry with the application of big data analytics for construction management. In general, machine learning in the construction industry focuses on construction efficiency throughout the project's lifespan, hence validating its efficiency and productivity. Several types of machine learning are often employed. These include supervised, unsupervised, semi-supervised, and reinforcement learning.

2.3.2 Supervised Learning

Machine learning is exceptionally good at spotting patterns, and it can use this knowledge to create predictions about current tasks using supervised learning. Thus, Cunningham et al. (2008), described the use of supervised learning as a mapping between a set off input variables C and an output variable Y and applying this mapping to predict the outputs for unseen data. According to Liu (2011), supervised learning is the most important methodology in machine learning.

2.3.3 Unsupervised Learning

Unsupervised learning works on data reduction and grouping challenges and discovers information from unlabelled data. Due to the limited information that can be recovered from unlabelled data compared to labelled data, unsupervised learning is not extensively employed in construction. As a result, while solving real-world building issues, academics prefer to employ supervised learning methods. Principal Component Analysis (PCA), kernel PCA, and t-SNE are the most used data reduction strategies in unsupervised learning (Tripathy et al., 2021). Clustering methods include K-means, EM, mean shift, and spectral clustering.

2.3.4 Reinforcement Learning

Reinforcement learning (RL) is a type of machine learning that is neither supervised nor unsupervised. In this method, a reward specification is used as the initial input to this sort of learning algorithm. Because this type of learning algorithm does not employ labelled data for training, it cannot be categorised as supervised learning. However, it is not categorised as unsupervised learning since the algorithm is supplied with knowledge about the reward specification, which guides the algorithm through the steps necessary to resolve the issue.

By relying on feedback, reinforcement learning attempts to continuously improve the techniques used to solve any challenge. The goal is to maximise rewards while also attempting to solve the problem. The algorithm determines the rewards based on the reward and penalty requirements. The objective is to determine the optimal technique for resolving the problem while maximising the benefits. The following diagram illustrates a robot that uses reinforcement learning to identify the optimal behaviour in a fire event.

According to Sugiyama (2015), four common reinforcement learning strategies include Q-leaming, state-action-reward-state-action (SARSA), deep Q network (DQN), and deep deterministic policy gradient (DDPG). In recent research, 3D scanning, artificial intelligence, and neural networks were utilised to scan a [project site and forecast the development of particular sub-projects, mitigating the danger of work being completed late or over budget. This technique enabled management to intervene and address issues prior to their escalation. Similarly, "reinforcement learning" (machine learning based on trial and error) can aid in spotting small defects and enhancing the preparatory phase of a project (Ma et al., 2019).

2.3.5 Semi-supervised Learning

Semi-supervised learning is a strategy that combines supervised and unsupervised learning. Machine learning requires a large quantity of data for training. Generally, the amount of data used for model training and the model's performance are proportionate. Not only does semi-supervised online learning handle practical applications, but it also reflects some of the problems encountered by people while learning new categories (Unhelkar and Gonsalves, 2020). In some disciplines, such as speech analysis, protein synthesis, and online content classification, large quantities of unlabelled data and a small quantity of labelled data are accessible. Semi-supervised learning has been shown to be beneficial in a variety of disciplines. Approaches such as generative adversarial networks (GANS), semi-supervised support vector machines (SBVMS), graph based techniques, and Markov chain methods are well-known in the field of semi-supervised machine learning.

2.3.6 Robotics

The concept of robotics is applied to perform repetitive physical activities to help lower costs and increase productivity (Raj & Seamans, 2019). In a study conducted by Manzoor et al. (2020), the systematic literature review stated that robots use sensors and actuators to interact with the environment and conducting highly specialized tasks. Such automated machines are, therefore applicable in different construction areas to ensure safety and greater reliability. Thus, the concept is applied in site monitoring and performance evaluation, energy, plants, and equipment management among others within the construction industry.

According to Pan and Zhang (2021), robots are capable of performing a series of 10 basic activities within the construction industry which include positioning, connecting, coating, building, concreting, inlaying, covering, attaching, finishing, and jointing. Hence, Davtalab et al. (2018) proposed a framework for integrating BIM into an automated robotic construction system through grafting. However, there has been a rise in robotics in the construction industry. Some real-life examples include ROMA is climbing inspection robot for moving in a complex 3D environment and ROCCO a project brick assembly robot, among others.

2.3.7 Natural Language Processing

This technique is used to investigate how machines can be used to mimic human linguistic abilities (Deng & Liu, 2018). Thus, this approach applies the capacity to understand and control the natural language text in speech in order to carry out practical actions. Although, this technique has been used across various studies and research projects. However, Zhang et al. (2019) have appraised the benefits of NLP in construction to boost an organisation’s efficiency with relation to time, cost and productivity which also aid in improving communication between stakeholders. Hence, natural language processing (NLP) encourages the boost in efficiency varying across time, cost and improved productivity with an inclination to improve communication between stakeholders. Wu et al. (2022) have signified that Some of the areas where this technique is applied in construction include risk planning, health and safety, project planning, conflict resolution among other. Also, Baldwin et al. (2021) have carried out study to appraise the response time and processing through NLP in construction industry by extracting relevant data from tweets and grouping them into clusters.

2.3.8 Computer Vision

According to Xu et al. (2021), computer vision uses human visual systems to gain high-level understanding through digital image processing; while performing comprehensive image research using algorithms, and providing image analysis to assist in decision-making in construction industry. However, studies within the construction industry use computer vision to increase productivity, precision, and speed. The technique is also used for health and safety, project planning, design, performance assessment, and site monitoring. For example, automatic generation of building information models (BIM) appraised by Paneru and Jeelani (2021) for visual tracking of construction site activities and detection of equipment on construction site among others.

2.3.9 Knowledge Based Systems

Knowledge-based Systems (KBS) is another aspect of AI where Esanakula et al. (2020) have signified that it decodes complex problems using computer programmes based on established knowledge. Therefore, this AI technique is applied for use in risk management and waste management, environmental assessment, health and safety assessment, logistics, and design. However, Wang et al. (2020) have highlighted that it is important to know that this system is categorised into Expert Systems, Intelligent Machines, Case-Based Reasoning (CBR) Systems, DBMS with Smart User Interfaces and Connected Systems. Examples of applications of construction research in knowledge-based systems are waste management, storm water management, assessment of safety performance, cost prediction models for building construction among others.

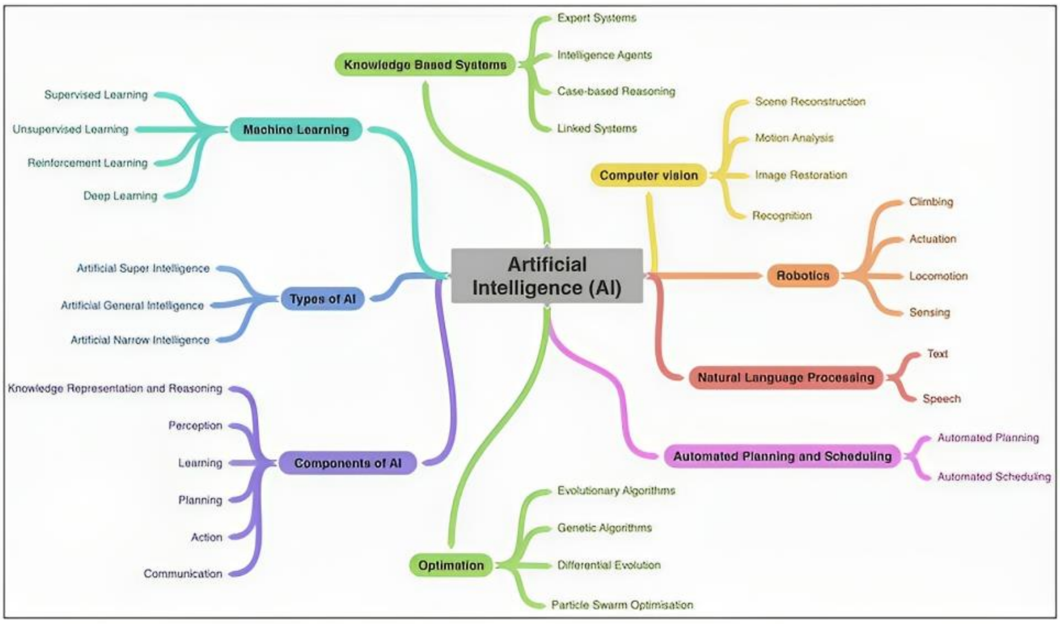
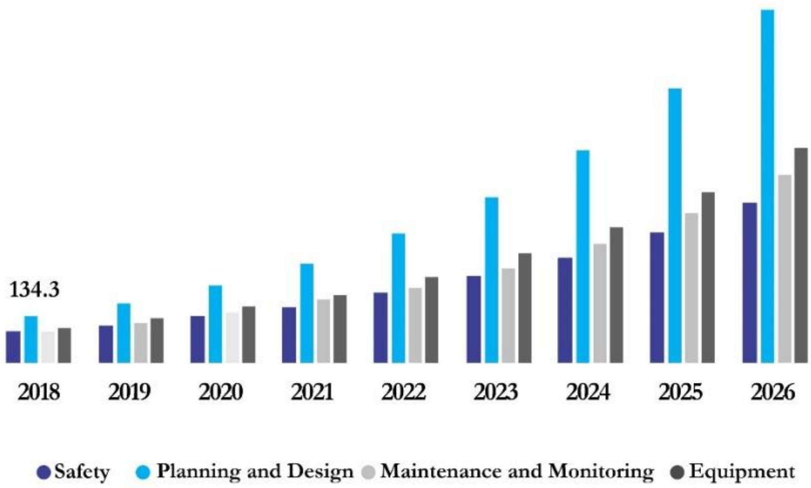


Figure 2.5 AI and its subfields (Source: Abioye et al., 2020)

2.4 Review of Artificial Intelligence Applications in the Construction Industry

Use-Cases of AI Applications in the Construction Industry

It has been documented in the literature that AI may be used in a number of different contexts where Robotics and AI are being studied for their potential to replace human workers in construction (Dwivedi et al., 2021). Thus, AI in construction is becoming more and more frequent in all phases of the process, from conceptualization through completion. Construtction professionals are increasingly using AI to improve project efficiency and accuracy, track equipment usage and location, and a slew of other AI-driven functions (Maskuriy et al., 2019). According to Research Dive (2021), the AI contribution to the construction industry is anticipated to grow by a CAGR of 26.3% during 2020-2026, driven by cost efficiency, neural networks, hiring professionals and managing overheads. Modern engineering and construction methods will not be complete without the use of AI, as Abioye et al. (2021) have defined that AI technology may help industries overcome some of the greatest difficulties, such as cost and schedule overruns as well as safety concerns. This includes project conception and design, bidding, funding, transportation management, and asset management and operations.



Source: (Research Dive, 2019)

2.4.1 Avoid Expense Overruns

The majority of important projects go over budget, even with the greatest project teams. Aertificial neural networks (ANNs) are often used to forecast project cost overruns depending on the scope, contract type, and project management skill set. Predictive models employ data from previous projects, such as predicted start and end dates, to generate realistic schedules for future projects. Using artificial intelligence, employees can access on-the-job training materials from a distance. As a result, hiring new employees for projects takes less time now. Thus, the timeline for completing the job is shortened (Hunt, 2021).

2.4.2 Risk mitigation

In terms of quality, safety, timeliness, and cost, every construction project includes some element of risk. The greater the size of the project, the greater the threat of several subcontractors working on different crafts at the same time. Using AI and machine learning, general contractors are now able to monitor and prioritise risk on construction sites, allowing the project team to spend their limited time and resources on the most critical risk variables (Khodabakhshian, 2023). AI is used to automatically prioritise challenges. Subcontractors might be assigned a risk score to help construction managers work more closely with high-risk teams.

2.4.3 Project administration

Construction intelligence firm declared in 2017 that the use of robotics and AI are likely to contemplate project deliverables in terms of cost, time and budget (Rao, 2021). The 3D scans of construction sites are collected by autonomous robots and fed into a DNN that classifies how far along particular sub-projects are. The management team can intervene if things start to go awry to prevent them from becoming serious problems. "Reinforcement learning" is an AI technique that will be employed in future algorithms (Srivastava, 2020). Algorithms can learn by doing, and here is how they do it. In addition, it can evaluate an infinite number of combinations and possibilities. Using this method makes project planning easier because it continually seeks out the optimum path and makes necessary corrections on its own.

2.4.4 Workplace productivity

Some organisations are offering self-driving consturciton machinery to execute repetitive activities, such as pouring concrete, bricklaying, welding, and demolition, more effectively than humans (Constructionexec.com, 2019). With the help of a human programmer, autonomous or semi-autonomous bulldozers can excavate and prepare a job site to exact specifications. As a result, the project's overall completion time is cut in half, freeing up human labour for construction (Hunt, 2021). It is also possible for project managers to monitor the progress of the project in real time, as well. Monitoring productivity and process compliance is done with facial recognition technology and other comparable tools.

2.4.5 Construction safety

Construction workers have a five-fold higher risk of dying on the job than any other kind of worker (OSHA, 2021). By OSHA's estimations, falls were the top cause of private sector construction deaths (excluding highway crashes), with electrocution and becoming caught-in-between in a close second place. It's been developed by a Boston-based construction technology business, which analyses photos from its job sites, assesses them for safety dangers such as workers not wearing protective equipment, and links the images with accident data (Woyke, 2018). When a high-risk event happens, the company could theoretically compute project risk assessments and hold safety briefings. Using COVID-19 compliance, it began assessing and sharing safety rankings for each state in the United States in 2020. (Hunt, 2021).

Construction workers are five times more likely to be injured or killed on-site in construction than other workers. Dong et al. (2019) have featured that falling, being struck by an object, electrocution, and getting "caught-in/between" many objects on the job site are all examples of workplace accidents. Hunt (2021) stated that predictive analytics can be used to identify prospective issues in images and video, which can subsequently be addressed immediately by site administrators using the programme. There are tools available that allow the public to rank projects according to their potential safety concerns, such as the presence of hazardous materials on the jobsite or a lack of Personal Protective Equipment (PPE) for the workers who are supposed to be wearing it.

2.4.6 Labour shortages

Companies in the construction industry are embracing AI and data science in an effort to increase efficiency and reduce labour shortages. McKinsey estimates that real-time data analysis might increase efficiency in construction by as much as 50%. (Barbosa et al., 2017). Construction companies are using AI and machine learning to better organise the deployment of labour and equipment across jobs.

McKinsey and Company (2017) reported that construction businesses might raise their efficiency by 50% with AI-enhanced analytics. This is welcome news for construction firms who cannot locate sufficient human employees to complete their projects. In addition to being tough to locate workers, it's also difficult to keep them. CNN (2019) claims that the business needs more than one million workers in the United States. Through the deployment of AI in construction, Abioye et al. (2021) have favoured the short training time, as well as people to amend labelling, which are needed to verify the performance of training models. The best AI algorithm for construction projects was also tested in a number of other research, which compared several AI algorithms (Abioye et al., 2021). Collecting and refining data would need a greater number of workers than training. It is necessary to manually modify each piece of training data in order to assess the most recent AI models, assuming they are fortunate enough to obtain training data. Due to a shortage of labour, data refining, which requires specialised knowledge, may be delayed.

2.5 Current Trends of AI Application in Construction and its Emerging Opportunities

Chui (2017) has underlined that individuals and organisations spend more than $10 trillion on construction-related activities annually, with an anticipated CAGR of 4.2% per year till 2023. Fast-moving technical developments that impact every part of the ecosystem are used to fund and facilitate a piece of this vast sum of money. In its 2020 report, McKinsey (2020) saw an increased focus on AI solutions. AI in construction has the ability to assist participants in achieving value in a range of areas, including design, bidding, financing, procurement and construction, operations and asset management, and business model change. Construction AI helps the sector address its obstacles, including worker safety, labour shortages, and cost and schedule overruns (Mohammadpour et al., 2019).

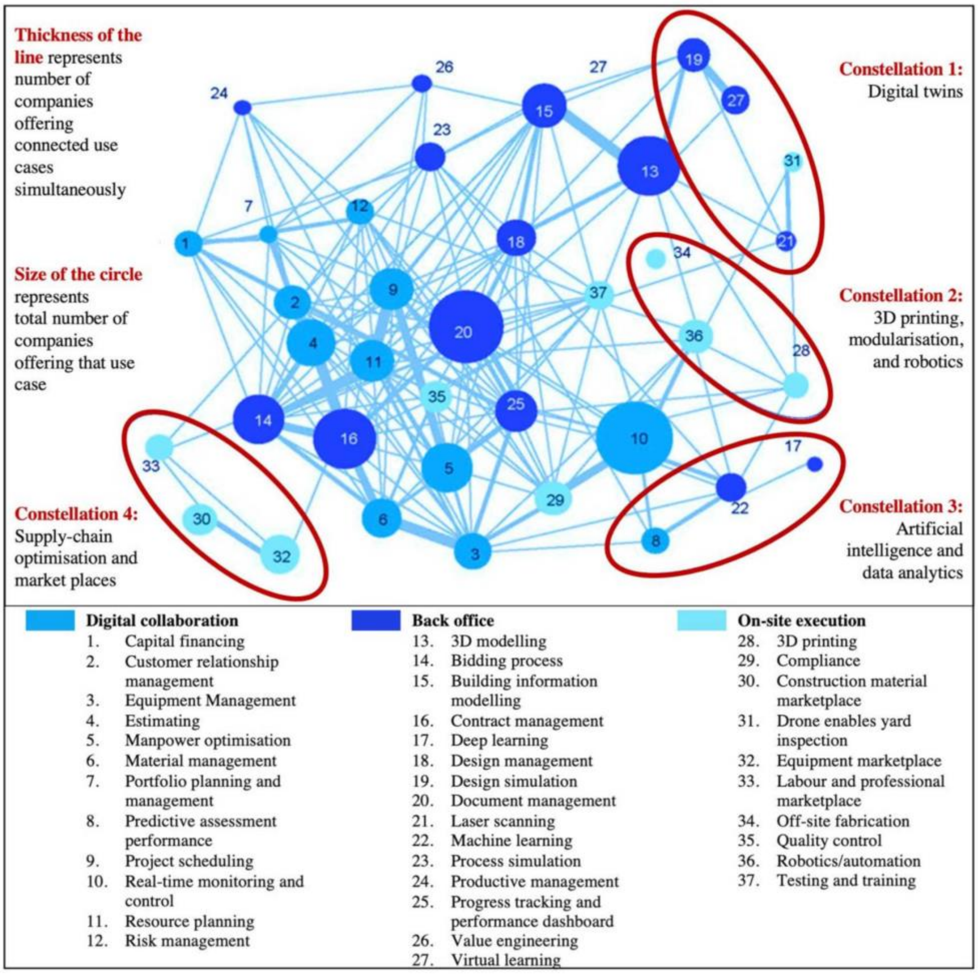


Figure 2.6: Construction Technology (Source: Blancco et al., 2018)

In the construction sector, machine learning and AI can be employed in a variety of ways. There are too many requests for information, ongoing problems, or requests for modifications in the sector. This is like having a personal assistant who can sort through all this data. Project managers are then informed of any urgent issues by means of the system (Seok-Jae et al., 2018). A wide range of applications already make use of AI in this manner. From spam filtering to thorough security monitoring, it has a wide range of advantages.

2.5.1 BIM and 3D modelling

During the past few years, it has arisen as a new and better technique to make the 3D models that construction professionals use to accurately design, build, and repair buildings. It is now possible for Building Information Modelling (BIM) platform developers to add smart, AI-driven features to the system. With the use of machine learning (ML), Sun et al. (2017) have appraised the use of BIM and underlined that it may help teams avoid the frequent yet expensive problem of duplicating effort. Sub-teams working on shared projects are all too often wasting their time generating models that othe sub-teams have already generated. Ullah et al. (2019) have further signified that by using BIM it becomes necessary to employ machines to develop designs that can be changed. Each repetition of the AI's model-building process is an opportunity for it to gain new knowledge and refine its original model. Building BIM is at the heart of construction and remains overwhelming for achieving digital transformation targets more efficiently.

2.5.2 3D Printing

Walch (2020) has stressed the growing adoption of AI in the construction industry, where machine learning promotes scheduling through historical data, what-if scenarios, and contingency planning. Furthermore, Kyivska and Tsiutsiura (2021) have elaborated that AI and machine learning increase monitoring in construction projects and give real-time estimations about quality measurements and project progress. Ghaffar and Mullett (2018) have appraised 3D printing in the construction sites, where a case company Droxel has developed robots equipped with cameras (AI-powered robots) to construct digital models of work sites. For construction organisations, the Internet of Things (IoT) is also altering how they manage their fleets of machinery and vehicles (Hunt, 2021). IoT devices may be used to track construction equipment, shipping crates, semi-trucks, tolls, and a wide range of other items. Anticipating when a piece of equipment will fail is a huge time and money saver in construction.

2.5.3 Generative design

Architects, engineers, and construction workers use BIM, a 3D model-based technology, to efficiently plan, design, build, operate, and maintain buildings and infrastructures (Han & Golparvar-Fard, 2017). 3D models must take into account architectural, engineering, mechanical, electrical, and plumbing (MEP) blueprints in order to plan and design the building of a project. Models from the various sub-teams must not collide with each other (For Construction Pros, 2021).

Rework can be avoided by using AI-powered generative design to discover and reduce differences between the various models developed by different teams. Machine learning methods may analyse all possible answers and design choices. Generative design software builds 3D models optimised for the limitations, learning from each iteration until the optimal model is discovered (Ashokkumar & Varghese, 2018).

2.5.4 Use of Robots

Using robots, project managers can quickly determine which job sites have enough staff and equipment to complete the project on schedule; and which need additional resources. To enable a huge contractor like Mortenson to conduct more work in remote regions where specialised labour is scarce like Spot the

Dog, an AI-powered robot can examine a project every night to assess progress (Gadgets 360 Newsdesk, 2021).

Figure 2.7: AI-powered Construction Robot (Source: Gadgets 360 Newsdesk, 2021)

2.5.5 Off-site construction

Construction businesses are increasingly using autonomous robots working in off-site workshops to assemble building components before they are assembled on-site by human workers. For example, walls can be built more quickly and efficiently on an assembly line by autonomous machinery than by human workers, leaving human workers to perform specialised labour, such as plumbing and HVAC (Ashokkumar & Varghese, 2018).

2.5.6 Large data

At a time when vast amounts of data are being created on a daily basis, AI systems are constantly exposed to a limitless quantity of data to learn from and improve on. There is a wealth of data to be mined from every construction site. Mobile device photos, drone footage, security sensors, building information modelling (BIM), and other data sources have built up a data reservoir (Han & Golparvar-Fard, 2017). AI and machine learning technologies will deliver data insights that construction industry experts and customers may study and benefit from. Na et al. (2021) have elaborated that construction material, depending on its intended purpose, can either be a product on-site or a waste product at a dumpsite. AI is capable of recognising materials, and it is able to differentiate between new and used products for efficient resource management purposes (Elhegazy et al., 2018).

2.6 Construction Industry: Identifying the Complexities and Implications for AI

Construction is a very broad domain. Construction includes pre-construction (design), actual physical development of the construct (construction) and post construction (facility management). According to the RIBA stages of construction, i.e., the physical development of the construct, there are eight steps within the physical construction stage. There are issues within each stage of construction as well as legacy issues across the entire construction process. Among the major challenges identified within the construction process are cost over-runs, slow technology adoptions, lack of communication, lack of skills, poor planning, unnecessary delays, and budgeting. According to Pan & Zhang (2021), using AI in constructions will boosts productivity, effectiveness, and profitability within the business sector. Some of the problems identified within the various stages of the construction projects are discussed in the following subsections:

2.6.1 Problems Identification at the design stage:

The design and construction stages heavily influence the impact of the quality of a construction project's outcome. The design stage serves as the primary phase that establishes the trajectory of the project and exerts a significant impact on the ultimate deliverables of projects. Insufficient preparation during the design stage may result in adverse consequences for the project budget, performance, and overall project process. Some factors that have the potential to influence the design process include:

2.6.1.1 Lack of Quality Control: Based on scholarly references, it has been observed that many construction projects prioritise cost reduction in response to clients' demands for timely and budget-conscious project completion. However, this emphasis on cost-cutting often results in a disregard for the potential consequences on the quality of materials and construction methods employed. Consequently, this oversight may give rise to various defects, including but not limited to foundation failure, insufficient maintenance, inadequate quality control, dampness, and subpar workmanship. Therefore, as a result of the inherent unpredictability of building projects, several risks may arise both during and after project completion, necessitating substantial expenditures for remediation.

2.6.1.2 Stakeholder involvement: It is widely acknowledged that there is often a lack of communication between top executives and other departments within the projects, such as contractors, subcontractors, engineers, the project owner, and architects, among others, during the design phase of construction projects. The absence of this has led to miscommunication issues, improper planning, lack of proper project coordination, mistakes and mismatches, contradictions and possible discrepancies during the design phase, which could require adjustments in the later stage of the project and impact time, cost and overall performance of the project.

2.6.1.3 Planning and scheduling: This is identified as one of the major challenges faced in construction projects, which can lead to project delays, result in cost overruns for all parties and cause safety hazards. The poor planning at the design phase also presents a risk of unexpected issues arising during the construction process. In construction project planning, AI-powered methods are significantly applied not just for construction project planning not only for quality enhancements but also to stimulate innovation due to the development of data-driven generative designs. With the use of AI strategies, there has been effective use and adoption of AI approaches for planning construction projects; one of the most substantial benefits is its capacity to acquire vast volumes of construction project data, analyse previous projects, and anticipate results, which aids in the creation of error-free designs during planning. As a result, it is expected that AI will enhance the whole value chain of construction project planning, which entails engineering design, procurement, and various stages of construction (Tumpa et al., 2019). AI can also be used as a defect detection and root cause analysis tool within the planning and design phases, allowing the project team to correct any faults prior to the phase of execution (Nawari & Ravindran, 2019).

2.6.1.4 Project Delays: The limited application and investigation of generative designs by engineers and architects highlight the need for increased AI involvement across the planning and design stages (BuHamdan et al., 2020). Problems such as unexpected delays usually pose serious issues in the construction of projects, and this problem is on the increase in the construction industry. However, Yigitcanlar et al. (2020) argue that AI can be applied to resolve the issue of delay in projects. The process is less time-consuming and provides a less expensive option by using AI to track and compare project plans and documentation with the current condition of construction projects (Yin et al., 2019). AI improves the process of design and is highly beneficial for the project team's building plans in terms of the detection of clashes and prevention of conflict. By comparing the digital twin BIM model to the real tangible representation, AI-based solutions are capable of identifying alterations in design, resulting in fewer disputes and unnecessary delays (Schober, 2020).

2.6.2 Problem Identification in the Construction Stage

During the construction stages, numerous problems can arise as a result of the nature of the project, its complications, the parties involved and external factors. Some problems that can arise during construction are as follows: Cost overruns: Construction projects frequently exceed budget.

Inaccurate cost projections, unanticipated site circumstances, alterations in project scope, changing material pricing, and insufficient project management are all factors which have contributed to cost overruns.

2.6.2.1 Cost overruns can cause financial pressure, delays in the project, and disagreements among the owner, contractors, and subcontractors. Based on a study conducted by Flyvbjerg et al. (2002), it was reported that in the global construction industry, 9 out of 10 projects had cost overrun issues. The problem of cost overrun is a critical issue in the construction industry in developed and developing countries (Angelo & Reina, 2002).

2.6.2.2 Safety hazards: Construction sites are intrinsically risky environments. Failure to take basic safety precautions can lead to accidents, injuries, and even death. Falls from great heights, electrical risks, insufficient personal protective equipment (PPE), and a lack of basic training are all potential safety concerns. Failure to prioritise safety might result in legal ramifications, delays, and higher insurance costs.

2.6.2.3 Delays: One of the major problems in construction is the problem of delay, which can be a result of several factors like severe weather, unanticipated site conditions, shortages of labour, material delays, or design adjustments. Delays can result in other issues, such as higher costs of materials as a result of market inflation, deteriorated stakeholder relationships, and possibly legal issues. Delays in construction projects can result in many dissatisfactions among all the parties involved in a project, and the primary responsibility of the project manager is to ensure that projects are executed and delivered within the budgeted time and cost (Sambasivam & Soon, 2007).

2.6.2.4 Quality issues: It is essential to uphold quality standards all throughout the construction process. Nevertheless, concerns with quality might arise from the use of inferior materials and insufficient supervision. These problems might not be discovered until after the project is finished, which could result in expensive reworking, warranty complaints, and damage to the construction company's image.

2.6.3 Problems at the facility management stage in the construction industry

In construction, this stage is known as the continuing process, maintenance, and management of a constructed facility after its completion. This phase is essential to assure the facility is used effectively and efficiently for the duration of its lifespan. In analysing maturity models, the initial steps of problem identification require painstaking attention to understanding the dynamics of the construction industry, various legal obligations, driving forces and involvement of both internal and external stakeholders. A number of issues can emerge during the facility management phase. Here are a few examples of some prevalent problems:

2.6.3.1 Safety and Security: a fundamental obligation of facility management is to ensure the safety and security of a facility and its occupants. Insufficient safety precautions, obsolete safety regulations, failing safety equipment, or inadequate emergency readiness can all cause issues. When such issues are not addressed, they could result in security problems, accidents, and legal implications.

2.6.3.2 Inadequate maintenance: Proper maintenance is essential for keeping the facility in top condition. Poor maintenance, on the other hand, can lead to equipment malfunctions, poor infrastructure, decreasing energy efficiency, and poor tenant satisfaction. This issue can be exacerbated by inadequate funds allocation, a lack of proactive maintenance planning, and restricted resources.

Therefore, a number of legacy issues across the entire construction industry have been identified, such as siloed digital tools, an ageing workforce, lack of skills, low productivity, poor health and safety due to the use of hazardous substances and manual handling, cost overrun, time overrun/delays, high levels of rework, discrepancies between design and construction, prolonged preconstruction process, margin erosion, absence of synergy between systems. AI subfields can and have been used to tackle these issues or similar issues. AI has subfields such as Machine learning, computer vision, natural language processing (NLP), robotics, expert systems, speech processing, and evolutionary computation.

According to the Gov.UK (2013), the UK government wants 33% reduction in the cost of construction and whole life cost of assets, 50% reduction in the time taken to build assets from inception to completion, 50% reduction in the greenhouse gas emissions in the built environment and a 50% reduction in the gap of the total export and total imports of construction materials and products generally. The industrial strategy 2018 published by the UK government highlights the construction industry as a key player in achieving its industrial goals. As such, the government discusses how it plans to lead the AI and data implementation revolution by employing AI-driven solutions to different stages of construction. These employments will improve certainty at the construction and operations stages, collaboration (data, people & processes) amongst the different teams involved, safety, quality and productivity across the entire construction process. These are the set milestones of the government with regards to their vision for the construction industry. Deductively from the points mentioned above AI will be more positively disruptive and impactful on construction legacy issues than BIM. As such, it is obvious that it would be in the interest of the government to commence their support for AI adoption within the construction industry by obtaining similar strategies they used for BIM in order to guarantee a rapid adoption of AI and data techniques within construction. Amongst mandatory policies, the introduction of a government-led guideline with standardised processes and steps for BIM adoption and assessment really aided the rates at which BIM was adopted. Therefore, creating a maturity model with the same intention is a step in the right direction. There is an array of opportunities in the construction industry where AI can be transformative. In the next section, we will review the future of AI in construction and the challenges faced in the construction industry.

2.6.4 Post-Construction Artificial Intelligence

Long after the work is finished, building managers can still use AI. Advanced analytics and AI-powered algorithms acquire data about a structure using sensors, drones, and other wireless technologies and then use that data to create vital insights into how a building, bridge, highways, and nearly anything else in the built environment operates and performs. This means that AI might be used to track problems, identify maintenance needs, and direct human behaviour to ensure maximum security and safety for all parties (Pan and Zhang, 2021).

2.6.5 The Future of Artificial Intelligence in Construction

Recent technologies, including Robotics, AI, and IoT might reduce construction costs by up to 20%. (Rao, 2021). Engineers can use virtual reality goggles to deploy mini-robots into still-under-construction buildings. Cameras are used to monitor the progress of these robots. The routing of electrical and plumbing systems in modern structures is aided by AI (For Construction Pros, 2021). AI is being used by businesses to create solutions for workplace safety. Real-time AI monitoring of the interactions between workers, equipment, and materials on the job site alerts managers to potential safety hazards, construction errors, and productivity challenges.

As predicted, human jobs will not be fully replaced by AI (Rao, 2021). Instead, the construction industry's economic models will be altered, avoiding costly mistakes, reducing workplace injuries, and enhancing construction operations' efficiency. Investing in areas where AI can have the greatest influence on a construction company's specific demands is the best strategy for executives in the business. This will have a huge impact on the industry's future and long-term benefits for early adopters (McKinsey, 2020).

2.7 Challenges of AI implementation in construction

For these reasons, and others, experts and lawmakers in the UK's construction industry are pushing for

greater use of AI-driven technologies (Wang et al., 2020). True, artificial intelligence is capable of disrupting construction and providing revolutionary solutions to long-standing issues. According to Mckinsey (2020), productivity and applied efficiency in 16 industries, including construction, would improve by 40% and 1.7%, respectively, by 2035 thanks to AI. Artificial Intelligence (AI) can help the government achieve its goals for projects like the Industrial Strategy 2025 (Jose Luis Blanco et al., 2018). Until 2030, the construction industry is expected to develop at a CAGR of 14.2 percent, according to a study conducted by Abioye et al. (2021). The ability of AI-driven technologies to solve construction-related difficulties is clearly improving. Construction waste and resource optimization, for example, has been a long-standing problem in the sector, and it has a global influence on the environment. One-third of all waste in the United States and more than a third of all waste in the United Kingdom are generated by construction, according to a report (Na et al., 2021). Machine learning, data analytics, and picture recognition may all be utilised to build an AI garbage analytic tool, according to the academics (Ashokkumar and Varghese, 2018). For predictive health and safety analytics, deep learning can be used to track and verify actionable technologies for on-site health and safety management (Mohammadi et al., 2018). AI chatbots are now being used to keep tabs on building sites, according to reports. AI-driven technology and data-driven solutions are a logical next step for the sector, as explained by Abioye et al. (2021). These difficulties include risk mitigation, off-site construction, labour shortages and job creation, project planning and cost overruns.

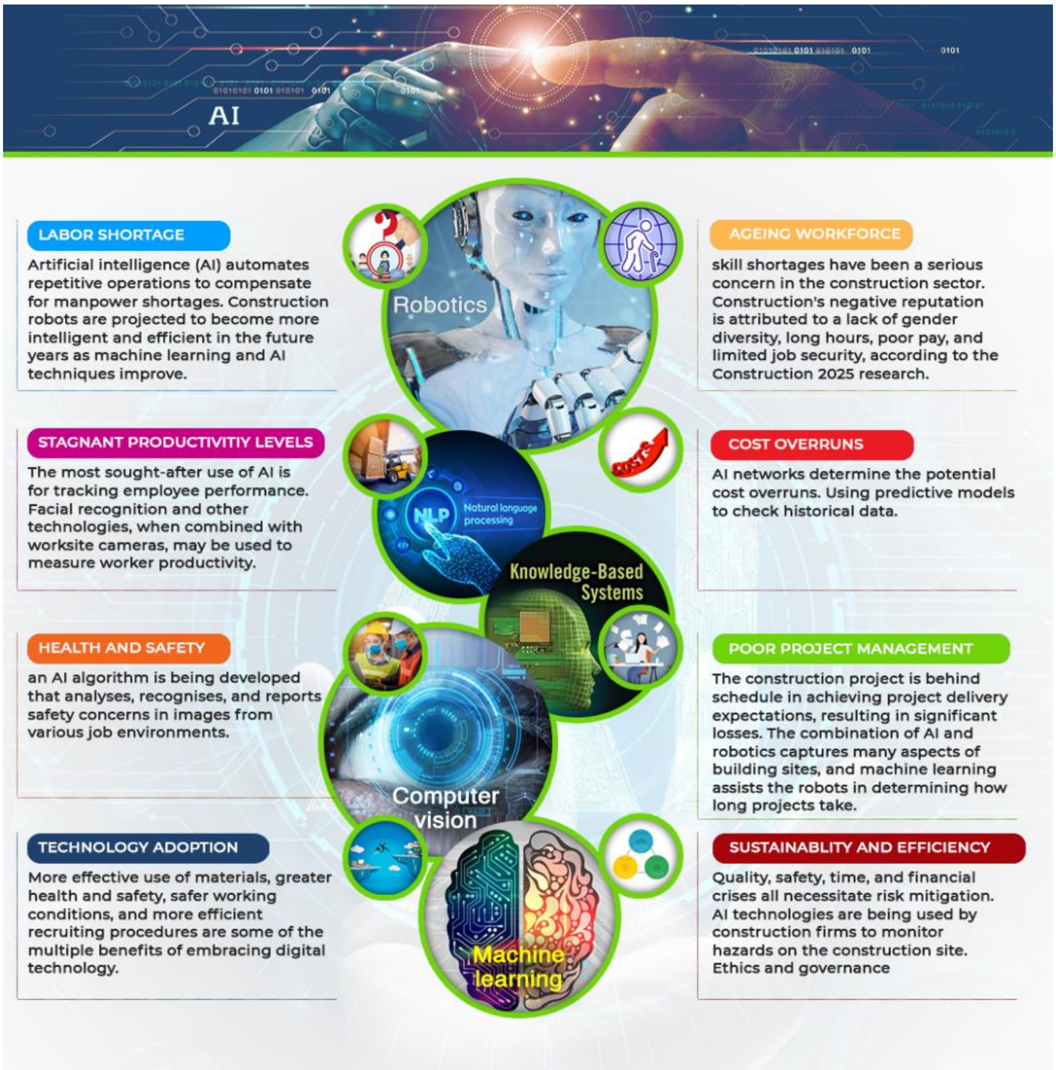


Figure 2.8: A representation of the challenges in construction and subsets of AI that can tackle them (Rong and Gao (2019); Akinosho et al. (2020); Pan and Zhang (2021))

2.7.1 Cultural Concerns

The construction industry is one of the least digitised and slow to adopt new technology (Rao, 2021), perhaps because of the risk and cost of most building projects, where even little mistakes can have enormous effects. Pre-existing procedures are chosen in the building business over new technology that promises huge returns. Thus, the building industry has been reticent to embrace new technologies. Unlike in other industries, construction sites require AI that can adapt fast to changing situations and learn from them. Construction contractors and organisations will only use AI solutions if they can be easily adapted to a variety of construction projects or sites (Woodhead et al., 2018).

2.7.2 Security Challenges

Hackers, cybercriminals, and others who would violate others' privacy can all use AI to their advantage (Abioye et al., 2021). Economic and financial ramifications could be dire if this is not addressed. It is common for small mistakes in the construction process to have a big impact on the project's quality, cost, and schedule (time, cost, supply chain, logistics, and procurement). The safety of construction workers is paramount; since they may be put in danger or perhaps perish as a result (Frontu, 2021). A computer vision system may be misled if a construction worker operating at a height is disguised as a piece of mechanised construction equipment. AI-enabled workforce replenishment or process automation must pose low to no security threats. Such techniques, such as adversarial machine learning, are required. Adversarial machine learning (ML) is the examination of successful machine learning algorithms when confronted with an adversarial opponent (Kumar et al., 2020). Adversarial machine learning emerged in response to the necessity to design algorithms capable of withstanding sophisticated security attacks. Additionally, research in this subject should focus on developing technologies, such as computer vision and robotics, which are already being used in construction research.

2.7.3 Lack of talent

Currently, there is a global scarcity of AI experts with the requisite skills to lead big advancements in a number of different businesses. It's challenging to locate AI experts who have worked in the construction industry before and can come up with tailored answers to the industry's many problems (Abioye et al., 2021). Due to the economic upheavals and layoffs caused by the COVID-19 pandemic, there has been an upsurge in demand for competent AI talent, as organisations strategize on ways to cut costs through automation and increased efficiency through the efficient use of AI. However, industries have been competing for top AI talent, which is believed to be scarce. Thus, Wang and Chen (2018) report that 85% of AI projects are in danger of failing due to a variety of AI skills gaps. Given the above, the government's investment in STEM education can contribute to resolving the situation by promoting AI education, upskilling employees, and leveraging the need for organisations to get certified AI professionals (Rosales et al., 2020)

2.7.4 High initial expenditures

In order to create innovative products that meet the demands of the building industry, construction professionals must collaborate with academics and industry experts in the field of AI (Na et al., 2021). The benefits of AI-driven solutions in the construction industry are apparent. Investments in AI technology, like robotics, on the other hand, usually have large initial costs. The level of upkeep required by these solutions should also be considered. Subcontractors and small enterprises in the building industry may find this prohibitively expensive. It's important to look at the cost savings and return on investment to see if it's worth it to invest. More and more small firms will be able to afford these technologies as they gain acceptance and use in construction.

2.7.5 Governance Challenges

Inclusive, transparent, and flexible governance are required to build and maintain public trust in AI technology. The ramifications of this issue for society as a whole are enormous (Chui, 2017). Even though AI holds great promise, if not properly regulated, it might be disastrous. Suppose a giant construction site robot goes down in the middle of a busy building site with many workers. Given that it has no way of knowing how many workers are on either side, how does it decide whether to fall left or right? Some AI solutions could provide construction firms with an unfair advantage, which is something that needs to be addressed.

Building ethics into AI was defined by Burton et al. (2017) as an investigation of ethical challenges, individual and group ethical decision frameworks, and ethics in human-AI interactions. There are some researchers who believe that ethics should be part of AI development, but there are also many who believe that such an approach is flawed and instead advocate for a whole new field called "AI safety engineering." Furthermore, the growth of AGI and ASI, which let computers think for themselves, could be hazardous if the issue of accountability is not properly addressed (Abioye et al., 2021). As a result, it is possible that AI adoption in the construction industry will be affected. There are still several governments working to develop effective AI governance legislation, including the UK government.

2.7.6 Challenges with Computer processing power and internet access

As a result, many construction sites are located outside the reach of phone lines and the Internet. Even construction projects may result in power interruptions and Internet connectivity concerns. AI tools, such as robots and site monitoring systems, that are largely reliant on stable Internet and power supply, face an uphill battle in construction sites. During construction, for example, sensors and actuators exchange data that must be calculated in real-time. This problem must be addressed in a timely and cost-effective manner. This challenge has been somewhat alleviated by the deployment of 4G (LTE/max) communication technology. 5G provides even higher construction site reliability thanks to its high data rate, reduced latency, energy savings, cost savings, increased system capacity, and massive device connectivity (Louis & Dunston, 2018).

2.7.7 Leadership is highly abstract and not tailored to the implementation of AI Systems

AI implementation in healthcare is expected to necessitate leaders who are familiar with the current state of various AI systems. Leaders must drive and support the incorporation of AI systems into existing or updated workplace procedures and processes, as well as how AI systems might be employed to increase efficiency, safety, and access to healthcare services. Independent of the healthcare field, there is compelling evidence that leadership is important for organisational culture and efficiency, the execution of anticipated organisational change, and the implementation and promotion of organisational innovation.

2.7.8 High Energy Consumption

Iterative learning procedures are used by some learning algorithms, including deep learning (Sutton & Barto, 1998). This method demands a high consumption of energy. Due to its outstanding precision and resemblance to the human brain in decision-making, the deep learning method is now employed to develop HLI-based robots. Deep learning models necessitate a high level of processing capacity from GPUs. Strubell et al. (2019) discovered that these models are expensive to train and develop in terms of both financial and energy use.

In order to provide self-awareness, an HLI-based agent may operate according to a predetermined strategy that involves simultaneously learning various models. Consequently, to enable additional cognitive capacities, high computational capacity is needed. Consequently, the HLI-based agent needs to be supplied with adequate energy to operate. Developing novel mathematical models with fewer computations, which consume less energy, may be necessary to address this difficulty (Wheeldon et al., 2020).

2.7.9 Robustness and Reliability

An AI-based model's robustness can be described as the reliability of the model's output following unusual changes in the input data. A malicious attacker, background noise, or the failure of other AI-based system elements could be the source of this change (Hanif et al., 2018). For instance, during tele-surgery, an unidentified crash in the machine vision component may allow an HLI-based agent to mistakenly identify a patient's kidney as a bean. The resilient model is given a higher priority in deployment among various models with comparable performance.

2.7.10 Fairness

This problem arises when the learning model results in a decision that is biased toward certain personal characteristics, including race, gender, religion, national origin, citizenship, age, pregnancy, familial status, disability status, veteran status, and genetic information (Zhang & Ntoutsi, 2019). The research on fairness in AI can be categorized into three types (Kamani et al, 2022). Firstly, the data itself may be biased, resulting in unfair choices. As a result, this issue should be addressed at the data level and as a pre-processing phase (Dwork et al., 2012). The study of Quy et al. (2021) discusses dataset errors and problems that lead to misleading outcomes. Some pointers for making acceptable versions of existing datasets generated during the last decade are provided. Secondly, the fairness parameters can be achieved by some model alteration after learning to achieve a fair model (Hardt et al., 2016). Lastly, a process is carried out in conjunction with a straining procedure to fulfil fairness constraints by enforcing them as a restriction to the fundamental learning objective (Morgenstern et al., 2019). There are no specific answers for implementing fair behaviour in human communities, and it is known that human history is plagued with unfair practices. As a result, a vast amount of data for machine learning may result in the construction of unfair learning system.

2.7.11 Explainable AI

Explainable AI is a growing field with numerous applications in fields such as healthcare, transportation, and military services (Adadi & Berrada, 2020). A collection of tools and procedures may be employed in this field to clarify a learning model. With such capabilities, humans may trust the models' decisions from a variety of perspectives, including bias and fairness difficulties, amongst others. This implies that explainability may influence solutions to other problems, such as justice and credibility.

2.7.12 Storage (Memory)

Memory is an essential component of any AI-based systems. One of the most extensively and frequently used forms of intelligent systems is a restricted memory AI-based system (Hassani et al., 2020). Historical records are utilised in this type to predict certain factors regarding the trend of changes in data. Some data-driven and statistical analysis are utilised in this technique to derive knowledge from data. This strategy is not new in the realm of artificial intelligence, and it is fed by data, storage capabilities, computational capacity, and learning capabilities. More data can help to boost learning capacities in many scenarios.

As the amount of data acquired by AI-based systems grows, effective algorithms for data analysis and decision-making become more important. With the massive expansion in data, storage and computing technologies may be transformed in the near future. Information can be kept in either short-term or long-term memory units, which causes issues in a variety of fields such as reading, computing, and writing. To address this issue, Widrow and Aragon (2013) presented a solution based on cognitive computation. It is worth noting that performing cognitive engines with vast data in memory via online learning algorithms may result in difficult tasks (Qiu et al., 2016). Other sub-challenges that occur during the design of HLI-based agents include real-time decision-making capacities, replicating functions of numerous kinds of memories (short term and long term) similar to humans, and supporting human thinking styles for computation, like those discovered in cognitive architectures (Kotseruba & Tsotsos, 2020).

2.7.13 Ethical Challenges

It has been apprehended that AI providers encounter ethical issues with defining who is responsible for errors and substandard service as more and more, machine performance may become independent of human input in the form of 'self-learning' AI systems. Rossi (2018) has elaborated that the AI's ethical conduct promotes trust by complying with Fairness, Integrity, Data Protection, right for all, Human-centred values and sustainability are key principles to ensure ethics in AI. While tracing the ethical dilemma in the construction industry, Arroyo et al. (2020) have highlighted the current issues of AI in the construction industry as planning and control, generative designs, claim analysis, and environmental performances.

2.7.14 Planning and Control

Artificial Intelligence is being applied in construction projects, particularly in the area of project scheduling analysis, where machine-learning algorithms are employed to make recommendations. It has been published that the software vendor (ALICE) stated that the goal of this technology is to help teams avoid onerous planning procedures. When it comes to implementing AI, trust between humans and AI is the most important component. Arroyo et al. (2020) have elaborated that a worker will also have difficulty comprehending how ALICE comes to its conclusions and, as a result, will be unable to place their faith in those conclusions. With independent decision making of AI, the critics are curious about schedule optimisation algorithm either derived through critical path approach, lean philosophy, and balancing conflicting objectives.

2.7.15 Algorithm Bias

Cyber risk can cause significant harm where human-machine contact necessitates new health and safety regulations. Irizarry (2020) have further unlocked that fidelity and diversity concerns in generative designs of construction industry with relation to AI. Hence, the algorithm bias is relevant where Arroyo et al. (2020) have attributed it to Groupthink and lack of diverse opinions which complicates the trust building on AI based scheduling and decisions. Furthermore, Rossi (2018) has underlined the trust issues in AI based algorithms for contemplating transparency and ethical conduct in construct

Table 2.1: Artificial Intelligence Implementation Challenges

	AI-implementation challenges	References
1	Lack of talent	Nica et al.,2019; Liu and Wang., 2021; Liu, 2021; Zhu, 2021; Jayakumar et al., 2021; Mori et al., 2023
2	High Initial Expenditure	Jebelli et al., 2019; Mak and Pichika, 2019; Chen et al., 2021; Regona et al., 2022
3	Governance and ethics	Cath, 2018; Dignum, 2018; Li et al., 2019; Taeihagh, 2021.
4	Computer processing unit and internet access	Lu, 2019; He et al., 2019; Turner et al., 2020; Sepasgozar et al., 2020
5	Security and Privacy and Consent issues	Braun et al., 2018; Khisamova et al., 2019; Pan and Zhang, 2021; Murdoch, 2021; Anshari et al., 2022; Sunarti et al., 2021
6	Cultural concerns	Xu et al., 2018; Felzmann et al., 2019; Robinson, 2020; Gardezi and Stock, 2021
7	Poor quality of data and lack of data	Liu, Y.C., 2006; Rossi, 2018; Abdallah et al., 2020; Sharma et al., 2021; Wahl et al., 2018; Ma et al., 2020; Merhi 2023; Sharma et al., 2023
8	Technological immaturity	Davenport and Ronanki, 2018; Yigitcanlar et al., 2020.
9	Algorithmic Bias	Raub, 2018; Kelly et al., 2019
10	Insufficient Stakeholder collaboration	Mikhaylov et al., 2020; Brunetti et al., 2020; Stahl et al., 2022

11	Lack of trust	Winfield and Jirotka, 2018; Guo, 2020; Shrivastava et al., 2022; Tucci et al., 2022;
12	Environmental Risk	He et al., 2019; Mao et al., 2019; Sharma et al., 2020; Ali et al., 2021; Salam et al., 2023

Table 2.1: Artificial Intelligence Implementation Challenges

2.8 Success Factors for Artificial Intelligence Implementation

2.8.1 The Case for Other Business Sectors:

The major variations between the construction industry and other sectors remains the key obstacle to loosely implementing the success factors discovered in other industries to construction. However, the adoption rates within these sectors, as shown in Figure 2 provide a strong basis for considering AI research within these industries. The study of related publications presented that success factors of AI implementation have been specifically studied in the healthcare, logistics, finance, and manufacturing sectors. For instance, investigated the CSFs for the integration of AI-robotics into massive eGovernment projects. The research synthesised research articles, government reports and experiential knowledge from AI experts to identify eight success factors (EMNEs, utility, manpower, governance, capital, software, data and hardware). Similarly, Alhashmi et al (2019), investigated the CSFs for AI deployment in the UAE Healthcare sector. Interviews with IT experts and healthcare employees revealed managerial, organisational, operational IT infrastructure as influential factors that drive the success of AI projects. Uren (2020) discusses adoption maturity as a key factor in the successful implementation of AI. The study states that a number of organisations pursuing AI implementation have not achieved adoption maturity. Using technology readiness level (TRL), the study contextualised business strategy (problem identification), selection of appropriate AI technology and functional understanding, data quality and capabilities, AI experts and usability (user interface) as CSFs for AI implementation.

Furthermore, Winkler and Zinsmeister (2019), investigated the CSFs for implementing digitalization in intralogistics. This study used online surveys to establish good processes, clear business objectives, data quality and security, management, usability, and employee trust as recurring success factors. Relatedly, Damljanovic (2019) studied the success factors for AI implementation in the cement industry. The result outlined five CSFs namely problem identification, shell characteristics, experts, developers' skills and user involvement. The research continued to stress employee encouragement, investment in talent acquisition and AI strategy as key factors too. The 54 success factors derived from these publications are as shown bel

Table 2.2 54 success factors for AI implementation across various sector

S/NO	Factors Description	Success Factors	Reference/Source
1	Data Management	Data Quality, Data Accessibility, Data Capability, Data Ownership, Data Interpretation, Data Strategy, Data Storage, Data Standardization, Data Centralization, Data Integration, Data Security	Naryan and Tan (2019), Yadav and Singh (2020), Dora et al. (2021), Ngo et al. (2020), Toole et al. (2010), Mantha and De Soto (2019), Gbadamosi et al. (2019), Woodhead et al. (2018), Martinez and Fernandez-Rodriguez (2015), Wolff (2021), Gambatese and Hallowell (2011), Perez et al. (2018), Brous et al. (2020), Provost and Fawcett (2013), Gunduz and Yahya (2018), Matheny et al. (2019), Choi et al. (2020), Choi (2013), Edmondson et al. (2019), Damljanovic (2019), Bilal et al. (2016), Alaloul et al. (2020).
2	Technical Infrastructure	Processing Power (GPU), Technical Solution Development, Robust Tools, Prototype Development, Continuous Iteration of Solution, Shell Characteristics	Mir et al. (2020), Grover and Dwivedi (2020), Wolff (2021), Zhang (2005), Ugwu and Kumaraswamy (2007), Oesterreich and Teuteberg (2016), Akinade et al. (2018), Damljanovic (2019), Park and Kim (2013), Abir et al. (2020), Martinez and Fernandez-Rodriguez (2015), Lockow et al. (2018), Nam et al. (2020), Krishnamoorthy (2018), Afolabi et al. (2019).

3	Governance and Strategy	Governance, AI Implementation Strategy, Set Clear AI-Driven Objectives, Adoption of Minimal Viable Products, Stakeholder Benefit Analysis, Benefit Measurement, Capital Structure, Operational Cost, Resource Optimisation, Co-operate Leaders and Staff Support, Stakeholder Identification	Mir et al. (2020), Narayanan et al. (2020), Cohen et al. (2018), Dora et al. (2021), Abd Rashid et al. (2018), Sun et al. (2018), Ugwu and Kumaraswamy (2007), Sharma and Kumar (2020), Yahya et al. (2019), Behzad et al. (2020), El-Sayegh et al. (2020), Woodhead et al. (2018), Furman and Seamans (2018), Perez et al. (2018), Yadav and Singh (2020), Das and Cheng (2020), Silvero-Fernandez et al. (2019), Bilal et al. (2016), Duan et al. (2019), Alhashmi et al. (2019), Gbadamosi et al. (2019)
4	Human Resources and Change Management	AI Staff Training, Adopt Digital Change Management Approach, Employee Motivation, Employee Trust, Behavioural Change Management, Inducing Behavioural Intentions, Increase Awareness & Knowledge of AI, Investment in Talent Acquisition, Internal & External Subject Matter Experts with Domain Knowledge, Acquire AI Skills, Develop In-house Competency in AI	Abd Rashid et al. (2018), Duan et al. (2017), Amuda-Yusuf (2018), Behzad et al. (2020), Alhashmi et al. (2019), Siau and Wang (2018), Marcus et al. (2019), Mir et al. (2020), Ugwu and Kumaraswamy (2007), Acquah et al. (2018), Hamma-adama et al. (2020), Kilu et al. (2020), Karacay (2018), Tabesh et al. (2019), Zhou et al. (2020), Wenger (2014), Masood and Egger (2019), Damljanovic (2019).

5	Usability and User Involvement	Usability (User Involvement), Awareness & Understanding of the Core of AI, Problem Identification & Statement, Utility, Shell Characteristics	Yahya et al. (2019), Yadav and Singh (2020), Das and Cheng (2020), Silvero-Fernandez et al. (2019), Kiu et al. (2020), Wang et al. (2017), Hamma-adama et al. (2020), Damljanovic (2019), Khaled Abu Awwab et al. (2020), Ugwu and Kumaraswamy (2007), Emam (2013), Duan et al. (2019), Krishnamoorthy (2018), Afolabi et al. (2019).
6	Financial Management	Capital Cost, Operational Cost	Yadav and Singh (2020), Das and Cheng (2020), Khaled Abu Awwab et al. (2020), Mir et al. (2020), Silvero-Fernandez et al. (2019).
7	Technical Skills and Development	AI Technique Selection, Process to Data Mapping, Multidisciplinary Team (Data Science & Traditional Software Development), AI Experts	Cai et al. (2020), Al Mansoori et al. (2021), Nasrollahzadeh et al. (2016), Gebretekie et al. (2021), Ugwu and Kumaraswamy (2007), Zou et al. (2014), Duan et al. (2017).
8	Hardware and Software Adoption	Hardware Adoption (Availability & Accessibility), Software Adoption (Availability & Accessibility)	Khaled Abu Awwab et al. (2020), Ugwu and Kumaraswamy (2007), Kiu et al. (2020), Mir et al. (2020), Midkiff (2008), Wachter et al. (2017).
9	Governance and Policy	Governance, Stakeholder Management	Mir et al. (2020), Narayanan et al. (2020), Cohen et al. (2018), Dora et al. (2021), Khaled Abu Awwab et al. (2020), Nguyen (2013).
10	Miscellaneous	EMNEs, Safety Features	Korrreck (2019), Mckinsey (2018), Ugwu and Kumaraswamy (2007), Oesterreich and Teuteberg (2016)

2.8.2 Success factors for Similar AI-driven Technologies in Construction.

The construction environment is complex and dynamic in nature. Various technologies such as BIM, 3D printing, Internet of Things (IoT), Blockchain, Cybersecurity, Robotics, architecture apples and cloud-based technologies have been successfully adopted into construction across the years to combat productivity and bring digitisation. Though, these technologies are not as broad nor as comprehensive as AI, the implementation rate of these technologies into construction and the recorded positive impact of their implementation to construction processes provide the necessary argument to examine the success factors of these implementations for the purpose of developing CSFs for AI Implementation. For instance, BIM has been adopted at an exponential rate and has levitated the industry (Chen and Luo, 2014). The major factor that drove this success was that the UK government drove BIM adoption with mandatory policies, processes, and implementation frameworks (Akanbi et al., 2018; Gbadamosi et al., 2019); a key factor that must be applied to AI to ensure similar results.

A review of literatures about BIM showed that studies outlined either technical or generic CSFs for BIM implementation. Antwi-Afari et al. (2018), identified five recurring CSFs that were effective for BIM implementation in construction. Amongst which was cooperation between stakeholders in design, engineering, and construction. Although Amuda-Yusuf (2018) also stated that collaborative synergy among industry professionals and the dedication of stakeholders are key factors for success, the study highlighted technology readiness and adoption as a key success factor too. Ozorhon and Karahan (2017) also reported that support from top management leads to a successful BIM implementation in construction. Thus, studies on BIM implementation demonstrate the critical role of leadership, technology, policy and stakeholder participation as the core factors driving success in the implementation of BIM in construction.

Like BIM, the success factors for implementation of blockchain technology have been researched. The review of this research revealed a broad range of CSFs. One of the most fundamental factors highlighted in these studies is social awareness. Yadav and Singh (2020) also investigated CSFs of blockchain application to sustainable supply chains. The study identified the necessity for project cost and performance to mitigate loss of productivity, contractual differences and ensure operational quality. Das and Rad (2020), also reported that policy regulations are mostly recognised as an impending factor in the adoption of blockchain for construction. Thus, researchers are advocating for a legislative provision to promote the implementation of technology in construction projects.

Conversely, Umar (2022) explored the CSFs specific to the implementation of 3D printing in construction. The study examined other environmental influence such as competitive pressure, business partners and market trends. Therefore, it notes that businesses are more likely to embrace 3D printing on the basis of competitive pressure. The analysis concludes that the implementation of 3D printing technology in construction is mostly challenged different cost related factors such as the machine cost, material cost and labour cost.

Some other technology researchers in the construction industry have also explored the CSFs for implementing ARVR, IoT and Cybersecurity. For instance, Masood and Egger (2019) conducted a study to define the CSFs for implementing AR in construction. The study indicated that user acceptance, which is closely associated with technology readiness is a primary factor to consider when implementing AR into any construction process. Mantha and De Soto (2019) identified data ownership as a critical success factor for the implementation of cybersecurity in construction. Woodhead et al. (2018), analysed the challenges that arise when implementing IoT into construction. The study discussed that the construction industry's dynamic nature and the fragmentation amidst stakeholders in the construction industry are key barriers to the implementation of IoT. They also expressed data ownership as a primary success factor.

According to a review conducted by Bilal et al. (2016), the cost implication of implementing big data solutions is a major barrier to its adoption in construction. In another related study, Narayan and Tan (2019) stated that data quality, data security and data ownership are key factors that determine the success of construction adoption projects. However, while other studies have continued to examine the CSFs in big data, IoT, Robotics, 3D printing and other disruptive technologies (Liu, 2006; Wang et al., 2020; Alaloul et al., 2020), there still remains a dearth in relevant literature pinpointing the success factors for AI implementation specific to the construction industry. Thus, the success factors identified from the review of the publications above are depicted in Table 2.3

Table 2.3: Success Factors for Technologies in Construction

S/NO	Factors Description	Success Factors	Reference/Source
1	Shell Characteristics	Shell characteristics	Damljanovic (2019)
2	Usability and User Involvement	Usability (User involvement), User Acceptance, Job relevance, Perceived usefulness, Computer anxiety	Yahya et al. (2019), Yadav and Singh (2020), Das and Cheng (2020), Kiu et al. (2020), Das et al. (2020), Dora et al. (2016), Akinradewo et al. (2018), Abd Rashid et al. (2018), Masood and Egger (2019), Narayan and Tan (2019)
3	Data Management	Data Quality, Data Ownership, Data Security	Naryan and Tan (2019), Yadav and Singh (2020), Mantha and De Soto (2019), Gbadamosi et al. (2019), Woodhead et al. (2018), Damljanovic (2019), Bilal et al. (2016), Alaloul et al. (2020), Dora et al. (2021)
4	Technical Infrastructure	Specific Implementation Requirements, Connectivity	Behzad et al. (2020), Wolff (2021), Azhar (2011), Hardin and McCool (2015), Bilal et al. (2016)
5	Human Resources and Change Management	Interweave Technology Job roles within Projects, AI Staff Training, Adopt Digital Change Management Approach, Inducing Behavioural Intentions, Provide Training for Staffs	Sargent et al. (2012), Rose et al. (2017), Hamma-adama et al.(2020), Abd Rashid et al. (2018), Duan et al. (2017), Amuda-Yusuf (2018), Behzad et al. (2020), Alhosani and Alhashmi (2024), Acquah et al. (2018), Ozorhon and Karahan (2017)

6	Governance and Strategy	Co-operate leaders and staff support, Top Management Support, Top Management Willingness, Top Management Sponsorship, Top Management Commitment, Stakeholders' Buy-in, Stakeholders Cooperation, Stakeholders Participation, Stakeholders Dedication, Ensure Trust and Transparency with Stakeholders (employees, top management, clients)	Alhosani and Alhashmi (2024), Gbadamosi et al. (2019), Ozorhon and Karahan (2017), Behzad et al. (2020), Yang et al. (2015), Martinez and Fernandez-Rodriguez (2015), Damljanovic (2019), El-Sayegh et al. (2020), Dora et al. (2021), Abd Rashid et al. (2019), Woodhead et al. (2018)
7	Governance and Policy	Regulatory Policy (government & industry), Industry Data Standards, Industry Usage Standards, Industry Evaluation Process & Methods, Industry Integration Standards	Hamma-adama et al. (2020), Yadav and Singh (2020), Ozorhon and Karahan (2017), Behzad et al. (2020), Abd Rashid et al. (2018), Dora et al. (2021), Bilal et al. (2016), Oke et al. (2021), Makridakis (2017), Brundage et al. (2018), Sun et al. (2018), Ugwu and Kumaraswamy (2007)
8	Technical Skills and Development	AI Experts, Construction Domain Experts	Ugwu and Kumaraswamy (2007), Duan et al. (2017), Behzad et al. (2020), Bilal et al. (2016), Hadidi et al. (2017)

9	Financial Management	Operational Cost, Economic Feasibility, Capital Cost	Yadav and Singh (2020), Das and Cheng (2020), Silvero-Fernandez et al. (2019), Ellatar (2008), Alinaitwe and Ayesiga (2013), Almarri and Abu Hijleh (2017)
10	Hardware and Software Adoption	Hardware Adoption (Availability & Accessibility), Software Adoption (Availability & Accessibility)	Ozorhon and Karahan (2017), Ugwu and Kumaraswamy (2007), Kiu et al.(2020), Midkiff (2008), Wachter et al. (2017)
11	External Influence	Competitive Pressure, Business Partners, Market Trends, Consideration of External Elements	Dora et al. (2021), Tu (2018), Damljanovic (2019), Yahya et al. (2019), Li et al. (2005), Gavali and Halder (2020), Alhosani and Alhashmi (2024), Chen et al. (2021)
12	Miscellaneous	Professional image	Samek et al. (2017), Wolff (2021)

2.9 A Comprehensive Critical Success Factors (CSFs) Framework for AI Implementation for UK construction Industry:

In light of the above discussion, AI has the power to modify how the business operates. If applied well the technology can reconstruct business processes by creating good user experiences and improving human decision making. AI feeds off data, and for the majority of enterprises facing data overload, this usually indicates a problem (O'Leary and Armfield, 2020). According to Kilkenny and Robinson (2018), the "garbage in, garbage out" principle suggests that your data should be in good shape to produce meaningful results. Another thing to note is that data is delivered in all forms and sizes, and some of it remains unused. Several studies indicate that data preparation is a critical activity, often the most important task in AI implementation (Bundy, 2017). Therefore, success factors of data, business process & management, skills & expertise, organisational culture, technology & tools, government & policies, and organisation sponsorship were addressed. Hence, highlights the important aspects to consider during AI implementation by avoiding inaccurate and inflated results in the underlying technical challenges.

Earlier studies have explored the CSFs depicted in AI implementation within other sectors. However, the review reveals a number of recurring success factors namely: Data, Business management, Technology and Government and polices. Consequently, to create intelligent algorithms used in the development of machines capable of imitating human intelligence, it all begins with Data. In accordance, Lee et al. (2018) specified that a bad quality data only yields unreliable intelligent algorithms. Hence, ensuring a truthful data acquisition. Thus, CSFs studies for AI deployment in healthcare, takes importance to data ownership as an ethical issue required to address the patient data privacy and information security (Kostkova et al., 2016). In another related study, Uren (2020) argued that the first determining success factor for the implementation of AI is accessing and scoping out the real problems in the organisation. The study identified that the roadmap to support AI implementation leads with the plan of action and strategic need to access the current state and nature of the organisation.

However, it is also eminent that without AI experts in the field, there is no AI implementation. In ensuring a successful deployment of AI projects, allocating skilled representative is paramount to increase efficiency, boost motivation and raise momentum within the organisation. Research has shown that domain experts with internal subject matter expertise are just as relevant as external experts. For instance, organisations cannot develop all the AI expertise internally to make the most of AI. Therefore, external forces are required to upgrade the workforce rapidly (Damljanovic, 2019). This allows in-house competency analysis to be stipulated, giving employees the opportunity to upskill and learn to gain AI expertise. According to Alhosani and Alhashmi (2024), understanding the skills and job roles intended and needed for this process is crucial to the deployment of AI. Some authors have also identified technology as a crucial success factor to AI deployment. Thus, a number of studies have identified a broad range of technological factors such as cost of tools, robustness, hardware and software adoption, technical solution development, user interface, processing power (GPU), agile development, prototype development and continuous iteration of solution (Alhosani and Alhashmi, 2024; ; Winkler and Zinsmeister, 2020). Chen et al. (2020), recognised that agile approaches are used to develop AI projects that enable the project to remain responsive. That implies, that a reiterative evaluation process should be followed by the best AI systems. Raj and Sah (2019), also stated that participants find it easier to get behind AI projects once they see it is working well as a pilot project within the organisation. Lastly, the issue of trust is mostly addressed in AI projects. This can be impacted by human involvement, organisational structure and technology characteristics (Rossi, 2019), some of the issues raised is the possibility of job loss, bias, inaccuracy, safety and discrimination (Hagendorff, 2020; Morley et al., 2020; Siau and Wang, 2020). Yu et.al (2018), indicated that to ensure project reliability, privacy and security issues, the ethical success is noted as one of the crucial factors for AI achievement.

A limitation of most of the studies is the reliant on quantitative statistical methods that allows the researcher to have an objective viewpoint to his/her research problem and also inform research generalisability when addressing a wider audience. However, the sample size used in the above research were narrow. The literature conducted by Winkler and Zinsmeister (2019) and Alhosani and Alhashmi (2024) verified its sample size limitation, thus stating that the clarity of the study was not prepared accurately. Therefore, illustrating a drawback in its sample size. However, this study carried out qualitative research, but the participants interviewed were still limited in number. Given that we have seen a rise in research articles and government reports addressing the crucial necessity for the exploration of CSFs in its relative sectors (Calof and Smith, 2010), it is important to note that there is no evident research at the time of this study that tackles the critical success factors of AI implementation in the construction industry. Consequently, the absence of CSFs for AI implementation in construction questions the credibility of the development of AIMM in construction. Therefore, through existing literature and qualitative research survey, one of the research problem criteria of this study is to investigate the CSFs of AI deployment unique to the construction industry. The purpose of the above research exercise is to identify the key success factors for the implementation of AI in different sectors in established literature. The exhaustive list is presented below. Table 4. consists of 89 success factors which were gotten from publications that studied success factors of AI in other sectors as well as studies about success factors of other technologies to constru

Table 2.4: Exhaustive list of success factors for AI implementation in various sectors and other Technologies in Construction

S/NO	Factors Description	Success Factors	References/Source
1	Technology Readiness	Shell characteristics, User Acceptance, Perceived ease of use, Perceived enjoyment, Perceived usefulness, Computer anxiety, Robust tools, Hardware Adoption (Availability & Accessibility), Software Adoption (Availability & Accessibility), Technical Solution Development, Processing Power (GPU), Agile Development, Prototype Development, Connectivity, Continuous Iteration of Solution	Damljanovic (2019), Kiu et al. (2020), Das et al. (2020), Abd Rashid et al. (2018), Alalol et al. (2020), Masood and Egger (2019), Narayan and Tan (2019), Akinade et al. (2018), Ozorhon and Karahan (2017), Ugwu and Kumaraswamy (2007), Kiu et al. (2020), Midkiff (2008), Wachter et al. (2017), Zhang (2005), Oesterreich and Teuteberg (2016), Grover and Dwivedi (2020), Lichtenthaler (2020), Yigitcanlar et al. (2020), Park and Kim (2013), Abir et al. (2020), Azhar (2011), Hardin and McCool (2015), Bilal et al. (2016), Martinez and Fernandez- Rodriguez (2015), Lockow et al. (2018), Nam et al. (2020)
2	Organisational Culture	Usability (User involvement), Awareness & Understanding of the Core of AI, Industry Data Standards, Industry Integration Standards, Increase Awareness & Knowledge of AI, AI Staff Training, Adopt Digital Change Management Approach, Stakeholder Identification, Employee Motivation, Employee trust, Industry Usage Standards, Industry	Yahya et al. (2019), Yadav and Singh (2020), Das and Cheng (2020), Kiu et al. (2020), Wang et al. (2017), Hamma-adama et al. (2020), Damljanovic (2019), Bilal et al. (2016), Oke et al. (2021), Abd Rashid et al. (2018), Ugwu and Kumaraswamy (2007), Hamma-adama et al. (2020), Kiu et al. (2020), Behzad et al. (2020), Abd Rashid et al. (2018), Duan et al. (2017), Amuda-Yusuf (2018), Alhosani and Alhashmi

		Evaluation Process & Methods, Construction Domain Experts	(2024), Duan et al. (2017), Ozorhon and Karahan (2017), Samek et al. (2017), Wolff (2021), Behzad et al. (2020), Hadidi et al. (2017)
3	Robust Business Case	EMNEs, Problem Identification & Statement, Set Clear AI-Driven Objectives, Specific Implementation Requirements, AI Implementation Strategy, Benefit Measurement, Capital Cost, Operational Cost, Economic Feasibility, Process Definition and Evaluation, Adoption of Minimal Valuable Products, Consideration of External Elements, Competitive Pressure, Market Trends	Korrreck (2019), Mckinsey (2018), Ozorhon and Karahan (2017), Ugwu and Kumaraswamy (2007), Behzad et al. (2020), Wolff (2021), Abd Rashid et al. (2018), Sun et al. (2018), Dora et al. (2021), Yadav and Singh (2020), Das and Cheng (2020), Silvero-Fernandez et al. (2019), Mir et al. (2020), Ellatar (2008), Alinaitwe and Ayesiga (2013), Almarri and Abu Hijleh (2017), Sharma and Kumar (2020), Yahya et al. (2019), Alhosani and Alhashmi (2024), Chen et al. (2021), Tu (2018), Li et al. (2005), Gavali and Halder (2020)
4	Data	Data Quality, Data Accessibility, Data Availability, Data Capability, Data Collection, Data Ownership, Data Interpretation, Data Strategy, Data Storage, Data Standardization, Data Centralization, Data Integration, Data Security	Naryan and Tan (2019), Yadav and Singh (2020), Dora et al. (2021), Ngo et al. (2020), Toole et al. (2010), Mir et al. (2020), Wolff (2015), Mantha and De Soto (2019), Gbadamosi et al. (2019), Woodhead et al. (2018), Martinez and Fernandez- Rodriguez (2015), Gambatese and Hallowell (2011), Perez et al. (2018), Brous et al. (2020), Provost and Fawcett (2013), Gunduz and Yahya (2018), Matheny et al. (2019), Choi

			et al. (2020), Choi (2013), Edmondson et al. (2019), Damljanovic (2019), Bilal et al. (2016), Alaloul et al. (2020)
5	Stakeholder Management	Stakeholder Identification, Stakeholder Benefit Analysis, Benefit Measurement, Stakeholder Management, Behavioural Change Management, Stakeholders' Buy-in, Stakeholders Cooperation, Stakeholders Participation, Stakeholders Dedication, Ensure Trust and Transparency with Stakeholders (employees, top management, clients), Top Management Support, Top Management Willingness, Top Management Sponsorship, Top Management Commitment	Dora et al. (2021), El-Sayegh et al. (2020), Behzad et al. (2020), Ozorhon and Karahan (2017), Siau and Wang (2018), Marcus et al. (2019), Gbadamosi et al. (2019), Martinez and Fernandez- Rodriguez (2015), Abd Rashid et al. (2019), Woodhead et al. (2018), Amuda-Yusuf (2018), Yang et al. (2015), Alhosani and Alhashmi (2024)

6	Human Capital Development	Interweave Technology Job roles within Projects, Job relevance, Professional image, Develop Inhouse Competency in AI, Acquire AI Skills, Provide Training for Staffs, Utility, Investment in Talent Acquisition, Internal & External Subject Matter Experts with Domain Knowledge, Process to Data Mapping, AI Technique Selection, Resource Optimisation, Multidisciplinary Team (Data Science & Traditional Software Development), AI Experts, Construction Domain Experts, Capital structure, Business Partners	Sargent et al. (2012), Rose et al. (2017), Hamma-adama et al. (2020), Dora et al. (2016), Akinradewo et al. (2018), Samek et al. (2017), Wolff (2021), Behzad et al. (2020), Damljanovic (2019), Karacay (2018), Tabesh et al. (2019), Zhou et al. (2020), Wenger (2014), Masood and Egger (2019), Nasrollahzadeh et al. (2016), Gebretekie et al. (2021), Cai et al. (2020), Al Mansoori et al. (2021), Bilal et al. (2016), Duan et al. (2019), Ugwu and Kumaraswamy (2007), Zou et al. (2014), Furman and Seamans (2018), Perez et al. (2018)
7	Legal Regulation	Safety Features, Governance, Regulatory Policy (government & industry)	Ugwu and Kumaraswamy (2007), Oesterreich and Teuteberg (2016), Narayanan et al. (2020), Cohen et al. (2018), Dora et al. (2021), Hamma-adama et al. (2020), Yadav and Singh (2020), Ozorhon and Karahan (2017), Behzad et al. (2020), Abd Rashid et al. (2018)

Chapter Summary

This chapter extensively explores the success factors associated with the implementation of Artificial Intelligence (AI) in various sectors, with a specific focus on its application in construction. It is structured around a comprehensive list of success factors, each tied to specific sources and accompanied by concise descriptions. The initial section focuses on the technological aspects and emphasizes the importance of shell characteristics and technology readiness. Additionally, factors such as usability, user involvement, and user acceptance highlight the significance of user-centric approaches and organisational culture in ensuring the seamless integration of AI technologies. Furthermore, this chapter explores the essential components related to data, including data quality, accessibility, availability, and ownership. Data-related factors like interpretation, strategy, storage, standardization, centralization, and integration, were discussed in detail, shedding light on the multifaceted nature of handling data in AI projects. More so, the human capital development aspect was explored in detail, as it encompasses job roles, professional image, perceived ease of use, enjoyment, and usefulness. Specifics regarding the relevance of AI-driven objectives, implementation requirements, and strategy, as well as interweaving technology job roles within projects, highlight the need for strategic planning and organisational commitment to foster a conducive environment for AI. Stakeholder management is another critical theme, with factors such as stakeholder identification, benefit analysis, and the role of top management support, willingness, sponsorship, and commitment being discussed. Insights from several authors stress the importance of a collaborative and supportive environment in achieving successful AI integration. This chapter also addresses external factors affecting AI implementation, including regulatory policies, industry standards, and governance. The literature emphasizes the need for organizations to align with regulatory frameworks and industry standards to ensure ethical and legal AI deployment. A significant portion of this chapter was dedicated to financial considerations and economic feasibility. Factors such as capital structure, economic feasibility, capital, and operational costs were discussed, drawing from research by several authors. These considerations highlight the necessity of a robust business case for AI implementation. The technological readiness perspective was explored through factors like robust tools, hardware, and software adoption, processing power, agile development, prototype development, connectivity, and continuous iteration of solutions. The contributions from several authors elucidate the technical prerequisites for seamless AI integration. This chapter concludes by emphasizing the importance of considering external elements, competitive pressures, business partners, market trends, industry usage standards, industry evaluation processes, methods, and the overall awareness and knowledge of AI. By covering a broad spectrum of success factors, the chapter provides a comprehensive overview of the multifaceted landscape of AI implementation in various sectors and provides valuable insights for researchers, practitioners, and organisations navigating the intricate journey of integrating AI technologies into their operations.

3 CHAPTER THREE: MATURITY MODELS: A CONCEPTUAL REVIEW AND CRITICAL ANALYSIS OF ARTIFICIAL INTELLIGENCE (AI) MATURITY MODEL.

Chapter Overview

Chapter three introduces the concept of doing a comprehensive assessment of the literature on maturity models by providing an overview of its history and theoretical underpinnings. Section 3.2 addresses the several characteristics of maturity models, while Section 3.3 explores the various approaches for maturity model development, including descriptive, prescriptive, and comparative application. Section 3.4 delves more into the challenges and criticisms related with the maturity model. Sections 3.5. reviews of existing maturity model in construction are examined. Section 3.6. reviews the AI maturity model and the state of the art of research. Section 3.7. explores and critiques the current AI maturity model and its contextual problems in further detail. Section 3.8. discusses the various benchmarking concepts used in the construction of maturity models. Finally, Section 3.9 addresses the conceptual foundation for constructing a domain specific AIMM for the construction industry in the UK.

3.1 Background and concept of Maturity Models

AI maturity model in construction draws inspiration from the broader concept of maturity models in organisational development, which assess an entity's maturity in adopting and benefiting from certain technologies. In the context of construction, the AI maturity model has evolved as a framework to evaluate and guide the level of artificial intelligence integration within construction practices. Its origin is rooted in the need for the construction industry to assess its readiness and progression in adopting AI technologies for improved project outcomes. Developed by industry experts and thought leaders, the model provides a structured approach to understanding the stages of AI adoption in construction, ranging from initial exploration to advanced, optimised utilisation. This model has gained prominence as construction professionals seek to navigate the complexities of integrating AI into their workflows for enhanced efficiency and project success.

The generic concept of a maturity model (MM) is to assess capability and encourage continuous improvement of an organisation or system using stage evolution theory (Scott, 2007; Becker et al., 2009). Some of the keywords used in the definition of MMs as seen in various studies include to identify, measure, evaluate, assess, guide, and encourage (Lahrmann, et al., 2011). For example, Röglinger et al. (2012) defined a maturity model as a tool used 'to guide' organisational maturity and process capability improvements which is illustrated in a hierarchical system. In another similar study, Langston and Ghanbaripour (2016) defined the possibility of subdividing the core application of the maturity model into three categories: people, organisations and technology across various sectors. Therefore, maturity levels used to describe the growth map in a model comprises of a sequence of processes sub-sectionalized into subdomain, domains primary process areas maturity indicating the critical success factors set to assess and benchmark the various levels. According to Demir and Kocabaş (2010), the fundamental objectives of organisations that implement MM is to understand their status quo, facilitate progressive-continuous improvement and enable performance analysis between similar organisations. As such, the ultimate benefit of MMs for organisations that adopt them is to gain a competitive advantage within their industry.

To create growth maps, MMs development relies on benchmarking rules, sectionalized into subdomains and then into domains that make up the phenomena. As such, benchmarking rules are used to evaluate the capability level of the object of interest within each subdomain, domain and then overall within the entity. For example, Building Information Model (BIM) MM comprises of three main domains that satisfies the evaluation of the maturity of an organisation with respect to BIM implementation. These three domains are technology, process, and project. Therefore, to evaluate the maturity of an organisation with respect to BIM implementation using the BIM Maturity Models, the evaluator must use the current BIM capabilities of the organisation to place them in a corresponding competence level outlined within the BIM MM. This exercise has to be carried out across all three domains to extrapolate the overall maturity of the organisation (Khosrowshahi & Arayici, 2012).

In another similar study on Business Process Management Maturity Model (BPMMM), the study identified that the model should consists of six domains namely, strategic alignment, governance, methods, information technology, people, and culture. However, MM may or may not be attributed to several characteristics that can be used as a key criterion in its development. Figure 1. shows the structure of a maturity model (CMM) which is an example of a model without domains.

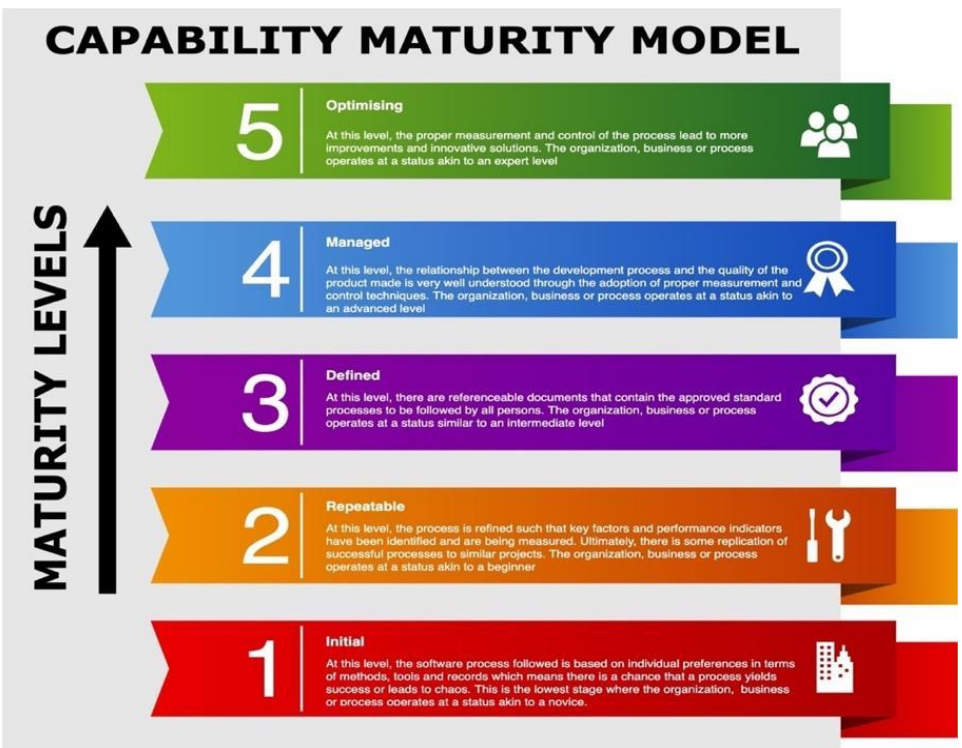


Figure 3.1: Maturity stages of CMM (Paulk, et al., 1993)

A lot has been covered above about MMs. However, some of the characteristics of maturity models and the purpose/benefits of implementation of the maturity model are outlined in subsection 3.2 in a bid to justify these with theories.

3.2 Characteristics of Maturity models

1. Maturity models are designed for the evaluation of an object of interest like a process, project/department, organisation/business. A maturity model can only evaluate one type of object. However, other objects can be domains/subdomains in the evaluation matrix of the principal object. For example, process and project can be domains or subdomains in the evaluation of a particular topic.

2. Maturity Models are usually developed for an artefact, object, business area, topic or model such as supply chain management, business management, software capability process etc. each subject area has domains and some subdomains that enable an all-around and detailed evaluation.

3. They are stage-based arrangements usually between 3 - 5 levels either in the format of 1 – 5 or 0 – 4

4. Comprise of a series of activities/questions/statements that categorize the object of interest into a level, in some cases the evaluation is a quantitative score similar to a Likert scale or a questionnaire, but all aimed at the same objective.

3.3 Classification of a maturity model.

Although maturity levels outline the hierarchical capability of a model, Röglinger et al. (2012) states that the evolutionary lifecycle of a maturity model could be broken down into three based on the type of application.

1. Descriptive application - serves as the foundation of the model describing the as-is situation. According to Tarhan et al. (2016), the descriptive mode of application has been adopted by most BPMMM models which provides the organisation a means to assess and identify its current capabilities.

2. Prescriptive application - creates or pinpoints an incremental improvement in the model to boost business performance. A study conducted by Klötzer and Pflaum (2017), stated the prescriptive model is used to help organisations identify their capability with a clear guide on how to achieve its desired proficiency.

3. Comparative application- gives a robust comparison between similar maturity models. The CMM and other notable MM are recognised to provide a comparative feature as they are classified as benchmarking models used to identify, assess, and justify the capabilities similar organisations possess in other to drive a competitive advantage amongst them which indirectly boosts and promotes continuous optimisation of processes. (Pennypacker and Grant, 2003; Pederiva, 2003). However, it is important to note that multiple applications can be used in a singular study or model.

Thus, Table 3.1. explores the use cases of maturity model application across a numerous number of studies.

Table 3.1: Classification and implementation purpose of maturity models

		Maturity Model use purpose		
S/N	**Maturity Models**	**Descriptive**	**Prescriptive**	**Comparative**
1	Cybersecurity capability maturity model	Yes	-	-
2	COBIT Maturity Model	-	-	Yes
3	E-Collaboration Maturity Model	Yes	-	-
4	IT Outsourcing Relationship Maturity Model	Yes	-	-
5	Digitalization maturity model in	Yes	-	-
6	Supply chain process maturity model	-	Yes	-
7	Change management maturity model in	-	Yes	-
8	E-government Maturity model	Yes	Yes	-
9	Value-based process maturity model (vPMM)	Yes	-	-
10	System Integration Maturity Model industry	-	-	Yes
11	Blockchain Maturity Model	-	-	Yes

12	Information Security Maturity Model	-	-	Yes
13	Project Management Maturity Model	Yes	-	-
14	PLM Maturity Model	Yes	-	-
15	Big Data Maturity Model	Yes	Yes	-
16	Meta Management Maturity Model	Yes	Yes	-
17	IT Risk Maturity Model	-	Yes	-
18	Smart City Maturity Model	Yes	-	Yes

The purpose of maturity models is categorically to perform descriptive, prescriptive, and comparative analyses for entities whether its process, project/department, organisation/business (Klötzer & Pflaum, 2017). Descriptive analyses aim to narrate the current capabilities of the object of interest e.g., process, project/department, organisation. Also, prescriptive analysis is the aspect that proposes the next steps for the object of interest to improve to a better stage from its current status. Strategic plans can be developed from these prescriptive suggestions. Lastly, comparative analyses provide the basis for competition analyses where it is possible to understand how the object compares and contrasts to similar objects. Hence, maturity models enable the understanding of a subject, guide the strategic plan to implement the subject and the realization stages which collectively lead to proper use of the subject to yield results (Canetta et al., 2018). The advantage then is that there is a shorter implementation time because of availability of support, a clear vision of the real benefits to implementing these changes and the path to achieve the benefits, performance improvement and competitive advantage.

3.4 Review of Maturity Model Development Framework

The use of methodological frameworks as a structured guide to completing a process or procedure has been widely recognised. According to Arksey and O'Malley (2005), methodological frameworks provide a systematic structure, or a practical guide used to organise a study or research using a step-by-step approach. As such, the progression of a staple framework development methodology progresses for identifying evidence to develop the research, developing the methodological framework, and evaluating and refining the results derived from the framework. According to Banerjee and Ghosh. (2018), the major approach used for the development of a methodological framework are based on existing methods and guidelines. In which case comprises of previous methodological guidance and published methodology being adapted and integrated in building methods. Other framework development methodology highlighted in research are experience and expertise, literature review, data extraction amongst others (Arksey & O'Malley, 2005; Sedlmair et al., 2012; Pham et al., 2014; Levac et al., 2020). Although, recent studies have benefited greatly from the use of methodological frameworks in research as a way of proving guidance for researchers to conduct a study, studies have also shown the lack of standardisation in the formation which defines a 'methodological framework' (Arksey and O'Malley, 2005; Cash et al., 2009). Therefore, a number of maturity model development and proposals have been presented in various research. For example, De Bruin et al. (2005) proposed a generic maturity model development methodology which comprises of six phases i.e., Scope, design, populate, test, deploy and maintain. The initial phase of this framework establishes the foundation for the maturity model's development. This phase can be regarded as an exploratory investigation that delves into the desired model's characteristics and nature. Specifically, it focuses on determining whether the model is domain-specific or a general maturity model, as well as identifying the key stakeholders involved in its development. The design phase primarily centres on the architectural design of the maturity model framework and the implementation of the maturity model. This involves the process of translating the intricate reality into a model that effectively captures the distinct characteristics of the domain, incorporating valuable insights from stakeholders (Van Steenbergen et al., 2010). The population phase entails evaluating the precise aspects that necessitate measurement and determining the optimal approach for measuring them. During this phase, the components of the domain and subdomain are defined. Following the completion of the population phases, the model undergoes a comprehensive evaluation and testing process to ascertain its validity, reliability, and generalizability. Lastly, the deploy phase entails the assessment of the model's capacity to be generalized. However, De Bruin et al. (2005), identified that each phase could be adjusted in an iterative manner from an end-to-end development process with its specific characteristics for each phase. Although, this research has been widely adopted with little or no bias in the results, the practicability of its uses has been limited to business process management and knowledge management (Mettler, 2011; Asdecker and Felch, 2018). Similarly, Langston and Ghanbaripour (2016) proposed a development of maturity model based on the use of existing maturity model analysis. The methodology involves a maturity model assessment criterion that defines the path to the development of the domain specific maturity model, thus, the applicability of this process has been widely used in business information systems, knowledge management and IT maturity model development. The model uses three progressive form of assessment question such as defining the questions, design the questions and application of the questions to define and ascertain the attributes of the model (Igartua el al., 2018). According to Lahrmann et al. (2011), the development of a maturity model consists of five distinct phases. The first phase involves identifying new opportunities by conducting surveys, interviews, and examining business needs through various exploratory methodologies. Furthermore, this study delves into the examination of the scope's definition in order to attain an in-depth understanding of the model. This entails identifying the distinct characteristics and attributes of the model. Subsequently, the design model phase is implemented to construct the model. The evaluate design phase is then employed to test the model, ensuring its validity, generalizability, and reliability. Lastly, the evolution phase is undertaken to determine the necessity for developmental advancements of the model, based on new opportunities or a renewed purpose. This methodology has been widely used in identifying the specific characteristics accompanied with the application of quantitative methods to construct the model based on assessment questionnaire. The process is aids in defining prescriptive and descriptive maturity models and finds its limitation in the identifying domain specific maturity models.

There are other proposed frameworks identified for the development of maturity models such as Pöppelbuß & Röglinger (2011), suggested a maturity development model that is grounded in design principles and aligned with the intended goal of maturity models. Van Steenbergent et al. (2011) proposed a maturity model development with the use of design science research, identifying four phases i.e., scope, design model, develop instrument and implement and exploit. Although, this model was derived from merging existing maturity model development approaches of De Bruin et al. (2005), Mettler (2009) and Becker et al. (2009). Table 5 shows the different activity steps identified in various methodologies used for developing maturity model. Given the above, the need for a valid design science approach is prominent to identify the gaps in literature, ensure that a robust analysis of all aspects of the study are considered in a systematic manner

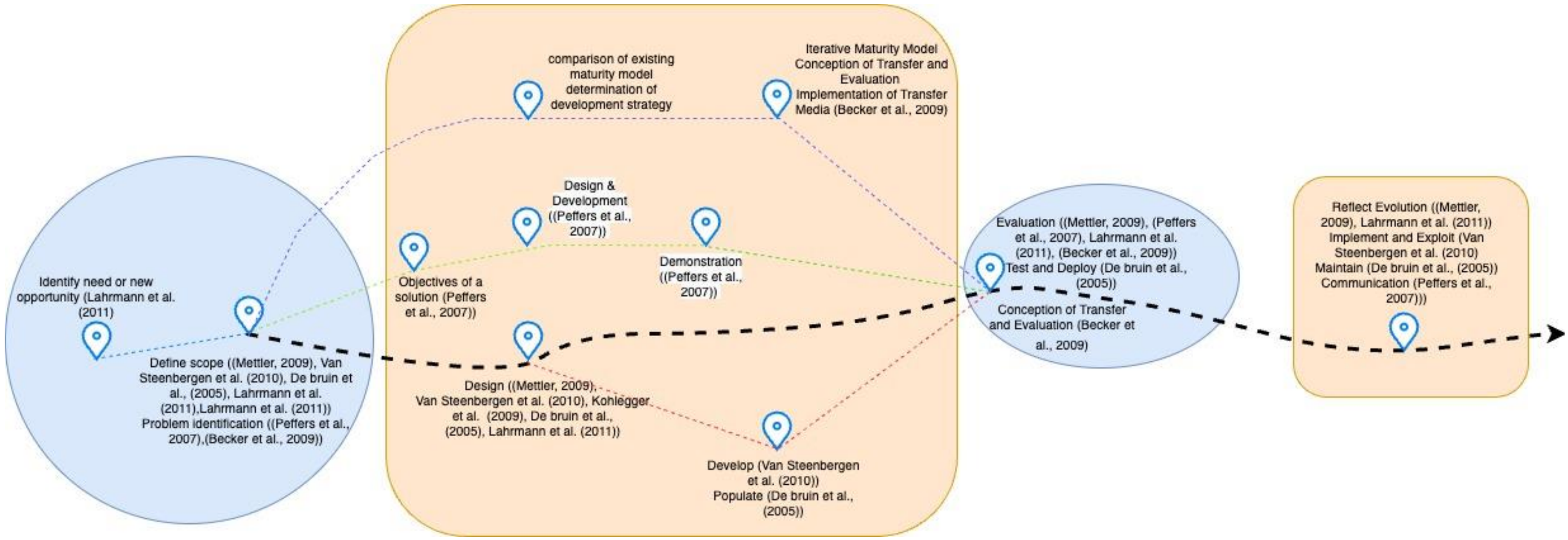


Figure 3.2: Analysis of the steps to create a MM i.e., review of Maturity Model development framework

Design science has been identified as the most popular framework development methodology adapted to a number of IS research to enable the logic behind the development or design of a new model or method (Peffers et al., 2007; Johannesson et al., 2014). According to Dresch et al. (2015), the use of design science research permits a measurable, testable, and grounded technological design innovation of a model or concept. Recent studies such as the development of digital information management maturity in universities (Keshavarz and Norouzi, 2022), business intelligence and analytics maturity models (Cardoso and Su, 2022), and digital transformation maturity model (Kirmizi and Kocaoglu, 2022), have used the design science research approach to not only systematically define the step-by-step evaluation of a process or procedure but also to ensure the required outcome our artefact in the process has been utilised effectively and satisfies the identified problem areas in the research. Furthermore, the use of design science research has been applied to science research as well as systematically project to ensure both theoretical and practical rigor is used to identify problem areas applicable to a particular sector or process and produce practical solutions which addresses a broad impact on the application domain. Thus, design science research journeys from the identification of the problem to the solution of the identified problem and lastly the evaluation of the problem to satisfy the key stakeholders applicable to the problem area. Studies by Riege (2003) and Peffers et al. (2007), show that there are different methods identified in the use of design science research such as the systematic literature review, interview, experiments amongst others.

Thus, the concept of a maturity model is known to enable a progressive capability growth that assesses and measures the focus areas in a stage-by-stage process (Elmaallam et al., 2019; Cataldo et al., 2020). The maturity model serves as a guide and a result-based tool which indicates an attainable performance within an organisation. Although a maturity model has the characteristic to be versatile in nature as such being descriptive, prescriptive and/or comparative (Cleven et al., 2014; Van Looy et al., 2017; Bley, 2021). Studies have shown that maturity models represent the as-is situation of an organisation, provides a solution driven roadmap, and ensures the model can be used to adapt to the organisation set objectives and goals as well as drive the progressive steps in the organisation (Chrissis et al., 2011). Therefore, a maturity model is identified as an artefact used to solve organisational problem, which highlight the prominent needs to find solution to unsolved problems or ensuring an effective roadmap is put in place to control the problem areas (Becker et al., 2009; Mettler, 2011).

Given the above, the design science research methodology (DSRM) developed by Peffers et al. (2007) was used in this study and this serves as foundation for the activity steps. The DRSM was used to create a design step framework with domain-dependent process specifications with corresponding activity steps. The MM design steps were then divided into process requirements, which comprised MM procedure requirements from Becker et al. (2009) as well as extra process requirements for creating a MM suitable for the construction industry. The DSRM activity involves six steps which are: problem identification, defining the objectives of a solution, design and development, demonstration, evaluation, and communication. The following activity steps are used to ensure accuracy in problem identification and its applicability to the domain area.

1. **Problem identification and motivation:** In order to provide an effective solution, Geerts (2011) stated that the start of the DSRM activity involves defining the research problem and presenting a justification for the proposed solution. Hence, the initial phase in constructing a Maturity model (MM) involves delineating the problem through the identification of domain characteristics and barriers found within the particular domain (Becker et al., 2009). This evaluation involves assessing the gaps and challenges that have been found and comparing them against the projected model goal. Additionally, their findings suggest that benchmarking the fundamental notion of a Maturity model might aid in this process. Moreover, an extensive understanding of the subject matter is essential. Consequently, conducting a gap analysis between the current AI maturity models and the construction sector can facilitate the identification of problems and serve as a catalyst for problem-solving efforts.

2. **Objectives of a solution:** The formulation of a clear problem description is useful in identifying the desired outcomes of a proposed solution, as well as the specific criteria that must be met to effectively address the problem. This process serves as a roadmap for acquiring the necessary problem-solving competence. According to Poels (2013), the approach to addressing this issue can be undertaken through either a qualitative method, such as conducting interviews to investigate the description and utilisation of the solutions for the identified problems, utilising the new model. Alternatively, a quantitative approach

can be employed, wherein statistical analysis is implemented to delineate the challenges encountered in the current maturity model. The objective of this quantitative approach is to logically derive the solutions' objectives from the problem specification. Therefore, this study conducts a literature review of existing AI maturity models and other AI- related technologies within the construction industry to develop solutions. Also, identifying the critical success factors for AI implementation in a bid to understand and review the complexities within the business domain.

3. **Iterative Maturity model design and development**: According to Lasrado et al. (2015), the four sub-characteristic components of the proposed new maturity model are design level, model strategy, model selection, and assessment. The design level is commonly known as the core structure. For example, the basic principle of the maturity model, the framework of levels, and the distinction between single or multidimensional aspects, as well as the sub-dimensions, can be considered. The design approach can often be categorised as either top-down or bottom-up (Lasrado et al., 2015). The bottom-up approach entails initially identifying mature dimensions and features, followed by the generation of descriptions based on these findings. The initial step involves establishing the hierarchical levels and their corresponding descriptions within the context of a top-down strategy. Based on the characteristics of artificial intelligence, it may be inferred that a bottom-up approach is particularly well-suited for domains that have reached a state of maturity (De Bruin et al., 2005). Dimensions are utilised as a conceptual framework for the examination of the topic matter within the context of maturity models (Hansmann, 2016). Various classifications or dimensions have been proposed by scholars to categorise different AI technologies for the purpose of conceptualising AI (Nilsson, 2014; Millington, 2016; Corea, 2017). According to Hansmann (2016), the initial dimension or domain of the model can be substantiated by drawing upon existing literature or expert knowledge. Within the existing body of literature, researchers have identified various dimensions of AI through the process of labelling primary characteristics and their associated themes at each level (Chen et al., 2021). These dimensions are considered highly significant and relevant within the context of study. Each step within each dimension can be characterised

by identifiable dimensions and maturity traits. The iterative procedure will continue until the model is deemed to be finalised.

4. **Demonstrate and evaluate model:** The subsequent stage of the DRSM activity entails a demonstration and assessment of the model's application, incorporating stakeholders that possess expertise in utilising the model to solve problems. Peffers et al. (2007) suggest that this particular process might be effectively illustrated by the use of case studies, experimental validation, or simulation techniques. The initial assessment component primarily involves the comparison of the initial problem requirements with the conclusions of the maturity model development. The efficacy of the maturity model can be assessed during the demonstration phase of the evaluation. This phenomenon is commonly referred to as model verification by certain scholars (Mettler et al., 2011). One approach to showcasing the effectiveness of a model involves conducting tests in an actual-life scenario to assess its ability to provide the expected results.

   After the method of iteration is complete, the new maturity model must be demonstrated and evaluated (Peffers et al., 2007). The initial assessment component essentially consists of comparing the initial problem specifications to the maturity model development findings. The maturity model's effectiveness may be evaluated during the demonstration phase of the assessment. This is known as verification of models by some (Mettler et al., 2011; Brooks et al., 2015; Blondiau et al., 2016). One method for demonstrating utility is to test the model in a real-world environment to see if it produces the anticipated outcomes.

5. **Evaluation:** The process of evaluation entails the assessment and determination of the significance or value of a given entity, such as an artefact or a model (Peffers et al., 2007). The evaluation activity step is employed to assess the efficacy of the demonstration and evaluation phase. Therefore, this activity entails the evaluation of the alignment between the objective of the solution and the anticipated outcomes derived from the use of the model, this can be measured by reviewing existing literature, quantitatively via surveys, feedbacks, stimulation or qualitatively through the use of interviews or focus group

interviews. Hence, several maturity model. Studies have employed the use of a maturity assessment framework where the dimensions, themes, scope, and maturity levels will be assessed. The outcome will suggest whether to reiterate back to design and development phase (activity step 3) to either improve the effectiveness of the model or progress to the final activity step.

6. **Communication:** The communication phase is the final phase of the DSRM activity step. This specific component in the activity serves as a means of effectively conveying the identified problem and its significance, the model being employed, the design process, and validating the model's dependability through stakeholder input. Hence, the presentation of design science research holds significance in appealing to both technology-oriented and management-oriented audiences (Hevner et al., 2004). Therefore, this research, which focuses on the development of an AI maturity model, is in line with both the managerial and technological frameworks. This necessitates a comprehensive comprehension of the framework, structure, and methodology involved in developing an AI domain-specific maturity model. In order to progress through the established stages of maturity, it is imperative for the business to possess an extensive awareness of the strategies encompassed inside the framework. This understanding is crucial for facilitating the proficient application of the AI maturity model.

3.5 Theoretical Criticisms of Maturity Models

Despite the rise in the adoption of MM across various industries, there has also been enormous controversies and debates regarding the effectiveness of MM (Röglinger and pöppelbuß, 2011). While some of the arguments have been against MM, a section of the literature has also considered MM a veritable tool for measuring, assessing, evaluating, and benchmarking processes within an organisation. For instance, the most highlighted criticism of MMs is that it is a gradual process that could lead to a loss of validation and identified as not pragmatic (Paulk, 2009; Rae et al., 2014). To further highlight the imperfection of current MMs, CMM, a highly significant study was conducted by Paulk (1993) has been revised 5 times due to inadequacies of the previous models. Shareef et al. (2011) stated that the issue with many maturity models is that they lack little or no formal theoretical basis.

Another study conducted by Chrissis et al. (2003) highlights that CMM focuses excessively on processes with no attention to people.

As suggested by the study of Mettler (2011), maturity models provide organisations with a "what to" guideline and not a "how-to" guideline on how to implement processes. Another major criticism of the maturity model is its lack of theoretical grounding which has been referenced in a number of studies (Cleven et al., 2014; Wendler, 2014). A comprehensive critical evaluation was also conducted by Lasrado et al. (2015) which addressed the collective summary of the criticism of maturity models by streamlining its major challenge as a lack of show of theoretical groundings, absence of empirical validation, ignorance of multiple and non-linear paths to maturity and methodological rigor. However, Mettler et al. (2010) suggested that the issue could be tackled if MM were developed with the use of extensive testing focusing on validation, generalisation, and reliability.

Nevertheless, studies such as Christoph Albrecht and Spang (2014); Andersen and Henriksen (2006) amongst others, have commended the implementation of MM. Therefore, it represents the potential to systematically enhance operational output and procedures by examining its advantages to increase productivity and streamline the problem of uncertainty. In addition, this process exemplifies a standardized level framework to facilitate continuous improvement. In another relatable study conducted by Hribar Rajterič (2010), emphasises the advantageous use of MM as a comparative study for the use of either internal or external benchmarking purposes between similar organisations which pose as a means for assessing and justifying an organisations situation. The CMM has proven to provide a well-documented guide on how to continually improve software development processes and serve as a benchmarking model to give similar organisations insight on their current proficiency alongside a guideline to promote improvement (Fraser and Vaishnavi, 1997; Lowe and Cox, 1996). Another notable example is a recent report published by Deloitte in line with the adoption of Bersin's Maturity model, which serves as a descriptive tool for understanding the current performance of the organisation and a prescriptive tool for facilitating and encouraging capacity improvement, technical manufacturing, and process management.

3.6 Review of Existing Maturity Models in Construction Industry

In a bid to provide an extensive overview for this study, an evaluation of a number of studies on Maturity Models in the construction industry was conducted to justify its effects on both research and practical applications. For example, Zhao et al. (2013), proposed an Enterprise Risk Management Maturity Model (ERMMM) for Chinese Construction Firms (CCFs). Through a sequential mixed methodology and fuzzy logic approach, Zhao et al. (2013) identified 66 ERM best practices, 16 key criteria for enterprise risk management and developed a quantitative maturity model for CCFs. The study concluded that the assessment of ERM by construction contractors can help provide a clearer view of their enterprise risk implementation and also address areas of weaknesses. However, despite the huge contribution of this study, the model is limited in that the best practices and maturity criteria identified are not exhaustive. In addition, the fuzzy logic method implemented is not robust because it assigns the same weighting to all factors.

In another related study, Succar (2010) came up with Building Information Modelling Maturity Matrix., which is also referred to as the BIM maturity matrix (BIm^3). BIm^3 is a knowledge tool that outlines a list of factors using 3 competency sets, 3 capability stages, and 12 organisational scales that are pertinent to BIM performance and improvement. The study also suggested 5 maturity levels that are attainable when a set of rules are fulfilled. Nevertheless, whilst this model is very comprehensive in nature, the study fails to consider the issue of context, organisational strategy or goal or the involvement of industry experts in the model development. More so, there is a very high level of subjectivity involved in the scoring method which is seen as a major flaw in its development.

In another similar study by Liang et al. (2016), a reiterative approach was used to develop a BIM maturity model that is considered useful to multiple stakeholders such as individuals, projects, teams, organisations and the industry as a whole. The study implemented an interpretable scoring method across domains and subdomains which were attained from previous frameworks through focus group discussion and the Delphi method. The study created a BIM Maturity for benchmarking a BIM development usable by company senior managers and policymakers alike. Whilst the research is innovative in its approach and coverage area, it fails to consider the context of size, goals, and strategy of users. In addition, the study also failed in guiding users' progress across the different BIM maturity levels. Several other studies on Maturity Models have also dominated construction literature including

Big Data Maturity Model (BDMM) (Comuzzi & Patel 2016), Supply Chain Maturity Model (SCMM) (Hansali et al., 2022), Integrated Management Systems Maturity Model (IMSMM) (Domingues et al., 2016), Construction Industry Macro Maturity Model (CIM3) (Willis & Rankin, 2012), Agile Maturity Model (AMM) (Leppänen, 2013.), and Project Management Maturity Model (PMMM) among others. Table 3.2. Shows an extensive review of other related studies and their shortcomings within the construction sector

Table 3.2: Review of existing maturity models within the construction industry

NO	Author	MM Title	Level	Methodology	Key Findings	Shortcomings
1	Oswald and Lingard (2019)	H&S leadership maturity model	3	Ethnography (Participant behaviour at 4 construction sites) & 4 focus groups. 6 stage thematic analyses.	The research derived 6 key areas where frontline behaviour affected H&S, the researcher came up with a 3-stage maturity model that could help the construction project to see where improvement is needed to achieve the best leadership behaviour towards good H&S.	Ethnography cannot be replicated therefore the research cannot be generalized across other projects or construction sites. The researcher also states that there is some research bias within the research.
2	Setiawan et al. (2019)	The green construction capability model	5	Conducted a comprehensive literature review in two main stages- both green construction and capability maturity A collection of interviews and discussions were conducted with experts validating the qualitative	The researchers identified 16 factors for assessing the green capacity of a contractor in Indonesia through literature review and expert confirmation. Based on this, the researcher created a MM across 5 levels using the CMM as a guide. To	The research cannot be generalized as the factors were derived from Indonesian documents

				analyses with the use of statistical means.	conclude, the researchers use the statistical mean of matrix-like data to describe the contractor's capability level within each factor and overall	
3	Mollasalehi et al. (2018)	BIM and Lean Maturity Model (IDEAL)	5	Review of existing maturity models in BIM and Lean to extract the main features and beneficial aspects to creating this combined MM. The outcome of the review plus a review of the relationship between BIM and Lean was used to create IDEAL	The research successfully created a MM to assess the maturity of projects across BIM and Lean implementation	The model has not been validated nor used on any construction projects
4	Santoso et al. (2018)	Safety maturity model	5	Expert validation of questionnaire contents, pilot study of respondents and 188 survey replies to identify the indicators for each of the five levels of safety maturity. Delphi and	A model that suggests improvement actions for increasing safety maturity level using 15 indicators from the UK Coal HSE and based on surveys the research boils down to 3 indicators for each level of	

				questionnaire survey methods	the safety maturity. The research also found that improving safety maturity improves safety performance which in turn reduces accidents on projects	
5	Gomez and Hamid (2018)	Continuous Improvement Maturity Model	5	The research used a combination of literature review and three rounds of Delphi survey to outline the critical success factors for CI. The results from the questionnaire were calculated based on mean score and standard deviation followed by the Average Index (AI). The categorization of the levels was gotten from Bessant and Caffyn and validated by Delphi experts.	Developed a maturity model using 8 critical success factors and 38 observable constructs for assessing the continuous improvement of organisations with regards to quality management, the research revealed that there is a significant difference of CI maturity between ISO certified and non-ISO certified construction contracting organisations.	The research is limited to Malaysia. The research did not consider other factors that come to play in the adoption of an ISO to investigate the effect of theoretically developed concepts

6	Arif et al. (2017)	Knowledge sharing maturity model	3	The use of literature review to identify factors affecting knowledge sharing, questionnaires to describe the variability of the factor, the results were validated and refined with the use of both interviews and semi structured interviews.	The research identified three groups of cultural factors that influence knowledge sharing in the jordanian construction sector namely management factors, leadership and management factors and motivation factors. Trust factors are core for knowledge sharing because the more employees trust each other the better information is shared between them.	There is no overall rating for the organisation to indicate their knowledge sharing maturity. There is a huge assumption that all variables within a factor have equal impact on KS. There is no cases study to assess the validity of the model created.
7	Liang et al. (2016)	Multifunctional BIM model		4 step reiterative research methods which includes literature review, Delphi method, focus group and interviews as well as semi-structured interviews were used to obtain domains, subdomains and evaluate maturity stages.	The maturity model is created from a different perspective of BIM. The MM looks at BIM from the technology, process and protocols point of view. The uniqueness of the model is the ability to assess the BIM maturity at the	

					project, company and industry level	
8	Kang et al. (2015)	capital project information integration capability model	3	With a team of experts (25), a broad literature review was conducted to develop the content of MM, case study was performed to evaluate and validate the MM which created descriptions for each maturity level.	The research created two maturity models; general and detailed maturity models for information integration which evaluates and encourages improvement of an organisation's current status with regards to information integration. The general maturity model is about organisational dimensions and consist of 5 dimensions to characterize different maturity levels each with its own underlying descriptions. the detailed maturity model describes the maturity levels for specific deliverables of the	The research did not take into account the persons involved at the different stages of the project work function. The results of the validation process through case studies were not further validated. Not all functions of the maturity model were reviewed during the process. the model is also time dependent as it only reflects the information integration opportunities in the 2000s.

					8-project level work function groups.	
9	Hartono et al. (2014)	Project Risk Management Maturity	4	With the use of 4 exploratory factor analyses, a broad literature review was conducted to outline some factors that influence risk maturity. Two pilot respondents were used to validate the layout, terminologies, flow of the model whilst four academic and industrial experts performed content validation. The validation of the tool was done empirically using a sample from the population of construction contractors in Indonesia.	The research identified four major dimensions for the model development which are culture, process, experience and application, methods and applications from theoretical sources and confirmation with experts. Along with these 13 sub dimensions were identified for the model development. the research further provides empirical evidence for the theoretically developed classifications and included a quantitative way of scoring organisations maturity by using Likert scale instead of	The experts used for validation of the layout of the tool are not experienced enough, study is limited to Indonesian organisation's

					categorization. the research proves through the means of criterion validity and regression analyses that the higher the maturity the better the performance.	
10	Albert et al. (2014)	Safety meeting quality measurement maturity model		The research was conducted with a team of experts. Validation of the MM was done through application by 6 crews on 2 different construction sites. the size of the research team allowed them to perform a rigorous quasi-experimental research using multiple baseline testing approach to p-curb cofounding variables.	Developed a maturity model that effectively helps workers in recognising and communicating hazards. The model along with mnemonics is recorded to improve hazard recognition by 31%.	Although the researchers claim that observer bias has been carefully thought about in the process with regards to considering using cameras as opposed to visiting sites, they cannot prove that it was entirely removed from the research. The calculation of the HRC index was not robust enough
11	Meng et al. (2011)	Supply Chain Maturity Model	4	The model is represented in a matrix format, with the use of interviews and semi-structure interviews the model was evaluated and a	The study highlights that the relationship is often dynamic during the whole project lifecycle which highlights the importance	

				case study was used to apply and examine the study.	of measuring the relationship continuously, a variation of observation could exist when making an assessment due to the different levels of relationship.	

3.7 Criticisms of Existing Maturity Model in Construction Domain and its Contextual challenges.

Several maturity models had been identified in construction industry such as BIM, LEAN, Green construction capability model etc. However, various gaps had been identified in the implementation of some of the models. The gaps are as follows:

3.7.1 Data incompatibility

According to Ku and Taiebat (2011), because multiple programmes cannot function seamlessly for instance in BIM, data created in one programme must be saved in another rather than exchanged between programmes, which is contrary to the model's main objective. This can also result into limited availability of benchmarking data and performance indicators to assess the effectiveness of green construction initiatives.

3.7.2 Insufficient trained professionals and lack of education

According to Chan (2014), a lack of trained professionals is a major impediment to the implementation of models such as BIM. According to Aranda-Mena et al. (2009), in situations in which there is shortage of workers to advocate for the implementation of BIM, there is problem in discussing its adoption because there are no workers who can implement it.

3.7.3 Irregular Framework

The implementation of some models must be agreed and incorporated into the contract from the beginning, it is unacceptable if a project is not properly structured and the procedures are not effectively specified (Prendeville et al., 2014). A number of firms avoided models like BIM because of the modifications that are required before it can be extensively applied.

3.7.4 Lack of Accountability

When investigating some MM challenges, the level of accountability from specialists and the individual liable for design error is a major issue (Aranda-Mena et al., 2009). In the conventional paper-based design process, it is easier to assign responsibility for a project's flaws than in a BIM programme, where architects, engineers, and other experts cannot immediately identify them.

3.8 Artificial Intelligence (AI) Maturity Model (AIMM) and Current State of the literature.

The construction industry includes components of AI MM too. Common components of AI maturity models in construction include data readiness, technology integration, skills and competencies, organisational culture, and strategic alignment. These models emphasise a holistic approach, recognising that successful AI adoption requires a multidimensional transformation. As a matter of fact, the construction industry is one of the least digitized industries in the world and most stakeholders acknowledge the age-long culture of resistance to change. The lack of digitisation and the overly manual nature of the industry makes the management of projects more complex and unnecessarily tedious. The absence of adequate digital expertise and technology adoption within the construction industry has also been linked to cost inefficiencies, project delays, poor quality performance, uninformed decision-making, and poor performance in terms of productivity, health, and safety. In recent years, it has become apparent that the construction industry must embrace digitisation and rapidly improve technological capacity especially with challenges of existing labour shortages, COVID-19 pandemic, and the need to provide sustainable infrastructures.

Therefore, the proliferation of information and digital technologies over the last two decades has brought about a sharp rise in the introduction of maturity models across diverse sectors. For example, the BIM maturity model has gained positive momentum within the UK construction industry (Böes et al., 2021). Other examples of these maturity models are the digital maturity model of telecommunications service providers (Valdez-de-Leon, 2016), SMEs Maturity Model Assessment of IR4.0 digital transformation (Hamidi et al., 2018), Blockchain Adoption Maturity Model by (Wang et al., 2016) amongst others. In the same vein, with the pervasiveness of AI and other associated emerging technologies, we are now also witnessing a considerable interest in the introduction of the maturity models for assessing AI implementation across a number of sectorial domains (in view of the significant growth of AI processes and projects across a number of organisations). Given the above, academic literature is already recording a handful of studies on Artificial Intelligence Maturity Models within various industries to determine and assess the maturity of AI technologies. Although it is fair to say that most of these studies` are still in its preliminary research stages.

Nevertheless, in one of the recent studies conducted by Sadiq et al. (2021), an AI maturity model was proposed to develop an assessment model and road map for communications and media service provider (CSP) businesses. Thus, this study aims to reshape the CSP business model and improve its existing process whilst providing a four-stage assessment model from being AI novice, AI ready, AI proficient to AI advanced. This study mainly focuses on 5 core domains namely Strategy, Organisation, Data, Technology, and Operations with a progressive criterion for each domain.

In a similar study conducted by Ellefsen et al. (2019), on the development of AI maturity model for logistics 4.0. This study presented a research aim to determine the actual state of digitalization and competency in particular companies. Interestingly, the study on AIMM in logistics 4.0 adopted a similar approach to AIMM for CSP business in close relation to its maturity levels, Domains and Key process areas (i.e. four levels of maturity phases, five domains namely strategy, organisation, data, technology, and operations benchmarking across each key process area for each domain). In this case, the methodology focused on conducting literature reviews and survey analysis while further testing the multiple-case studies and expanded quantitative study.

In another related study by (Alsheiabni et al., 2019), a framework for AI maturity model at an organisational level was initiated in a bid to give insights into successful evolution across a number of businesses. This study outlines the need for five-maturity phases namely Initial, Assessing, Determined, Managed, and optimised across four domains (i.e., AI functions, Data structure, People and Organisation). The study applied a mixed method approach for the purpose of carrying out the research and therefore validated through Delphi techniques. In contrast to the previous maturity models discussed above, the machine learning maturity model approach to delivering an assessment model differ. This study adopted a 4 x 3 matrix method using a robust 12 field framework. To give an illustration, this framework consists of both an x and y axis where the x-axis comprises of the three-machine learning initiatives namely people, tools, and operation. One the other spectrum of the matrix, the y-axis consists of the key process areas which are the four stages of machine learning scaling-up from the fundamental stage till its maturity. These stages consist of the Data, Training, Deployment and Management. Interestingly, this method has a three- level intensity ranging from low, medium to a high-level maturity stage across all the core domains. A representation of MHC AI maturity levels and definition of the specific domains depicting the journey to an organisation's destination is as shown below in Figures 2 and 3.

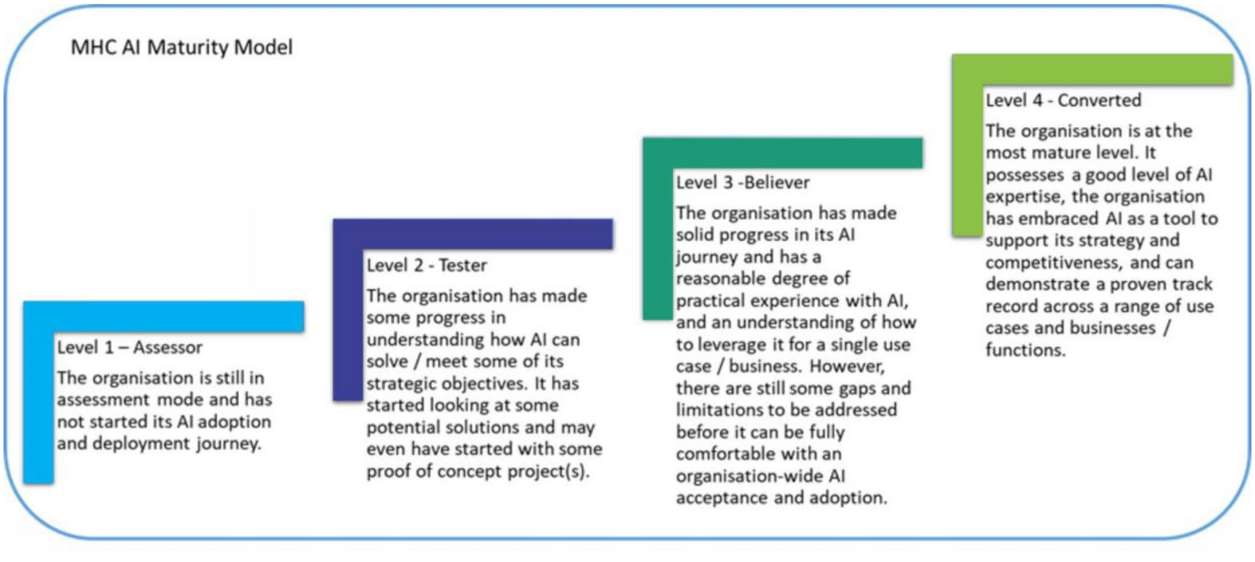


Figure 3.3: MHC AI Maturity Model Levels (Source: MHC, 2021)

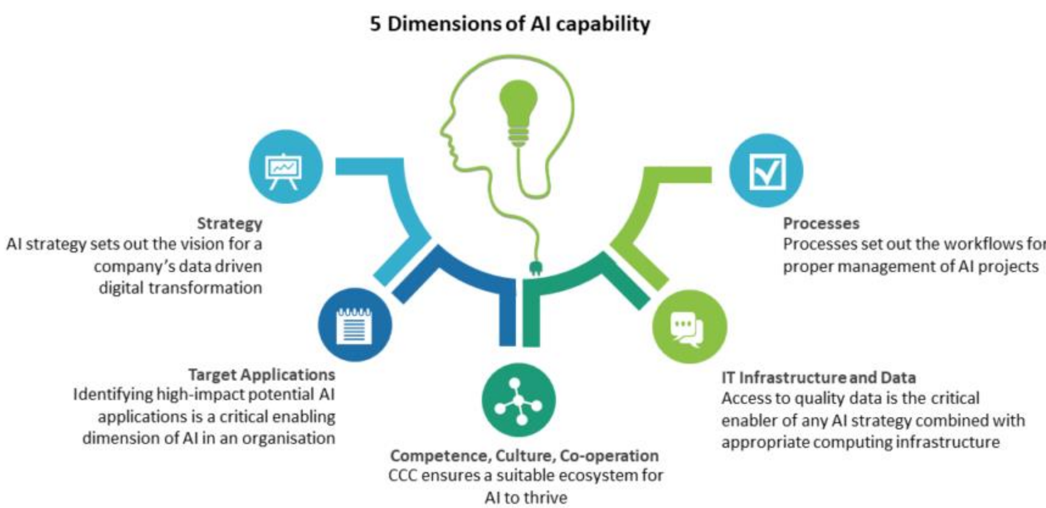


Figure 3.4: MHC AI Maturity Model Domains (Source: MHC,2021)

Nevertheless, despite the examples of AI maturity models cited previously, several other studies in this domain include the process maturity of organisations using AI, the maturity of the enterprise to implement AI solutions (IBM, 2021), AIMM for organisation (Sadiq et al, 2021), Developing an AI maturity model for Auditing (Fukas et al., 2021), AI ethics maturity model (Vakkuri et al., 2021) and among others.

3.9 Review of existing Artificial Intelligence Maturity Models (AIMM) and their Contextual challenges

While the above studies have gradually brought forward the momentum of the AI maturity model in an attempt to improve business process, however, there is still a need for a study that specifically addresses the distinctive demands of the construction industry. With various companies predicting that the use of AI can boost business productivity by up to 40%, the dramatic increase in the number of AI start-ups has magnified 14 times since 2000. The application of AI can range from tracking asteroids and other cosmic bodies in space to predict diseases on earth, exploring new and innovative ways to curb terrorism to make industrial designs. The amount of power these power-hungry algorithms use is a factor keeping most developers away. Machine Learning and Deep Learning are the steppingstones of this Artificial Intelligence, and they demand an ever-increasing number of cores and GPUs to work efficiently. There are various domains where we have ideas and knowledge to implement deep learning frameworks such as asteroid tracking, healthcare deployment, tracing of cosmic bodies, and much more. The construction industry, according to (Mohammadi et al., 2018), exhibits a complex nature and has an evident apathy for the adoption of emerging technology. Hence in order to gain an awareness of AI readiness and capabilities in the Construction industry, the organisation needs to understand AI. Thus, it is important to understand the dynamics of the domain and how AI specification and maturity can positively boost the UK construction market.

The body of literature on AI maturity models has significantly advanced the understanding of how AI can optimize business processes across various sectors. Studies have demonstrated the potential of AI to enhance productivity, streamline operations, and drive innovation. However, there remains a substantial gap in research specifically addressing the distinctive demands of the construction industry. The construction industry is characterized by its complex and ever-changing nature. This complexity arises from the temporary and unique nature of projects, the interaction of multiple stakeholders, and the substantial resources involved. These factors contribute to the industry's hesitance in adopting emerging technologies, including AI (Mohammadi et al., 2018). While numerous industries have benefited from AI's capabilities, the construction sector's specific challenges necessitate a tailored approach to AI maturity.

Mohammadi et al. (2018) emphasize the intricate dynamics within the construction industry that differentiate it from other sectors. The temporary nature of construction projects, coupled with the involvement of diverse stakeholders, creates a dynamic environment where standard AI models may not be directly applicable. Therefore, there is a pressing need for an AI maturity model that considers these unique characteristics and addresses the specific needs of construction firms.

The rapid increase in AI adoption globally, with AI start-ups multiplying 14 times since 2000, indicates a significant momentum towards integrating AI into business processes. Companies predict that AI can enhance productivity by up to 40%, yet the construction industry remains largely apathetic to these advancements. This reluctance is partly due to the high computational power required for AI algorithms, such as machine learning and deep learning, which demand substantial investment in cores and GPUs.

Despite these challenges, the potential applications of AI in construction are vast and transformative. From optimizing project management and resource allocation to improving safety and predictive maintenance, AI can revolutionize the construction industry. However, for AI to be effectively integrated, there needs to be a clear understanding of the industry's readiness and capability to adopt such technologies. The studies reviewed provide a foundation for understanding the benefits and challenges of AI adoption across various sectors. Yet, they collectively indicate a need for a focused investigation into AI maturity within the construction sector. A coherent pattern emerges from these papers: while AI has proven benefits, the unique nature of the construction industry requires a specialized AI maturity model to realize these benefits fully.

This study aims to bridge this gap by developing a robust AI maturity model tailored to the construction industry. By understanding the dynamics of AI specification and maturity, the model will provide construction firms with the tools needed to boost productivity, enhance project outcomes, and drive innovation within the UK construction market. This targeted approach ensures that the construction industry can harness AI's full potential, overcoming current barriers and paving the way for a more technologically advanced future.

The advancement of AI maturity models has significantly contributed to understanding how AI can be integrated into business processes to optimize operations and drive innovation. Lichtenthaler (2020) reviews Gartner's AI Maturity Model, identifying five levels of maturity: Isolated Ignorance (Level 0), Initial Intent (Level 1), Independent Initiative (Level 2), Interactive Implementation (Level 3), Interdependent Innovation (Level 4), and Integrated Intelligence (Level 5). This model offers a structured approach to evaluating AI maturity, highlighting that several leading firms have achieved Level 3, Interactive Implementation. However, these firms predominantly use AI for optimization rather than developing innovative solutions for their current and potential customers. This limitation underscores a crucial gap in leveraging AI for strategic innovation.

Alsheiabni et al. (2019) further explore AI maturity at the firm level through the AI Maturity Model (AIMM). This model integrates AI maturity dimensions with a five-level maturity scale akin to the Capability Maturity Model Integration (CMMI). The AIMM provides a comprehensive framework for organizations to embrace AI, offering business managers valuable insights into their AI readiness. Moreover, the model facilitates the evaluation and enhancement of AI competencies within firms, thereby promoting a more structured and effective AI adoption process.

The critical review of these studies reveals a consistent pattern: while AI maturity models provide essential frameworks for assessing and advancing AI capabilities, there is a predominant focus on optimization rather than innovation. Lichtenthaler (2020) and Alsheiabni et al. (2019) both emphasize the structured progression through maturity levels, yet highlight that many firms are not fully leveraging AI's potential to innovate.

In the construction industry, this gap is even more pronounced. The sector's inherent complexity, characterized by unique and temporary projects, multi-stakeholder interactions, and substantial resource requirements, presents distinct challenges for AI adoption. Mohammadi et al. (2018) point out, the construction industry's dynamic nature and its cautious approach towards new technologies necessitate a tailored AI maturity model.

The current models, such as those reviewed by Lichtenthaler (2020) and Alsheiabni et al. (2019) provide valuable insights but fall short of addressing the specific needs of the construction sector. The industry's unique demands call for a specialized AI maturity model that not only facilitates optimization but also drives innovation tailored to construction's unique challenges. This entails developing AI applications that can handle the complexity of construction projects, enhance stakeholder collaboration, and optimize resource management in a dynamic environment.

Therefore, this study aims to fill this gap by proposing an AI maturity model specifically designed for the construction industry. By building on the existing frameworks and addressing the unique characteristics of construction firms, the proposed model seeks to provide a comprehensive approach to AI adoption. This model will help construction firms not only achieve operational efficiency but also foster innovation, thereby enhancing their competitiveness and ability to meet future demands.

The review conducted by Sadiq et al. (2021) offers a comprehensive examination of the application of Artificial Intelligence and Machine Learning (AIMM) techniques in organisational settings. This study highlights a significant trend in the development of AI maturity models, noting that many of these models are domain-specific and often developed with a particular focus. The authors observed that a considerable portion of the existing literature concentrates on the creation of these models, whether or not they are supported by empirical evidence. This emphasis on model development indicates a foundational phase in AI maturity research, where establishing robust frameworks takes precedence over widespread application and validation.

Sadiq et al. (2021) also point out that the process of developing a maturity model frequently employs a bottom-up approach, with many models incorporating a descriptive component. This approach suggests that AI maturity models often begin by understanding and detailing the existing state of AI capabilities within organizations before moving towards more prescriptive or normative models. The descriptive nature of these models helps organizations identify their current maturity level and provides a baseline from which they can plan their AI integration strategies.

The study further notes that maturity models in the construction sector are starting to adopt maturity grids and continuous representations comprising five levels. This structure is beneficial as it offers a clear, staged pathway for organizations to progress in their AI maturity journey. However, the research also indicates that these models are still in a developmental phase and require further refinement and validation within the specific context of the construction industry.

While the review by Sadiq et al. (2021) contributes significantly to understanding how organizations employ AI, it also underscores a critical gap. The majority of AI maturity models are tailored to specific domains and might not be universally applicable. This specificity can limit the models' utility across different sectors, particularly in industries like construction, which have unique challenges and requirements.

Yablonsky (2019) undertook a comprehensive study on multidimensional data-driven AI innovation, introducing a framework that evaluates the human-machine relationship supported by Big Data/Analytics (BD/AA) platforms. The study's primary contribution is the development of a multidimensional BD-driven AI enterprise maturity framework and an AI/BD/AA value framework with a five-level maturity scale. These frameworks offer a structured approach to understanding and implementing AI across various levels of automation and sectors.

The study's strength lies in its multidimensional approach, which encompasses a range of business components including technology, leadership, people and skills, ecosystem, and new data-driven business models. This holistic perspective is essential in capturing the complexity and interdependence of factors influencing AI maturity. By considering these dimensions, the framework provides a comprehensive tool for organizations to assess their AI capabilities and identify areas for improvement. One significant aspect of Yablonsky's framework is its emphasis on the evolving landscape of data sources. The incorporation of data from the Internet of Things (IoT), sensor networks, open data, mobile applications, and social networks reflects the modern data environment. This inclusion is particularly relevant given the exponential growth of data within organizations and the increasing importance of data-driven decision-making. By recognizing these new avenues for data collection and utilization, the framework ensures its applicability in contemporary contexts and supports ongoing innovation.

However, despite its strengths, Yablonsky's study has limitations. The framework's broad applicability across sectors may lead to challenges in addressing sector-specific differences. While the multidimensional approach is comprehensive, it might lack the granularity required for certain industries, such as construction, which have unique challenges and operational characteristics. Additionally, the framework's reliance on new data sources like IoT and social networks assumes a certain level of technological infrastructure and data maturity that may not be present in all organizations, potentially limiting its usability in less advanced contexts. Another critical aspect to consider is the framework's implementation and validation. While Yablonsky (2019) provides a robust theoretical foundation, practical validation across diverse sectors and use cases is necessary to confirm its effectiveness and adaptability. Without empirical evidence demonstrating successful application, the framework remains largely theoretical

Ellefsen et al. (2019) conducted a study focused on developing an AI Maturity Model specifically tailored for Logistics 4.0. The study outlines potential avenues for AI deployment and practical methods for addressing big data and optimization challenges that impact both large organizations and small to medium-sized enterprises (SMEs). The research methodology was comprehensive as it incorporated literature analysis, the expansion of an existing AI maturity model, the development of a questionnaire, and multi-case studies in Norway and Poland. A notable strength of Ellefsen et al.'s study is its targeted focus on Logistics 4.0, an emerging paradigm that integrates advanced AI and big data analytics to enhance logistics operations. By concentrating on this specific sector, the study provides valuable insights into the unique challenges and opportunities that logistics companies face when adopting AI technologies. The tailored AI maturity model developed in this study can help logistics firms assess their current AI capabilities and identify areas for improvement, thus facilitating more effective AI integration. The study's methodology is robust; it employed a multi-faceted approach that includes both qualitative and quantitative methods. The literature analysis provides a solid theoretical foundation, while the development of a questionnaire and multi-case studies ensures practical applicability. Conducting case studies in two different countries (Norway and Poland) adds a comparative dimension to the research; it highlights regional variations in AI maturity and readiness. This approach enhances the generalizability of the findings and provides a broader perspective on AI adoption in logistics. One significant finding of the study is the cognitive gap identified due to the limited literature on AI maturity models in the context of Logistics 4.0. This gap demonstrates the novelty of the research and highlights the need for further studies in this area. By integrating AI maturity levels with Logistics 4.0 maturity models, Ellefsen et al. (2019) provide a valuable framework for understanding the relationship between logistics maturity and AI readiness. This integration is crucial for businesses aiming to leverage AI technologies to optimize their logistics operations.

However, the study has some limitations. While the case studies provide practical insights, the sample size is relatively small, and the focus on only two countries may limit the generalizability of the findings to other regions. Additionally, the study could benefit from a more detailed exploration of the specific challenges faced by SMEs compared to large organizations, as these challenges can significantly differ in scope and nature. More empirical validation across a wider range of logistics companies and geographic locations would strengthen the conclusions and enhance the applicability of the AI maturity model.

Sadiq et al. (2021) conducted a study on the AI Maturity Model specifically tailored for Communications Service Providers (CSPs). The study introduced four primary stages of AI maturity: AI Novice, AI Ready, AI Proficient, and AI Advanced. Alongside these stages, Ovum developed a corresponding evaluation model in collaboration with Amdocs. This model is designed to help CSPs assess their AI capabilities and limitations, providing a strategic roadmap for AI development and enhancement. A notable strength of Ovum's study is its clear categorization of AI maturity stages. The defined stages—AI Novice, AI Ready, AI Proficient, and AI Advanced—offer a straightforward and accessible framework for CSPs to evaluate their current AI positioning. This structured approach allows CSPs to identify where they stand in their AI journey and what steps are necessary to progress to higher levels of maturity. By offering a clear pathway for development, the model aids CSPs in systematically advancing their AI capabilities. The collaboration with Amdocs adds significant value to the study. Amdocs' expertise in the telecommunications industry provides practical insights and ensures that the model is grounded in real-world applications. This partnership enhances the model's credibility and relevance, making it a more reliable tool for CSPs. The practical applicability of the model is one of its key strengths, as it is designed to be used by CSPs to evaluate their AI capabilities comprehensively. One of the major contributions of this study is the development of a thorough evaluation mechanism. This mechanism allows CSPs to conduct a detailed assessment of their AI strengths and weaknesses. Such an evaluation is critical for strategic planning, as it enables CSPs to identify specific areas that require improvement and to allocate resources effectively. The ability to pinpoint both strengths and weaknesses provides a balanced perspective, facilitating more informed decision-making. However, the study has some limitations. While the model offers a structured evaluation framework, its effectiveness largely depends on the accuracy and comprehensiveness of the input data provided by the CSPs. Inaccurate self-assessment or incomplete data could lead to misleading evaluations, undermining the utility of the model. Additionally, the study does not elaborate on the specific criteria used to define each stage of AI maturity. A more detailed explanation of these criteria would enhance the model's transparency and usability. Another limitation is the study's focus on CSPs, which may restrict the generalizability of the findings to other industries. While the telecommunications sector has unique characteristics and challenges, the model may need adjustments to be applicable in different contexts. Broadening the scope of the study to include a wider range of industries could provide more comprehensive insights into AI maturity models.

Oracle (2020) conducted a study on the AI Data Science Maturity Model designed for enterprise assessment. The model delineates a set of dimensions crucial to data science, each having five maturity levels, where level 1 represents the least mature and level 5 the most advanced. The dimensions include strategy, roles, collaboration, methodology, data awareness, data access, scalability, asset management, tools, and deployment. This comprehensive framework allows enterprises to evaluate their maturity in various aspects of data science and strategize for further development. One significant strength of Oracle's study is its holistic approach. By covering a wide array of dimensions, the model ensures a thorough assessment of an enterprise's data science capabilities. This multi-dimensional perspective is critical for organizations looking to develop a well-rounded data science strategy. Each dimension represents a key aspect of data science implementation, from strategic planning and role definition to technical considerations like scalability and deployment. This broad scope makes the model highly versatile and applicable to various organisational contexts. The five-level maturity scale provides a clear and structured pathway for progression. This granularity allows organizations to pinpoint their current status and identify specific areas for improvement. The ability to exist on different levels in various dimensions acknowledges the complex and non-linear nature of data science maturity. This flexibility is a notable strength, as it accommodates the unique trajectories of different enterprises and encourages a tailored approach to development.

However, the model's complexity may pose challenges for some organizations. While the detailed dimensions and levels offer a comprehensive framework, they also require significant effort and expertise to assess accurately. Enterprises may need to invest in training or external consultancy to effectively utilize the model, which could be a barrier for smaller organizations with limited resources. Additionally, the model assumes a level of baseline competency in data science, which may not be present in all enterprises. Another potential limitation is the study's emphasis on creating a new Level 6. While this concept promotes continuous improvement and innovation, it may also create unrealistic expectations for some organizations. The pursuit of an ever-evolving maturity level could lead to resource strain and strategic misalignment if not managed carefully. Clear guidelines on when and how to aim for Level 6 would be beneficial to mitigate these risks. The study's focus on data science as a key competency shows its relevance in the modern enterprise system. As data science becomes increasingly integral to business success, frameworks like Oracle's maturity model are essential tools for strategic planning and capability development. However, the study could benefit from more empirical validation and real-world case studies to demonstrate the model's effectiveness and applicability across different industries.

Chen et al. (2021) embarked on research on AI maturity model for smart manufacturing. The research methodology used was a systematic review of studies on evaluating I-AI-related technologies to find pertinent measurable indicators for the maturity model and semi-structured interviews with professionals in the field to ascertain the model's maturity levels. The I-AI maturity model created in the study includes two primary dimensions, specifically "Industry" and "Artificial Intelligence," as well as 12 first-level indicators and 35 second-level indicators within these dimensions. The maturity stages are classified into five categories: planning level, specification level, integration level, optimisation level, and leading level.

Chen et al. (2021) undertook a study on developing an AI maturity model specifically tailored for smart manufacturing. The research methodology employed a systematic review of literature on evaluating industrial AI-related technologies and semi-structured interviews with professionals in the field. This dual approach aimed to identify relevant measurable indicators for the maturity model. The resultant model comprises two primary dimensions—Industry and Artificial Intelligence—along with 12 first-level indicators and 35 second-level indicators. The maturity stages are categorized into five levels: planning, specification, integration, optimization, and leading. A significant strength of this study lies in its comprehensive methodology. By combining a systematic literature review with semi-structured interviews, the researchers ensured that the model was both theoretically grounded and practically relevant. The literature review provided a robust foundation by identifying established indicators, while the interviews with industry professionals added practical insights and validated the relevance of these indicators in real-world settings. This methodological rigor enhances the model's credibility and applicability. The division of the model into two primary dimensions—Industry and Artificial Intelligence—along with 12 first-level indicators and 35 second-level indicators, is another notable strength. This detailed categorization allows for a nuanced assessment of maturity across various facets of smart manufacturing. It ensures that the model captures a broad spectrum of factors influencing AI implementation, from strategic planning and technological integration to optimization and industry leadership. This granularity facilitates a comprehensive evaluation of an organization's maturity and helps identify specific areas for improvement.

However, the complexity of the model could also be seen as a limitation. The extensive number of indicators and levels may pose challenges for organizations attempting to implement the model. Smaller firms or those with limited resources might find it difficult to gather and analyze the necessary data across all indicators. The model's complexity could necessitate significant time and expertise, potentially acting as a barrier to its widespread adoption. Another limitation is the potential for subjectivity in the interpretation of indicators and maturity levels. While the model provides a detailed framework, the semi-structured interviews that informed its development may introduce some degree of subjectivity. Different professionals might have varying interpretations of what constitutes a particular maturity level or indicator, leading to inconsistencies in assessment. Clear guidelines and standardized criteria for evaluating indicators would help mitigate this issue and enhance the model's reliability. The classification of maturity stages into five levels—planning, specification, integration, optimization, and leading—is a practical and intuitive approach. These stages offer a clear progression path that guides organizations from initial planning through to industry leadership. However, the study could benefit from providing more specific examples or case studies to illustrate how organizations can move between these stages. Real-world examples would make the model more tangible and provide practical insights into the challenges and best practices associated with each stage.

Saari et al. (2019) conducted a study on the AI Maturity Web Tool designed to assist organizations in assessing and advancing their AI maturity levels. The tool was developed based on research from the Finnish Digibarometer 2018, facilitated by Finland's Artificial Intelligence Accelerator and collaborated on by the VTT Technical Research Centre of Finland Ltd. (VTT) and the University of Oulu. It was launched in early 2019 as a free web-based resource for organizations to self-assess their AI maturity. One of the significant strengths of Saari et al.'s study is the practical utility of the AI Maturity Web Tool. By offering a free and accessible platform, the tool democratizes the assessment of AI maturity, making it available to organizations of varying sizes and sectors. This accessibility is crucial in promoting widespread adoption of AI technologies by enabling organizations to identify their current maturity level and plan accordingly for AI implementation and development.

The tool's foundation on research from the Finnish Digibarometer 2018 and collaboration with prominent research institutions like VTT and the University of Oulu enhances its credibility. The use of empirical data and expert input ensures that the tool is grounded in robust research findings and reflects current trends and best practices in AI maturity assessment. This scholarly foundation increases the tool's reliability and relevance to organizations seeking to leverage AI effectively. Furthermore, the tool's capability for maturity comparison across organizations is a valuable feature. By allowing organizations to benchmark their AI maturity against others, both locally and globally, the tool promotes a competitive and collaborative environment. This comparative aspect encourages organizations to strive for continuous improvement in their AI capabilities and fosters knowledge sharing within and across industries.

However, the study could benefit from more detailed information on the specific metrics or dimensions used in the AI maturity assessment. While the tool is described as comprehensive, a clearer outline of the criteria and indicators used to evaluate AI maturity would enhance transparency and facilitate more informed assessments by organizations. Providing examples or case studies of organizations that have benefited from using the tool would also illustrate its practical impact and effectiveness. Another potential limitation is the tool's reliance on self-assessment. Organizations may vary in their ability to accurately self-assess their AI maturity, potentially leading to biased or inflated results. Clear guidelines or validation mechanisms within the tool could help mitigate this issue by ensuring more objective assessments.

Gentsch (2018) explores AI Business: Framework and Maturity Model in her book, focusing on how marketers, even without a data science background, can effectively utilize AI, Big Data, and bots in business contexts. The study systematically connects AI technologies with explicit business strategies, offering insights into various applications and benefits across different sectors. One of the strengths of Gentsch's study lies in its practical orientation towards entrepreneurs and marketers. By emphasizing real-world applications and case studies, the book bridges the gap between theoretical AI concepts and their implementation in business settings. This approach makes complex AI technologies accessible and actionable for professionals who may not have technical expertise in data science, thereby promoting broader adoption and integration of AI solutions.

The inclusion of interviews and case studies from leading organizations and executives enhances the study's credibility and relevance. These firsthand accounts provide valuable insights into how AI, Big Data, and bots are currently being leveraged to optimize media planning, improve customer communications through chatbots and virtual assistants, enhance customer journeys, and conduct market research more effectively. Such practical examples illustrate the transformative potential of AI technologies in driving business innovation and competitive advantage. Moreover, Gentsch's focus on strategic optimization and automation of business processes underscores the pragmatic benefits of AI adoption. By highlighting specific strategies for leveraging AI and Big Data to enhance consumer insights, market profiling, and customer engagement, the study offers actionable guidance for businesses seeking to capitalize on these technologies. This strategic perspective is crucial for aligning AI initiatives with overarching business goals and maximizing return on investment.

However, one potential limitation of the study may be its emphasis on success stories and cutting-edge applications without sufficiently addressing implementation challenges or potential pitfalls. While showcasing exemplary cases is inspiring, a more balanced discussion of the practical barriers, ethical considerations, and organisational readiness required for successful AI adoption would provide a more comprehensive view. Addressing these aspects would help prepare businesses for the complexities and uncertainties associated with integrating AI into their operations.

AI maturity models frequently adopt a static approach, indicating that organisations go through phases and eventually arrive at a steady state (Lichtenthaler, 2020; Alsheiabni et al., 2019; Chen et al., 2021; Oracle, 2020). Nevertheless, AI implementation is an iterative procedure that necessitates continual learning, adaptation, and advancement. Companies should be urged to experiment, learn from their mistakes, and adjust their strategy as needed.

From the reviewed studies, the complex nature of AI adoption is sometimes oversimplified by AI maturity models. They often proceed in a linear fashion, presuming that organisations develop from one stage to the next in a logical manner. The real-life scenario of AI implementation, on the other hand, is significantly more intricate, with many dependencies, obstacles, and iterations. Also, numerous AI maturity models fail to take into account the contextual context and industry-specific elements that drive AI adoption. Companies in various industries have varied needs, challenges, and regulatory contexts. A one-size-fits-all solution might not be appropriate for many enterprises, resulting in misalignment and restricted adaptability. Likewise, current AI maturity models emphasise the technical components of AI deployment, such as data infrastructure, algorithms, and models. While technology is clearly crucial, failing to consider other critical variables such as company culture, people management, and ethical considerations could impede AI adoption.

According to Sadiq et al. (2021), a number of research conducted to develop AIMM are identified as Generic AIMM, these generic maturity models do not apprehend the necessary elements that would be captured in a domain specific AIMM. Although most of these AIMM cover generic elements transferable to the construction industry, these do not consider that construction firms are project-based organisations neither does it consider complexities like how construction firms are subjected to margin erosion on projects or that the construction firms have low investment income index. Another key area is in the plant and equipment used for construction. Table 3.3 analyses the different existing AI maturity models within different domains to determine if the current process and complexities are addressed and can be adopted in the development of AI-maturity model in construction projects. Table 3.3. examines various maturity models, focusing on their maturity levels, domain, key process areas, consideration of organisational and people processes, data from external sources and gap analysis of the interconnection of capabilities specific to the business areas.

In summary, the existing studies on Artificial Intelligence Maturity Models (AIMM) in various domains, including construction, have made significant contributions to understanding the progression of AI adoption within organisations. However, several research gaps and challenges in the current body of literature can be identified. While some AIMMs are considered generic and applicable across industries, they may lack specific elements crucial for the unique characteristics of the construction industry. Construction firms operate as project-based organisations, facing challenges such as margin erosion and significant reliance on plant and equipment. There is a need for AIMMs that are tailored to the specific dynamics of the construction sector, considering its project-oriented nature, financial intricacies, and reliance on specialized equipment. Additionally, the complexities inherent in construction projects, such as the temporary and unique nature of each project, interaction with multiple stakeholders, and substantial resource involvement, are not comprehensively addressed by existing AIMMs. AIMMs need to account for the dynamic and ever-changing nature of construction projects, incorporating factors like stakeholder collaboration, resource management, and adaptability to project-specific challenges.

Furthermore, many existing AIMMs adopt a one-size-fits-all approach, overlooking the contextual context and industry-specific elements that influence AI adoption. Construction firms have diverse needs, regulatory contexts, and challenges, which are often not adequately considered in current AIMMs. There is a need to focus on developing AIMMs that are adaptable to the unique requirements of different industries, including construction, considering factors such as regulatory constraints, project variability, and industry-specific challenges. Besides, current AIMMs often emphasise the technical components of AI deployment, such as data infrastructure, algorithms, and models. However, they may neglect other critical factors, including company culture, people management, and ethical considerations, which are integral to successful AI adoption. Many AIMMs adopt a static approach and assume a linear progression from one maturity level to the next. However, the iterative and evolving nature of AI implementation, which requires continual learning, experimentation, and adaptation, is not sufficiently addressed. There is a need to explore models that better capture the dynamic nature of AI implementation that allows organisations to iterate, learn from mistakes, and continually adjust their strategies as the technology evolves.

Table 3.3: Review of Artificial Intelligence Maturity Model

S/N	Models	Author	Maturity Level	Key Process Area / Domains
1	Gartners AI maturity Model	Lichtenthaler, 2020	Five levels (5)	Not Specified
2	AI- Maturity Model: AI readiness at Firm level	Alsheiabni et al., 2019	Five levels (5)	AI functions, Data structure, People and organisation
3	AIMM for CSPs: Ovum AI maturity model	Ovum, 2018	Four Levels (4)	Strategy, Organisation, Data, Technology and operations
4	AI Data Science Maturity Model for enterprise assessment	Oracle, 2020	Five levels (5)	Strategy, roles, collaboration, methodology, data awareness, data access, scalability, assessment management, tools and deployment.
5	AIMM for logistics 4.0	Ellefsen et al., 2019	Four levels (4)	Strategy, organisation, Data, Technology and operations
6	Machine Learning Maturity Model	Algorithmia Research, 2019	Three levels (3)	Data, training, deployment and Management
7	AI maturity model for smart manufacturing	Chen et al., 2021	Five Levels (5)	Smart data acquisition, Big data quality, smart data analysis, smart decision making, big data security,

				big data management, smart cloud storage, AI dimension
8	AI Maturity Web Tool Helps Organisations Proceed with AI	Saari et al., 2019	Five levels (5)	Strategy and management, products and services, competencies and cooperation, process, data and technology
9	Striving for excellence in ai implementation: Ai maturity model framework and preliminary research results	Ellefsen et al., 2019	Four levels (4)	Not Specified
10	MHC AI maturity model	MHC, 2021	Four levels (4)	AI organisational knowledge and culture, AI strategy and initiatives, data management, AI deployment capabilities and AI risk management
11	Artificial Intelligence Maturity Model: Business	Gentsch 2018	Four levels (4)	Strategy, Data, Analytics, people and decisions

12	AIMM for organisation	Sadiq et al, 2021	Not specified	Data, Analytics, Technology and tools, intelligent automation, governance, people and organisation
13	Multidimensional data- driven artificial intelligence innovation	Yablonsky, 2019	Five Levels (5)	Who produce insight, who decide and how, who acts based on, AA
14	AI Ethics Maturity Model	Krijger et al., 2023	Five Levels (5)	Awareness and culture, Policy, Governance, Communication and training, Development process and Tooling
15	AI Smart Production Planning and Control System Maturity Model	Colangelo et al., 2022	Five Levels (5)	Data, Organisation, General Conditions, Technology, PPC (Production, Planning and Control)
16	AI Maturity Model for Government Administration and Service	Noymanee et al., 2022	Five Levels (5)	Strategic, Organisation, Information and Technology
17	AI Maturity Model for Management Organisations	Fukas, 2022	Five Levels (5)	Technology, Data, People and Competences, Organisations and Processes, Strategy and Management, Budget, Products

				and Services, Ethics and Regulations

In a general view of complex organisations such the construction sector, the business process/strategy, organisational culture, people, and data are noted as the primary key process areas. However, as shown in Table 3.3, AI critical success factors identified are AI functions, Data structure, AI strategy management, policy management, technology, organisational structure, people management, operations, AI deployment capabilities and management and also AI ethics and risk management as common themes of key process areas in artificial intelligence.

3.10 Benchmarking Concept in Maturity Model Development

From another conceptual view, maturity models are tools that enable organisations to achieve superior performance by applying themselves through a set of best practices derived from numerous successful previous implementations (Demir & Kocabaş, 2010). This method of drawing out best practices from previous implementations is called benchmarking. Benchmarking is a known catalyst for performance improvement such that Ajelabi and Tang (2010) attest to benchmarking being "an efficient tool" for a performance boost. The concept of benchmarking in maturity models serves as a comparative tool used in most to access and measure growth, performance and drive a competitive advantage between similar organisations. Numerous studies have adopted benchmarking concept to allow evaluation and comparison of standards between similar organisations (Braun, 2015; Simatupang and Sridharan, 2004). Despite the various classification of maturity models, the overall idea behind MM is to benchmark competencies and set a clear path for development, it is appropriate to say that the benchmarking approach suits all maturity models.

The primary benchmarking concept behind a maturity model consists of numerous significant components that is distinct amongst maturity models. The standard framework, in accordance with Braun (2015), establishes a connection between the objectives, assessment, and standard procedures. By making sure they are pertinent to the aims and objectives of the organisation, which also strengthens the connection between the existing maturity model capabilities and the improvement roadmaps. The major components of a maturity model are:

1. Maturity Levels: Maturity models are developed through the progression from one level, stage, or maturity score to the subsequent level. The aforementioned stages serve to illustrate and explicate the current state of an entity's maturity, encompassing a comprehensive evaluation of each level's description and corresponding significance. Each level of analysis

offers a representation of the attributes and the means by which they are achieved. Each level is also accompanied with a descriptive. The progressive stage in question offers unique functionalities at each stage, thereby offering a precise evaluation of the condition of an entity, accompanied by clear guidance on advancing to the next stage. For instance, the Capability Maturity Model (CMM) encompasses descriptors that pertain to several stages of process maturity, namely initial, repeatable, specified, managed, and optimising processes.

2. Dimensions: The objective of a maturity model is to assess the condition of an entity from different perspectives and provide an improvement roadmap. Dimensions which are also termed themes or domains in some maturity models (Niazi et al., 2005; Williams et al., 2016; Ronaghi, 2021) derived from the identification of key process areas to be measured using maturity assessment criteria. These dimensions are categorised by noticeable different key functions within the entity i.e., organisation which impacts the general state of the organisation. For example, the Capability Maturity Model Integration (CMMI) identified 22 process areas for both CMMI for development v1.3 and CMMI for Acquisition v1.3, and 24 process areas were identified for CMMI for services (CMMI Product Team, 2010; Phillips and Shrum, 2010; Farid et al., 2016).

3. Key Benchmarking Process Areas: This is a set of attributes that describe the characteristics for each of the dimensions specified in the model. The primary benchmarking process areas are referred to as the maturity model's goals or scope, which clarifies the intent of each dimension. According to Crowston and Qin (2011), this is a set of Key Process Indicators (KPIs) aligned to each dimension area that helps organisations in evaluating and monitoring the performance of their improvement roadmaps.

4. Improvement Roadmaps: This outlines a process recommendation guideline, or a maturity path used as an improvement guide for the model. This includes a guide on how to execute long-term improvements, as well as a roadmap approach for progressing from one maturity level or stage to the next. As a result, ensuring that the goals specified in the maturity process include comprehensive guidelines or recommendations on how to proceed from one level to the next.

5. Maturity Assessment Framework: This can be achieved by taking advantage of many different strategies, such as the application of a numeric value-maturity score, a maturity matrix, maturity grid or an assessment framework. The tool is employed for the purpose of assessing and evaluating an entity's maturity level across many dimensions, with the aim of identifying possible trends. This enables the development of evaluation inquiries and boosts the depth of the maturity results.

Based on the aforementioned, other prevalent characteristics employed for the purpose of identifying maturity models appropriate for benchmarking processes have been identified. These characteristics encompass the taxonomy of the maturity model, including CMMI, BPMM, BIMM, and DSCMM, as referenced by Paulk et al. (1993), Lahrmann et al. (2011), and Gökalp et al. (2022). The primary focus of the model can be categorised as either a general maturity model or a domain-specific maturity model (Brooks et al., 2015; Canetta et al., 2018). The entities encompassed within the model consist of people, processes, and technology (Mettler, 2011; Ifenthaler and Egloffstein, 2020). The stakeholders involved in the model include academia, government, and organisations (Kreiling and Bounfour, 2020). The model's domain focus can be directed towards technology, processes, or organisations (Liang et al., 2016; Comuzzi and Patel, 2016). The target of the model is determined by Huang and Tilley (2003) and Wißotzki and Koç (2013). The structure of the model can take the form of a Capability Maturity Model (CMM)-like approach, Likert-like questionnaires, or a stage growth model (Burnstein et al., 1996; Wendler, 2012; Paulzen et al., 2022). The Model Flow may be categorised as either a fixed or continuous model, as discussed by Battista et al. (2012) and Lasrado et al. (2015). Additionally, the purpose of using the Model Flow can be classified as prescriptive, descriptive, or comparative maturity model, as explored by Becker et al. (2010), Pöppelbuß and Röglinger (2011), and Canetta et al. (2018).

Hence, the examination of strategies employed in the development of maturity models is crucial in order to guarantee the development of a viable Artificial Intelligence Maturity Model (AIMM) that takes its form of a roadmap. This roadmap aspires to encourage the adoption of AI (AI) and its applications into the construction sector. This industry has shown a lethargic adoption of groundbreaking and transformative technologies, mostly due to the construction sector's inherent challenges and the failure to capitalise on potential AI- implementation opportunities. Hence, it is crucial to acknowledge that evaluating the effectiveness of AI maturity models through the application of basic and major maturity model methodologies presents a means to evaluate the tools and the construction domain. This assessment aids in identifying the most ideal strategy to instigate change and promote the adoption of AI within the construction industry.

Given the above, the following analysis involved a comparison of the different maturity model development strategies utilised in five recent publications on the Artificial Intelligence Maturity Model (AIMM) across various industries due to the infancy stage of the development of AI maturity models. The comparison was undertaken through an assessment of the primary components involved in the development of maturity models. This approach was employed to obtain a comprehensive perspective of AI maturity models for benchmarking pu

Table 3.4: Benchmarking Review of Artificial Intelligence (AI) Maturity Models

Maturity Model Benchmarking Concept	**Assessing the maturity of AI implementation in Production Planning and Control (PPC) systems within manufacturing companies.**	**Assessing and improving AI maturity in organisations**	**Assessing the maturity of AI implementation**	**Assessing the adoption and diffusion of AI in auditing, with a focus on audit-specific requirements**	**Assessing the development and application of AI-related technologies in smart manufacturing**
Maturity Model Name	Maturity Model for AI in smart production planning and control systems.	Artificial Intelligence Maturity Model (AIMM)	Maturity Model Artificial Intelligence 4.0	Auditing Artificial Intelligence Maturity Model (A-AIMM)	Industrial Artificial Intelligence (I-AI) Maturity Model
Focus of the Model	Domain Specific	General AIMM	General AIMM	Domain Specific	Domain Specific
Entity of the Model	Organisations within the context of PPC in manufacturing companies.	Organisations across various industries	Organisations across various industries	Audit firms	Manufacturing firms
Stakeholder	Manufacturing companies looking to implement AI in their PPC systems.	Organisations, researchers, and practitioners	Researchers, AI practitioners, and company executives	Researchers, audit professionals, and audit firms	Researchers, manufacturing professionals, and decision-makers
Domain Focus (Unit of analysis)	Production Planning and Control (PPC) within manufacturing companies.	Artificial Intelligence (AI)	Artificial intelligence, logistics, Industry 4.0	Auditing and adoption of AI in auditing	Smart manufacturing and AI development

Target of the Model (Audience)	Manufacturing companies interested in assessing their AI maturity in PPC, researchers, and consultants in the field of AI and PPC.	Organisations looking to assess and enhance their AI capabilities	Companies looking to implement AI, and researchers	Audit firms, auditors, and researchers	Manufacturing firms, decision-makers, researchers
Respondents	Manufacturing companies	Professionals and experts involved in process improvement within an organisation.	Middle management professionals in companies	Audit experts	Domain experts
Structure of the Model	Five maturity levels, 18 dimensions, and specific requirements for each level	Typically, bottom-up design approach with various dimensions	Five core pillars: strategy, organisation, data, technology, and operations	Eight different dimensions and five different maturity levels	Two main dimensions: "Industry" and "Artificial Intelligence," 12 first-level indicators, 35 second-level indicators, and five maturity levels
Model Flow	Progressing through the five maturity levels, with each level representing a stage of increasing AI integration and capability in PPC. It starts with the initialization phase and ends with the optimisation phase.	Organisations progress through maturity levels by implementing AIMM best practices and achieving higher levels of process maturity.	Assessing current AI maturity, identifying readiness levels, potential improvement roadmaps	Assessing the adoption and diffusion of AI in auditing, providing recommendations based on audit-specific requirements	Assessing AI-related technology capabilities, guiding smart manufacturing improvement
Purpose of use	To help manufacturing companies understand their current AI maturity in PPC, identify areas for improvement, and create a roadmap for AI implementation in PPC.	To evaluate and enhance AI capabilities within organisations	Evaluating the maturity of AI in logistics and its readiness for implementation, guiding companies in AI adoption	Benchmarking AI adoption in audit firms, guiding them in integrating AI technologies	Benchmarking AI development in manufacturing, guiding improvement strategies

Maturity levels	five maturity levels: Initialization phase, Definition phase, Preparation phase, Implementation phase, and Optimisation phase.	Typically includes five levels of maturity	AI Novice, AI Ready	Five maturity levels	Five maturity levels
Improvement Roadmaps	Each maturity level represents a step towards achieving full AI integration and capability in PPC. The requirements for each level serve as guidelines for creating these roadmaps.	Each level provides guidance on the implementation of AIMM processes.	Assessing the readiness and suggesting steps for improvement	Recommendations for audit firms to enhance AI adoption	provides guidance on improving AI-related technology capabilities
Dimensions	There are 18 dimensions in the model, categorized into five categories: Framework conditions, Data, PPC understanding, Technology, and Organisation.	Data, Analytics, Technology and Tools, Intelligent Automation, Governance, People, and Organisation	Technology readiness, strategy, organisation, data handling, and operations	Eight dimensions, including Ethics & Regulations, among others	Two dimensions, including "Industry" and "Artificial Intelligence"
Key Benchmarking Process Areas	The key benchmarking process areas in this context would be the stages of AI implementation and integration in PPC, as defined by the five maturity levels. These stages represent key milestones and benchmarks for assessing an organisation's progress in adopting AI in PPC.	AI capability, maturity assessment	Logistics 4.0 readiness, AI maturity assessment	AI adoption and diffusion in the auditing sector	AI development and integration in smart manufacturing
Maturity Assessment Framework	Evaluating where a manufacturing company stands in terms of AI implementation in PPC, based on the five maturity levels and their associated requirements.	Assessing AI maturity within organisations	Assessing AI maturity levels within companies	Assessing AI maturity levels within audit firms	Assessing AI maturity levels within manufacturing firms

The five maturity models outlined in Table 3.4 serve a specific purpose in assessing and improving AI maturity, but they vary in terms of their focus, target audience, structure, and domain of application. The "Maturity Model for AI in Smart Production Planning and Control Systems" concentrates on evaluating AI maturity in the context of Production Planning and Control (PPC) within manufacturing companies. It provides a detailed framework for organisations in this specific domain. The "Artificial Intelligence Maturity Model (AIMM)" has a broader focus, as it aims to assess and enhance AI maturity across various industries. It offers a more generalized approach to AI maturity assessment. The "Maturity Model Artificial Intelligence 4.0" extends its focus to AI in logistics and Industry 4.0. It evaluates AI maturity in a wider context related to industrial processes. On the other hand, the "Auditing Artificial Intelligence Maturity Model (A-AIMM)" zooms in on the adoption and diffusion of AI in auditing, addressing audit-specific requirements and practices. Lastly, the "Industrial Artificial Intelligence (I-AI) Maturity Model" is centred around AI development and application in smart manufacturing organisations, concentrating on the manufacturing industry.

The target audience for the five models varies. The PPC-focused model is primarily for manufacturing companies, while AIMM is designed for organisations across industries. AI 4.0 aims at companies implementing AI, and A-AIMM is meant for audit firms. Conversely, I-AI focuses on manufacturing firms and decision-makers. The stakeholders for the five models include manufacturing professionals, consultants, researchers, AI practitioners, audit professionals, and decision-makers, depending on the specific model.

With regards to focus, the models differ in their domain of focus. While the PPC model narrows down to PPC processes in manufacturing, AIMM looks at AI in general. AI 4.0 focuses on AI, logistics, and Industry 4.0, A-AIMM specializes in AI adoption in auditing, and I-AI centres on smart manufacturing and AI development. In terms of structure and framework, the models have distinct structures. The PPC model uses five maturity levels and 18 dimensions. AIMM takes a bottom-up approach with various dimensions. AI 4.0 relies on five core pillars: strategy, organisation, data, technology, and operations. A-AIMM uses eight dimensions and five maturity levels, while I-AI incorporates two dimensions, 12 first-level indicators, 35 second-level indicators, and five maturity levels.

These five models involve a flow or process for assessing and improving AI maturity, typically involving progress through maturity levels or dimensions. However, the specifics of this flow and the criteria for assessment vary based on the model's objectives. The purpose of each model is unique.

The PPC model helps manufacturing companies understand their AI maturity in PPC and create roadmaps for implementation. AIMM aims to evaluate and enhance AI capabilities in organisations. AI 4.0 assesses AI maturity in logistics and guides AI adoption. A-AIMM benchmarks AI adoption in audit firms. I-AI benchmarks AI development in smart manufacturing and guides improvement strategies.

Similarly, all models incorporate multiple maturity levels to gauge AI maturity, although the number of levels and their definitions may differ. Each model provides guidance or requirements for organisations to create improvement roadmaps based on their current AI maturity levels. The models use different sets of dimensions and benchmarking process areas to assess AI maturity, reflecting their specific focus areas and domains. In conclusion, the five maturity models offer valuable tools for organisations looking to assess and improve their AI maturity. The choice of which model to use should align with an organisation's goals and specific AI-related needs.

3.11 Conceptual framework for developing Artificial Intelligence (AIMM) for UK Construction Sector Organisations

The AIMM framework, based on the work of Peffers et al. (2007), is a structured approach tailored for the construction industry to evaluate and enhance the maturity of artificial intelligence (AI) adoption. It encompasses seven key components, each representing a critical stage in the journey towards AI integration within construction organisations.

Problem Identification and Motivation: The initial step involves recognising the unique challenges and issues within the construction sector that AI can potentially address. It's crucial to clearly articulate the motivation for adopting AI technologies, as this sets the foundation for the entire process.

Objectives of a Solution: Once the challenges are identified, the model emphasises the importance of defining clear and specific objectives for the AI solution. These objectives serve as guiding principles throughout the AI development and implementation phases.

Design and Development: This phase focuses on the technical aspect of AI implementation. It entails designing the AI systems, developing the necessary technology infrastructure, and creating the associated processes. It's where the theoretical plans start taking tangible shape.

Demonstration: Demonstrating the AI solution is a pivotal step to gain stakeholder buy-in and ensure that the technology aligns with the predefined objectives. It acts as a proof-of-concept and allows for early feedback and improvements.

Evaluation: To measure the success of AI adoption, organisations must rigorously evaluate the implemented solution against the set objectives. This step involves performance assessments and gathering feedback from various stakeholders.

Communication: Effective communication is critical throughout the AI maturity journey. This involves sharing the results of the evaluation with stakeholders and promoting awareness within the construction industry and government agencies.

The Peffers framework was chosen as the framework of the AIMM model because it offers a robust foundation for creating an AI maturity model for the UK construction sector. Its holistic approach, problem-centric focus, clear objective setting, consideration of technical development, stakeholder buy-in through demonstration, rigorous evaluation, and emphasis on effective communication collectively make it well-suited for addressing the complexities and challenges associated with AI adoption in construction.

The framework also introduces the concept of Maturity Levels, drawn from the Capability Maturity Model (CMM). These five levels, ranging from Initial to Optimised, help organisations gauge their progress in AI adoption and identify areas for improvement. This approach aligns with the structured approach commonly found in maturity models. More so, the AIMM framework is domain-specific; it tailored explicitly for the construction sector. It recognises that AI adoption is not solely a technological endeavour but encompasses people, processes, and technology within organisations. Moreover, it identifies the key stakeholders as the construction industry itself and the UK Government; this indicates a broader societal impact.

Furthermore, the target audience for this model is construction practitioners and government entities. This underlines its practical applicability and relevance in the construction industry. Its CMM-like structure implies a staged approach to AI maturity, with organisations progressing through levels as they enhance their AI capabilities. The continuous model flow highlights that AI maturity is an ongoing journey rather than a one-time project. It also serves both prescriptive and descriptive purposes, offering guidelines for improvement while providing insights into the current state of AI maturity.

The AIMM framework's foundation (Fig 3.4) is based on critical success factors derived from literature and confirmed by experts in the field, making it a robust and informed model. Additionally, it outlines key benchmarking process areas, aligning with industry standards for performance assessment.

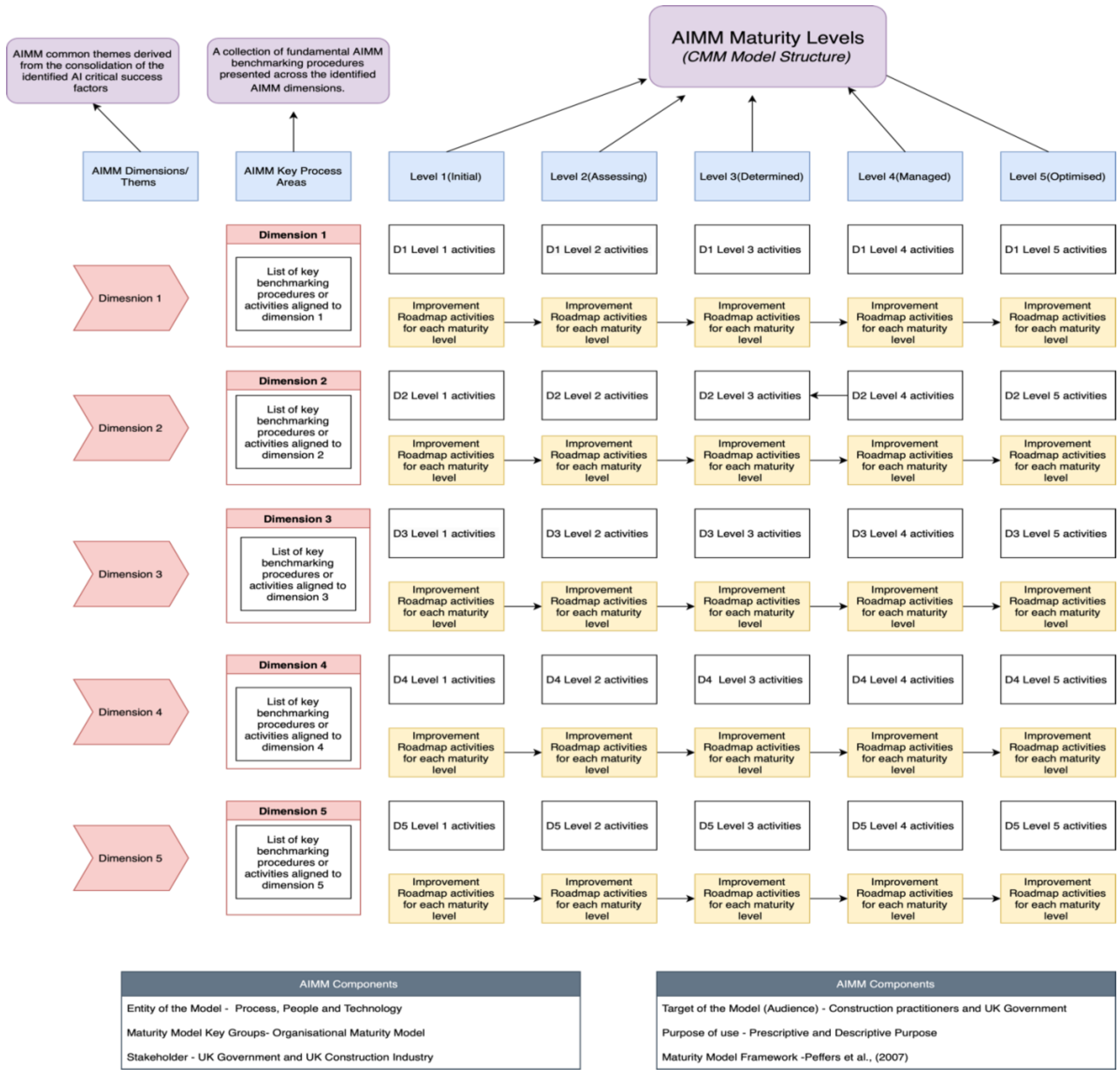


Figure 3.5: Conceptual Framework of an AI- Maturity Mode

Chapter Summary

This chapter explored the history and many concepts of maturity models, as well as recognising the crucial role of domains in the maturity model's application. Section 3.2. examined the various characteristics of maturity models in greater detail, including stage-based arrangements, the evaluation and design structure of maturity models, subdomains/domains used in the evaluation of maturity models, and the series of activities used to classify each maturity level. Additionally, the various methodologies to constructing a maturity model were discussed, including descriptive, prescriptive, and comparative application lifecycle models. Whereas the challenges and criticisms associated with the maturity model were widely examined. Section 3.5 focused on reviewing existing maturity models in construction, while Section 3.6 conducted a review of the AI maturity model and the current state of the literature, highlighting a number of AI maturity models and their associated domains that are currently being used in studies and organisations. Additional investigation was undertaken to evaluate the criticism of the identified AI maturity models and their contextual implications. Finally, a conceptual framework for constructing a domain specific AIMM with applicability to the UK construction sector was developed using the identified critical success factors for AI implementation in construction.

4 CHAPTER FOUR: THEORETICAL UNDERPINNING OF THE STUDY

Chapter Overview

The term "theory" refers to a collection of explanations that link a set of facts together (Leedy & Ormond, 2005). Theories are crucial in determining the primary drivers and outcomes of social science research, with theories serving as the foundation for all types of study. According to Jonassen (2000), the benefits of theories in resolving the "why" issue in research differ. Thus, theory may be utilised in certain instances to explain away the existence of common sense in research and to develop a cohesive framework around an idea. Indeed, some academics have proposed that ideas developed in one discipline may be impacted by theories developed in other subject areas. The above argument demonstrates that when an area of study lacks proper theory, relevant ideas from adjacent or complementary disciplines can be merged to better understand the behaviours seen in that field.

Given the above, a prominent and open criticism levelled towards maturity models is that the majority of the elements used to develop them are sourced from guiding principles rather than proven theory (Mettler, 2011). This argument casts doubt on the models' credibility, as it indicates that organisations are not assured of the widely promoted growth improvement and related use of the maturity model. As such, this section reviews pertinent theories, identifies specific theories, and assesses their relevance to the PhD research's philosophical and methodological stance. Numerous relevant theories were evaluated to the maturity model framework and processes, including stage theory, lifecycle process theory, and capability maturity model. This section, however, outlines specific concepts that are directly relevant to the philosophical perspective taken in developing an Artificial Intelligence Maturity model. Thus, the following theories are discussed in this chapter:

- Stage-based theory
- Diffusion of Innovation theory
- Decision theory
- Core competency theory and
- Technology acceptance model
- Technological-organisational-environmental (TOE) framework

These theories influenced this PhD research study which exemplified the study's assumptions and identified the application area. A detailed explanation of these theories will be discussed in the succeeding sub-headings.

4.1 Review of Relevant AIMM Theories

Artificial intelligence is a key technology that is employed in a wide number of sectors. However, its use in these sectors is still in its infancy. The objective of AIMM is to examine the current status of AI and to enhance quality in a variety of industries. As a result, this study's objective is to gather and analyse data on recent publications on the issue. The bulk of AIMM research aim is focused on the development of maturity models, followed by validations. This perspective appears to be consistent with findings from several maturity model domain evaluations (Wendler, 2012). It is a reaction to the dissatisfaction with current methods as reflected in extant literature. On the other hand, theoretical considerations of the maturity model concept are essentially lacking, as suggested by (Wendler, 2012). Hence, a theoretical basis is essential to build an acceptable and ready-to-use maturity model for practise that is also valuable to other researchers. This leads to the conclusion that this topic necessitates further investigation, particularly considering the paucity of evidence in comparison to other areas' historical publications on maturity models. Therefore, relevant theories are examined in the following subsections to identify specific use of theories relevant to the development of an AIMM in construction.

4.1.1 Diffusion of Innovation

The diffusion of innovation theory was developed by E.M. Rogers, a professor of communication studies in 1962. It was adjudged to be one of the oldest social science theories. This theory explains why, how and at what rate new technology and ideas spread (Miller, 2015). It also describes the pattern and speed at which new ideas, products practices spread through a population. Rogers further argued that diffusion is the process by which an innovation is communicated over a period of time in a social system. According to Rogers and Williams (1983), there are five main elements influencing the spread of new ideas. These elements are the innovation, the adopters, communication channels, time and social system. These elements are vital in enhancing information system or information communication technology and foster organisational development (Greenhalgh et al., 2004).

The diffusion of innovation curve from innovators to the late majority (Baker, 2017) is used to investigate factors affecting the speed with which new products are introduced. (A collection of) interdependent groups Factors that influence diffusion speed, lowering financial uncertainty and shortening the time to value creation, are referred to as "game-changing" variables. The trajectory of innovation from inspiration to market saturation is described by the diffusion of innovation curve. It is made up of "innovators," "early adopters," "early majority," "late majority," and "laggards" user roles. In most cases, the job of the invention is overlooked.

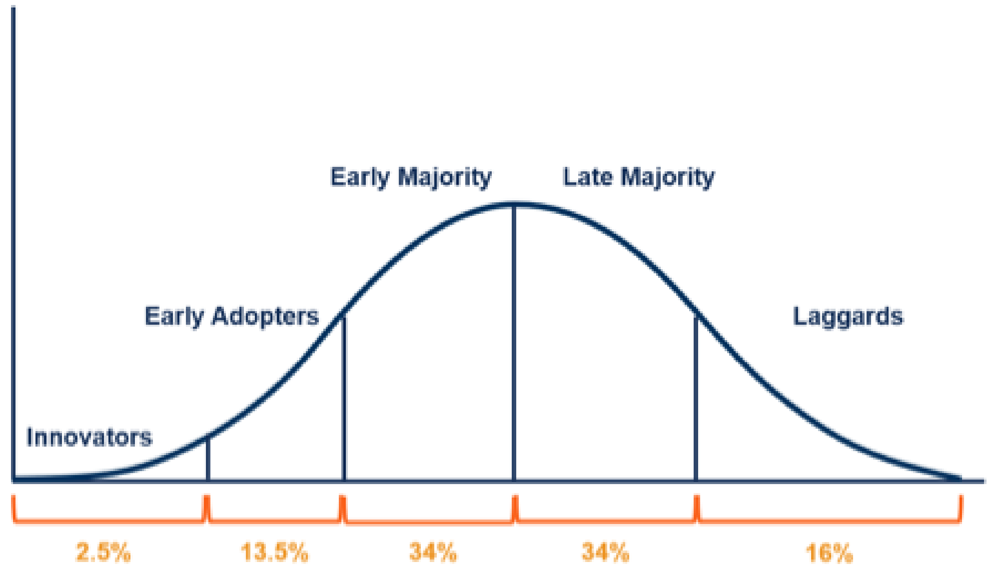


Figure 4.1: Distribution of adopter innovativeness based on time of adoption.

Innovators are enthusiastic users who enjoy experimenting and frequent work with inventors. Innovators account for about 2% of the total market share. Early adopter users are usually (in-)formal opinion leaders who act as influencers by sharing product success stories. They are less interested in experimenting than innovators and are more concerned with efficiency and improvements. Because they are open to change, engaging with innovators involves no effort. Early adopters account for 14% of the overall market share. Early majority adopters are sincere followers who are open to change through innovation, but they need confirmation from their user peers who have gone before them. The early majority adopters account for 34% of the total market share. Late majority adopters are generally uninterested in change and only adopt innovations if they have a strong sense that they must be a part of mainstream changes. The late majority adopters account for 34% of the entire market share. Laggard adopters want substantial evidence of change benefits before adopting them carefully. Laggard adopters account for about 16% of the entire market.

In construction industry, maturity models such as the Capability Maturity Model Integration (CMMI) are commonly used to analyse an organisation's or system's ability to improve continuously (Boushey, 2016). This "spread use" is thought to correspond to diffusion's late majority stage. Late adopters benefit from maturity models because they provide a simple starting point for an assessment that takes into account earlier experiences and is based on common language and shared visions. The models allow for easy entry into prioritisation activities and a shared understanding of what this means within an organisation or system, as well as the definition of relevant performance indicators for learning and control, which is then driven by culture and behaviour, making adoption easier and faster.

4.1.1.2 Relevance of Diffusion of Innovation Theory to AIMM

The Diffusion of Innovation theory is a foundational framework ideal for understanding how new technologies permeate societies (Kaminski, 2020). It delineates the innovation adoption process into distinct phases—innovators, early adopters, early majority, late majority, and laggards. This well-established theory provides valuable insights for the development of the Artificial Intelligence Maturity Model (AIMM) by offering a thorough understanding of the progressive stages of technology adoption, particularly mirroring the AI implementation within the construction industry. One of the key pillars of the Diffusion of Innovation theory is its classification of adopters into specific categories based on their readiness to embrace new technologies (Aizstrauta et al., 2015). Innovators, constituting approximately 2% of the market, are characterised by their enthusiasm for experimentation and collaboration with inventors (Rogers and Williams, 1983). Early adopters, forming 14% of the market, are influential opinion leaders who share success stories, acting as early influencers (Rogers and Williams, 1983). This categorisation aligns seamlessly with the multifaceted nature of AI implementation in the construction sector. The construction industry, akin to other sectors, witnesses a phased adoption of AI technologies. Early innovators explore and experiment with novel AI applications, setting the stage for subsequent adoption phases. Early adopters contribute to the dissemination of successful AI implementations, gradually paving the way for the early majority. This pattern continues until the late majority and laggards, who adopt AI technologies as they become more established and essential. The theory's delineation of adopter categories is thus instrumental in comprehending the dynamics of AI integration within the construction landscape (Rogers and Williams, 1983).

The Diffusion of Innovation theory's emphasis on adopter categories is particularly pertinent when examining the stakeholder dynamics within the construction industry. Innovators and early adopters, representative of the initial stages, often correspond to forward-thinking organisations or professionals at the forefront of AI integration. As the technology matures, the industry witnesses a transition towards the early and late majority, symbolising a broader acceptance and assimilation of

AI technologies. The late majority and laggards, reluctant to change without substantial evidence of benefits, align with the later stages of AI adoption. AIMM, as a model seeking to evaluate AI maturity, can draw from this understanding to tailor assessments, recommendations, and resources for organisations positioned in the late majority and laggards' stages. This tailored approach ensures that the model addresses the specific concerns and challenges faced by these adopter categories (Rogers and Williams, 1983).

The application of the Diffusion of Innovation theory in AIMM development extends beyond theoretical alignment. The assessment alignment between the theory and AIMM is evident in the latter's focus on evaluating an organisation's AI capabilities. Late majority adopters, according to diffusion theory, stand to benefit from maturity models. AIMM, as a maturity model for AI in construction, thus serves as a strategic guide for organisations navigating the later stages of AI adoption (Morris et al., 2011). The shared understanding and language facilitated by maturity models align with the communication channels emphasised in the diffusion theory. AIMM aims to provide a framework that fosters effective communication and understanding of AI implementation, directly addressing the challenges faced by late majority adopters (Miller, 2015). The cultural integration aspect of diffusion theory, considering culture and behaviour in late adoption stages, resonates with AIMM's emphasis on organisational culture and behaviour as determinants of AI implementation success (Miller, 2015). By acknowledging and integrating these cultural factors, AIMM can provide tailored recommendations for organisations to foster a conducive environment for AI maturity.

Understanding Stakeholder Dynamics in AI Adoption

The Diffusion of Innovation theory provides a valuable framework for understanding the dynamics of AI adoption within the construction industry. Examining the diffusion curve, which categorises adopters into different stages, offers insightful perspectives on how various stakeholders engage with and embrace AI technologies. In the context of AI adoption in construction, innovators and early adopters play a pivotal role. Innovators are characterised by their enthusiasm for experimentation and collaboration with inventors. These are the entities or individuals within the construction industry who are at the forefront of exploring and implementing cutting-edge AI technologies. They are the pioneers who embrace novelty and are often involved in the early stages of AI development and testing.

Early adopters, on the other hand, are influential opinion leaders who share success stories and act as influencers within the industry. In the context of the construction sector, early adopters could be forward-thinking organisations, professionals, or even projects that are willing to take risks and integrate AI solutions. These stakeholders contribute to the initial dissemination of successful AI implementations, acting as catalysts for broader adoption. As AI technologies demonstrate their value and feasibility through successful implementations by innovators and early adopters, the industry witnesses a transition to the early majority. This phase includes sincere followers who are open to change through innovation but require confirmation from their peers who have adopted AI technologies earlier. In the construction sector, this could involve organisations observing the positive outcomes and efficiency gains achieved by early adopters, prompting them to consider and integrate AI solutions. The later stages of the diffusion curve encompass the late majority and laggards. The late majority consists of stakeholders who, while generally uninterested in change, start adopting innovations if they sense a strong need to be part of mainstream changes. In the construction industry, this might involve organisations or professionals who initially resisted AI adoption but now perceive it as a necessary and beneficial change.

Laggards are entities that demand substantial evidence of the benefits of change before cautiously adopting innovations. In the context of AI adoption in construction, laggards might represent conservative organisations or professionals who only embrace AI technologies when there is overwhelming evidence of their advantages. This group typically comprises a smaller portion of the industry, but their adoption is crucial for achieving widespread integration. Understanding these stakeholder dynamics is vital for the development and application of the Artificial Intelligence Maturity Model (AIMM). AIMM, as a tool to evaluate and enhance AI maturity within the construction industry, needs to be sensitive to the varying needs, attitudes, and concerns of stakeholders at different stages of the diffusion curve.

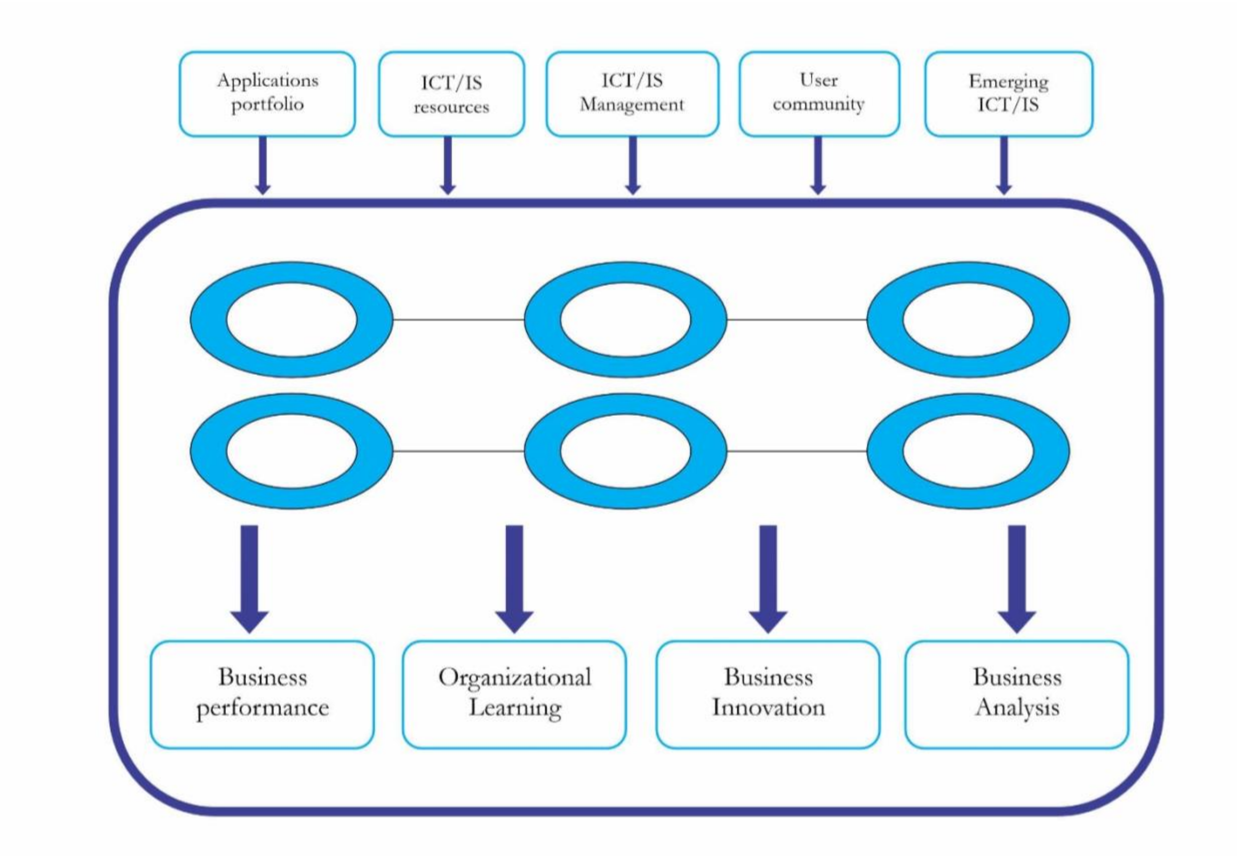
For innovators and early adopters, AIMM can serve as a benchmarking tool to assess the sophistication and effectiveness of their AI implementations. It can provide insights into areas of improvement and guide them in maintaining their pioneering roles. As the industry transitions to the early and late majority, AIMM can offer tailored assessments and recommendations to address the specific challenges faced by these stakeholders. This might include guidance on overcoming resistance to change, providing evidence of AI benefits, and facilitating knowledge transfer from early adopters. For the late majority and laggards, AIMM can serve as a roadmap for initiating AI adoption. By providing a structured and phased approach to maturity, AIMM helps these stakeholders navigate the complexities of AI implementation, making the adoption process more manageable and less daunting.

4.1.2 Stage theory

The stage theory is based on the fact that growth associated with any elements can be represented/shown/categorised in a sequence of stages, where each stage has clear distinct characteristics that categorises an element into that stage and each characteristic can be empirically tested. Also, the factors that cause an element to move from one stage to the next. Therefore, in creating a roadmap to handle a constantly changing phenomenon like AI technology implementation and adoption trend, the use of a stage mapping to define maturity levels from the initial stage till it reaches maturity is important. Hence, maturity models are theories on how organisational capacities evolve step by step, through a planned, desired, or logical maturation, based on the assumption of predictable patterns (Lasrado et al., 2015). This is why maturity models are sometimes referred to as growth stage models. A hierarchy of human requirements, economic growth, and the progression of information technology in businesses are all instances of maturity models. Academics and professionals found Nolan's stage model valuable, and it spawned a slew of maturity models based on a progression of levels (Solli - Gottshalk & Saether, 2010). Therefore, this research study will focus more on the Nolan's stage model.

The Nolan's stage model refers to information system planning model developed by Richard Nolan in 1974. It's based on the assumption that any organisation will move through stages of maturity in relation to management and usage of information system. It further argued that an organisation must go through each stage of growth in order to achieve meaningful development. In addition, the Nolan's stage model emphasised general approach to information technology in business.

Favaretto and Meirelles (2015) proposed a research framework to assess Information Technology and Information System initiative as presented in Figure 4.2.



Stages of growth of ICT/IS

Figure 4.2: Framework for the assessment of Information Technology/Information System based on Nolan's stage theory.

Based on the information provided in Figure 4.2, it was found that the stages of growth of information and communication technology/information system are six. These are initiation stage, contagion stage, control stage, integration stage, data administration stage and maturity stage. According to Nolan (1979), initiation involves ability of an organisation to have operational focus and get operational efficiency. Contagion as the second stage of information system growth refers to the ability of an organisation to move towards online system after having tested success in the initiation stage. Control is the third stage of information system growth. At this stage, management exercises and make a cost-benefit assessment. At integration stage, an organisation moves away from an adhoc isolated solution to a service-based information system, here, organisations adopt more holistic information-based decision making. The data administration stage is the stage where an organisation begins to appreciate the value of information. Thereby making effort to centralize the data management in order to maximize the benefits of information-based decision making. The final stage is the maturity stage, here, organisations create synergies in the corporate objectives and information systems planning in order to enable these two to work harmoniously in a synchronized manner.

In addition, these six stages of growth of information and communication technology/information system have helped in improving business performance, enhancing organisational learning, promoting business innovation, and ensuring effective business analysis. It is a guide to current technology usage in many organisations' todays (Favaretto & Meirelles, 2015). Furthermore, the Nolan's growth stage model has a lot of implication on information system development. It has helped greatly in facilitating growth and development of information and communication system in many organisations (Favaretto & Meirelles, 2015). The stage theory can improve the development of employees' information security behaviour in an organisation (Karjalainen et al., 2020) De Bruin and other authors, for example, emphasise that the benefit of a generic technique resides in the potential to construct a model that is characterised by high generalisability and uniformity, rather than a specific stage-model. A state of model development can be attained using a defined technique, and incremental enhancements can be made over time. The capacity to monitor and assess domain competencies at a certain point in time, as well as achieve sustainability, is the value of using such a model to businesses (De Bruin et al., 2005).

4.1.2.1 The Stage Theory and AIMM Model

As earlier highlighted, Nolan's Stage Theory unfolds the journey of organisational growth from initiation to maturity. Drawing parallels between Nolan's stages and the Artificial Intelligence Maturity Model (AIMM) illuminates a symbiotic evolution that provides a structured roadmap for the construction industry's AI adoption. In Nolan's model, the stages encapsulate distinct characteristics and objectives that mirror the natural progression of organisations in embracing information systems. AIMM, tailored for the construction sector's AI technology adoption, seamlessly aligns with Nolan's stages. Each AIMM maturity level serves as a reflection of the corresponding phase in Nolan's model and creates a coherent and adaptable framework for evaluating AI evolution. In the Initiation stage, the genesis of information system growth in Nolan's theory, there is a resonance in AIMM's early maturity levels. Here, construction organisations initiate their AI journey and establish operational focus and efficiency. Additionally, Contagion, the transition to online systems, parallels AIMM's progression as organisations, having tasted success in initiation, move towards broader AI implementations. Control, the third stage in Nolan's model, resonates with AIMM's intermediate maturity levels. Management exercises greater control and performs cost-benefit assessments which aligns with the construction industry's strategic decision-making processes in AI implementation. More so, Integration, the stage where organisations adopt holistic information-based decision-making, echoes AIMM's advanced maturity levels and reflects a shift from adhoc solutions to service-based information systems. Furthermore, Data administration, Nolan's stage where organisations appreciate the value of information, aligns with AIMM's focus on maximising benefits through centralised data management. Finally, maturity in Nolan's model corresponds to AIMM's pinnacle, where organisations achieve synergies between corporate objectives and AI planning to create a harmonious integration of AI technology with strategic goals. In this alignment, AIMM leverages Nolan's well-established principles to carve a path for the construction industry's AI maturity. By embodying the characteristics and goals of Nolan's stages, AIMM ensures a comprehensive and tailored approach and facilitates a symbiotic evolution that propels the construction sector towards the zenith of AI technology adoption.

4.1.2.1 Integration of Decision-Making Processes

Nolan's Stage Theory underscores the evolutionary journey of organisations towards information-based decision-making, transitioning from adhoc solutions to holistic approaches (King and Kraemer, 1984). Nolan's emphasis on strategic decision-making with the Artificial Intelligence Maturity Model (AIMM) reveals a strategic confluence, wherein AIMM becomes the beacon guiding construction organisations through a progression from basic AI implementations to sophisticated, strategic decision-making processes. In Nolan's model, the emphasis on information-based decision-making unfolds progressively as organisations traverse through stages. AIMM, tailored for the construction industry's AI adoption, mirrors this evolution by integrating decision-making processes across its maturity levels. At the initial stages of AIMM, construction organisations embark on their AI journey, experimenting with basic implementations. This aligns with Nolan's early stages, where organisations move from adhoc solutions, experimenting with the newfound capabilities of information systems.

As construction organisations advance through AIMM's maturity levels, a parallel progression occurs, akin to Nolan's model where a shift towards more sophisticated decision-making processes takes center stage. AIMM guides organisations towards comprehensive AI implementations, where decision-making becomes strategic, informed, and aligned with overarching business objectives. This parallels Nolan's emphasis on holistic approaches to decision-making as organisations mature in their information system capabilities. The integration of decision-making processes within AIMM is not merely a technical advancement but a strategic transformation. The maturity levels in AIMM encapsulate the gradual shift from using AI for specific tasks to employing it strategically across various facets of construction operations. Strategic decision-making becomes ingrained in the organisational culture as AIMM propels construction entities towards a mature AI adoption, echoing the essence of Nolan's stages.

4.1.2.2 Organisational Learning and Innovation

Nolan's model posits that as organisations progress through growth stages, they contribute to organisational learning, foster business innovation, and enable effective analysis (Favaretto and Meirelles, 2015). AIMM, tailored for the construction industry's AI adoption, aligns with and accentuates this narrative. At its core, AIMM emphasises the pivotal role of AI technology in enhancing organisational learning. In the early stages, organisations embark on their AI journey, exploring and experimenting with the technology. This aligns with Nolan's notion of learning through the initiation and contagion stages. As construction organisations advance through AIMM's maturity levels, the model places a deliberate emphasis on fostering innovation. This aligns with Nolan's stages, where organisations, having gained proficiency in information systems, can leverage AI for innovative solutions and practices. AIMM's maturity levels encapsulate elements that promote continuous learning and innovative thinking, creating an environment where AI is not just a tool but a driver of transformative ideas. Effective business analysis, another key component of Nolan's narrative, finds resonance in AIMM's higher maturity levels. As organisations mature in their AI adoption, AIMM guides them in leveraging AI for strategic business analysis. This aligns with Nolan's stages where the progression leads to a more sophisticated and comprehensive analysis of information. AIMM ensures that construction organisations don't merely adopt AI for the sake of technology but integrate it strategically into their business analysis processes.

4.1.3 Decision theory

Decision theory studies how people make choices. The decision theory was developed by Leonard Savage in 1954. It is a branch of applied probability theory which focused on making decision based on assigning numerical consequences and probabilities to various factors and outcomes. The decision theory proposed three uncertainty variables including states, consequences, and actions. According to this theory, state connotes facts that exists in the universe which can affect decisions. Consequences implies the features of a decision made which influence a decision-maker at a micro level while action connotes the link between state and consequences. In addition, there are four basic elements in decision theory these are acts, events, outcomes, and payoff. Acts refer to actions being considered by people. Events refer to occurrences taken place outside the control of the people making decision. Outcomes occur as a result of the occurrence. Payoffs are the values the decision maker ascribe to the occurrences.

Furthermore, the decision theory can be divided into two main categories namely, normative, and optimal decision theory. The normative decision theory analyses the outcome of decisions. It aims at determining the optimal decision based on outcomes. Also, the normative decision theory focuses on the ideal decision maker for a specific situation. It asks question like what the person should deciding do in order to make such decision. On the contrast, the optimal decision theory tries to analyse and investigate rationale behind people's choice of decision. It investigates assumptions made individuals making decision and assumptions they make when deciding. The most relatable of these to maturity model development is the normative decision theory which has to do with making an optimal decision by referring to an ideal decision maker who has shown experience in making these decisions accurately. This meaning can be extended to include a process whereby reference is made to a decision-making process that has proven its credibility in the past such as using the best practices collated together in a maturity model. Therefore, the AI-maturity model is aimed at being undertaken with the notion that it encourages decision-making and provides a well-guided approach when confronted with uncertainties or in a case where growth is needed.

The decision theory has a lot of implications for information system, information technology adoption in any organisation. It helps organisations to ascertain the rationale behind how employees, customers and other stakeholders make choices. It also helps organisations in determining the behaviour of their customers and improve organisational effectiveness (Negulescua & Dovalb, 2014). This theory is relevant to this research study in the sense that it helps in ascertaining the decision-making process in construction companies in the United Kingdom and understand how these decisions influence adoption of AI in construction companies in the country.

4.1.3.1 Decision Theory and Its Relevance to AIMM

Decision theory, especially the normative aspect, aligns with the principles of the Artificial Intelligence Maturity Model (AIMM). AIMM designed for the evaluation of AI adoption within the UK construction industry, intricately involves a sequence of decisions made at diverse maturity levels. The normative decision theory, characterised by its pursuit of determining optimal decisions grounded in outcomes, integrates with AIMM's overarching objective of guiding construction organisations toward informed and optimal decisions throughout their AI adoption journey. This implies that the essence of decision theory and its normative aspect is strategically synchronised with AIMM's mission. More so, AIMM, functioning as a comprehensive guide for construction entities, navigates the intricacies of AI adoption. In this synergy, decision theory becomes the guiding framework that provides a structured approach for decision-making at every stage of AI maturity. The alignment with normative decision theory signifies that AIMM does not merely assess AI implementations but actively contributes to the optimisation of decision-making processes within construction organisations.

Furthermore, normative decision theory, at its core, focuses on determining optimal decisions based on outcomes (Taroni et al., 2020). This aligns with AIMM's commitment to ensuring that every decision made in AI adoption is not just informed but strategically optimised for the best possible outcomes. Construction organisations, guided by AIMM's principles influenced by decision theory, are empowered to make choices that propel them toward higher levels of AI maturity. The link between normative decision theory and AIMM extends to the shared goal of guiding construction organisations toward making decisions that align with their organisational objectives. AIMM does not exist in isolation but as an integral part of the decision-making framework within construction entities and leverages decision theory principles to elevate the maturity of AI adoption in alignment with broader organisational goals.

Decision-Making Elements

In the intricate landscape of Artificial Intelligence Maturity Model (AIMM), decision theory unfolds as a crucial framework and introduces essential elements that shape and define the journey of AI adoption within construction organisations. The elements - acts, events, outcomes, and payoffs – are intricately woven into the fabric of AIMM, as they contribute to a structured and informed decision-making process. In the context of AIMM, Acts represent the actions considered by decision-makers within construction organisations. At each stage of AIMM, acts come to the forefront as organisations deliberate and contemplate different AI implementations. These acts embody the strategic choices made by construction entities, reflecting the dynamic nature of decision-making in the realm of AI maturity. In addition, events which are occurrences outside the immediate control of decision-makers are significant in AIMM's landscape. Typical examples of events include industry trends, technological advancements, and regulatory changes; these constitute the events that influence decisions reflected in AIMM. As construction organisations navigate through AIMM's maturity levels, the evolving events shape and redefine the trajectory of AI adoption to necessitate adaptive decision-making in response to external forces.

Furthermore, Outcomes represent the tangible results of decisions made by construction organisations. The effectiveness and success of AI implementations, evaluated by AIMM, hinge on the outcomes derived from strategic decisions. The link between decision theory and AIMM ensures that the decision-making process is oriented towards achieving positive and impactful outcomes at each stage. Payoffs is linked with AIMM's evaluation of the benefits derived from AI implementations. The holistic approach of AIMM, guided by decision theory, ensures that the payoffs extend beyond mere quantitative gains. They encapsulate the strategic value, organisational growth, and enhanced capabilities accrued from decisions made in the complex landscape of AI adoption.

Optimising Decision-Making Processes

The normative decision theory is strategically linked in the Artificial Intelligence Maturity Model (AIMM), as both converge with the shared objective of optimising decision-making processes within construction organisations. Normative decision theory, at its core, champions optimal decision-making based on outcomes (Brunsson, 2007). This aligns well with AIMM's overarching objective of optimising decision-making processes within the dynamic context of AI adoption in construction organisations. AIMM is not merely an evaluative tool but a strategic guide that leverages normative decision theory principles to propel organisations toward decisions that yield the most favorable outcomes for their AI initiatives. AIMM serves as a structured framework that aligns with the principles of normative decision theory. It provides a comprehensive guide for construction organisations to ensure that decisions related to AI adoption are not made in isolation but are optimised based on established norms and desired outcomes. The model, influenced by normative decision theory, becomes a compass that directs organisations through the intricacies of decision-making that facilitates a coherent and logical progression in AI capabilities.

Furthermore, the synergy between normative decision theory and AIMM extends beyond individual decisions. AIMM's design inherently fosters a progressive enhancement of AI capabilities within construction organisations. Normative decision theory principles infuse a forward-looking perspective and ensures that decisions made at each maturity level contribute to a continuous improvement in AI adoption. The result is a systematic and strategic evolution of AI capabilities, in alignment with the organisational goals envisioned by AIMM. Besides, normative decision theory emphasises not just making decisions but making informed and strategic decisions (Ahmed et al., 2014). AIMM, as a model deeply influenced by normative decision theory, echoes this emphasis. It ensures that construction organisations, guided by AIMM, navigate their AI maturity journey with a clear understanding of the optimal decisions needed at each stage which leads to enhanced capabilities and effectiveness.

4.1.4 Core competency theory

The core competency theory refers to a management concept proposed by C.K. Prahalad and Gary Hamel. According to Prahalad and Hamel (1990), the core competence is the ability of a firm to learn collectively how to coordinate various technologies and skills within the organisation in order to deliver better value. They argued further that the core competency formed the fundamental basis upon which value added by an organisation is built. Yang (2015) conceived core competence as the effective incorporation of technology, techniques, knowledge, resources, management skills and employee skills of an organisation. Also, Hirindu (2017) perceived core competency as a unique characteristics or future possessed by organisations in combating their competitors. It is an essential competitive advantage and strategic management tool used by business organisations today. It is a strategy that specifies the activities needed to gain a competitive advantage (Edgar & Lockwood, 2021). It is worthy to note that the core competence has some attributes which make it unique. Ljungquist (2007) argued that a core competence must make a meaningful and significant contribution to customers of an organisation, it must provide access to various marketplaces, and it must not be easily replicate or imitate by others.

According to Enginoğlu and Arıkan (2016), the success of an organisation is defined by the drive to focus on their core competencies in identified areas and functions within the business. Additionally, it outlines what constitutes a core competency and pinpoints parameters that ensures the processes are not easily mimicked by competitors. In other words, an organisations core competency is said to be the bedrock of its value, thus, its strategy should be aimed towards capitalising core skills and talents.

Furthermore, the core competency theory proposed four core competencies areas including: resources, capability, competitive advantage, and strategy. Resources refers to an input to value process found in the basic activities and processes within an organisation which core competencies often form a major part. These resources could be human, financial, information technology and natural resources. Enginoğlu and Arıkan (2016), argued that if resources are effectively managed by an organisation, they will turn into higher or greater value in the future. Also, capability refers to various possibilities to build core competencies. Firm capabilities are adjudged to be the most important factor in determining firms' success (Bontis & Fitz-enz, 2002). It addressed complex process of a firm like supply management, product development, customer relations and others (Schreyogg & Kliesch-Eberl, 2007). Competitive advantage refers to the ability of the organisation to develop and acquire the largest possible market share of core products. It also implies the need to consider the strength of an organisation ahead of the competitive market (Prahalad & Hamel, 1990). Strategy as the fourth core component refers to the measure taken by an organisation in developing and ensuring largest possible market share of finished products. Developing sustainable strategy enables an organisation to project into the future, compete favourably, enhances quality production and service delivery (Asobee, 2021; Brorstrom, 2020; Bryson et al., 2018).

The core competency theory has been criticized by some researchers as a result of its ambiguities and overlapping misconception (Ljungquist, 2007). Despite its criticism, it has a lot of advantages to organisations and technological development. It argued that organisations should focus on their competencies and draw their strengths from these if they want to get ahead of competitiveness (Hirindu, 2017; Prahalad & Hamel, 1990). With this, business organisations can identify their areas of strength and devise means of providing quality service to their customers, use state of art technology in staying firm in the competitive market (Edgar & Lockwood, 2021; Hirindu, 2017; Yang, 2015). In addition, this theory assists executives and managers of all organisations to stay firm ahead of the competitive global market and demand. Therefore, managers must respond sharply to the recommendations of this theory as a measure towards improving quality service delivery, enhancing customers' satisfaction, enhancing technological development, and meeting global demands (Edgar & Lockwood, 2021; Enginoğlu and Arıkan, 2016). Finally, the core competency theory gives room for innovation and enhances organisational development in Northeast England (Seddighi & Mathew, 2020). Based on the aforementioned relevance of the core competency theory, the theory is relevant in construction industry, technology, and innovation development in the United Kingdom.

4.1.4.1 Core Competency Theory and Artificial Intelligence Maturity Model (AIMM)

The Core Competency Theory provides a strategic lens for organisations to excel through collective learning, coordination of technologies, and skill integration (Feng, 2023). This theory, while not directly focused on Artificial Intelligence (AI), offers valuable insights that can be seamlessly linked to the goals of the Artificial Intelligence Maturity Model (AIMM).

Resource Optimisation Nexus

Resource optimisation stands as a cornerstone principle in both the Core Competency Theory and the Artificial Intelligence Maturity Model (AIMM). According to Eriksen and Mikkelsen (2013), the Core Competency Theory posits that a firm's ability to coordinate various technologies and skills collectively forms the basis for delivering superior value. This coordination inherently involves the judicious utilisation of resources – be it human capital, financial investments, or technological assets. In the context of construction organisations in the UK, this theory suggests that those excelling in AI maturity strategically manage their resources to foster innovation and technological integration. AIMM, as an evaluative tool, can seize upon this principle to scrutinise the resource optimisation strategies employed by construction organisations. This entails assessing how effectively human resources are deployed for AI initiatives, how financial investments are allocated, and how technological assets are utilised to propel AI adoption.

Furthermore, AIMM's assessment could encompass the multifaceted dimensions of resources. Human resources play a key role, and AIMM can delve into training programs, skill enhancement initiatives, and the overall readiness of the workforce for AI integration. More so, financial resources can be scrutinised for strategic budgeting, investment prioritisation, and financial commitment to AI projects. Additionally, technological resources can be evaluated in terms of infrastructure, compatibility, and adaptability to AI technologies. By aligning with the Core Competency Theory on resource optimisation, AIMM not only evaluates the status quo but becomes a catalyst for driving effective AI implementation. It offers constructive insights for construction organisations to enhance their resource management strategies to ensure that human, financial, and technological assets synergistically contribute to advancing AI maturity.

Capability Building Harmony

The concept of capability building is intricately woven into both the Core Competency Theory and the goals of the Artificial Intelligence Maturity Model (AIMM). As the Core Competency Theory accentuates the importance of capabilities for organisational success, AIMM can easily mirror this by scrutinising the various capabilities construction firms possess, particularly in AI adoption. In the Core Competency Theory, capabilities are deemed indispensable for organisational triumph. Prahalad and Hamel argue that the ability of a firm to learn collectively, coordinate technologies, and integrate skills forms the bedrock for delivering superior value (Gökkaya and Özbağ, 2015). In the context of construction organisations in the UK, capabilities extend beyond mere technical skills to encompass a holistic spectrum, including supply management, product development, customer relations, and intricate processes integral to the construction industry.

AIMM, in its mission to evaluate AI maturity within construction organisations, can mirror the Core Competency Theory by conducting a thorough examination of the capabilities inherent in these organisations. This involves a thorough exploration of how construction firms manage and enhance their capabilities concerning AI adoption processes. For instance, AIMM could delve into the level of expertise in supply chain management, the adeptness in developing AI-driven products, the effectiveness of customer relations strategies enhanced by AI, and the overall proficiency in navigating complex processes vital to the construction industry. AIMM can also assess how construction organisations leverage AI to optimise supply chain processes. This includes evaluating the integration of AI in procurement, logistics, and inventory management, ultimately gauging the organisation's capability to enhance efficiency and reduce operational costs. AIMM's scrutiny can extend to complex processes inherent to the construction industry. Assessing how AI is integrated into intricate workflows and decision-making processes reflects the organisation's capability to navigate and enhance these essential facets.

Competitive Advantage Nexus

The principle of competitive advantage, which is intrinsic to the Core Competency Theory, is linked to the objectives of the Artificial Intelligence Maturity Model (AIMM). As the Core Competency Theory underscores the link between competitive advantage and the ability to develop and acquire a significant market share, AIMM can easily explore how construction organisations position themselves to gain a substantial market share through AI applications and innovations. Prahalad and Hamel posit that an organisation's competitive advantage lies in its ability to develop and acquire the largest possible market share of core products or services (Prahalad and Hamel, 1990). In the context of construction organisations in the UK, this translates to the strategic integration of AI applications and innovations, positioning the organisations as industry leaders with a substantial market presence.

As AIMM is designed to assess and enhance AI maturity within construction organisations, it can leverage the principles of the Core Competency Theory to explore how these organisations garner a competitive advantage through AI applications. This involves a comprehensive evaluation of how AI is strategically employed to differentiate products or services, capture market attention, and ultimately secure a substantial market share. AIMM's assessment can also delve into how construction organisations strategically position themselves through AI applications. This includes the incorporation of AI-driven technologies in project management, construction processes, and other facets of the industry that leads to operational efficiency, cost-effectiveness, and ultimately, a competitive edge.

Furthermore, the Core Competency Theory posits that competitive advantage stems from innovation. AIMM can scrutinise how construction organisations leverage AI innovations to set themselves apart in the market. This encompasses innovations in construction methodologies, smart infrastructure solutions, and AI-driven project optimisations that elevate their market presence. AIMM's evaluation can also consider market share as a metric of AI maturity. Organisations exhibiting a significant market share driven by effective AI applications and innovations would be indicative of advanced maturity levels. This aligns with the Core Competency Theory's proposition that the ability to develop and acquire market share is a manifestation of organisational competence and strategic capability (Kabue and Kilika, 2016).

4.1.5 Technology Acceptance Model

This is another relevant theory in this research study. The Technology Acceptance Model is conceived as information system theory which provides an explanation on how people use and accept technology. This model was developed by Davis in 1989. According to Davis, the Technology Acceptance Model clarifies the determinants of technology acceptance by users. Also, Davis (1989) identified five constructs of Technology Acceptance Model namely: perceived ease of use (PEU), perceived usefulness (PU), attitude towards use (ATT), behavioural intention (BI) and actual use (AU). These five constructs are considered the primary determinants for technology acceptance and usage till date (Alshammari & Rosli, 2020). According to Davis (1989), perceived ease of use refers to the level at which an individual assert that using a particular technology will require less effort. He further argued that perceived usefulness refers to the level at which an individual believes that using a particular technology will improve his or her job performance. Also, he conceived attitude as an individual's positive or negative perception towards conducting the intended behaviour in the application of a particular information system or technology. Furthermore, behavioural intention was adjudged to implies the level at which a given information system or technology users have shaped a plan of intent to continue using or stop using a particular information system or technology with their future behaviour. Lastly, actual use refers to the degree of users' application of a particular technology or system in terms of measure value and frequency when using the technology or system by users. Based on the explanation made above, Figure 4.3 depicts the technology acceptance model.

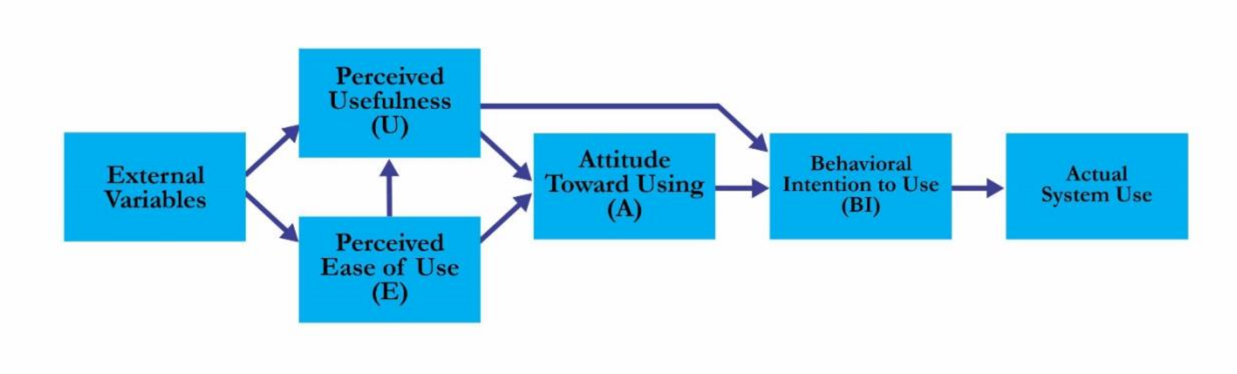


Figure 4.3: Technology Acceptance Model

Based on the information presented in Figure 4.3, Davis (1989) argued that perceived ease of use has effect on perceived usefulness. Also, perceived ease of use and perceived usefulness affect the attitude of individuals towards the usage of information system or technology. Also, attitude and perceived usefulness affect users' behavioural intention to adopt or use information system or technology. Finally, the diagram claims that positive behavioural intention of users has influence on actual usage of information system or technology.

Moreover, the constructs explained in Figure 4 omits attitude towards using information system or technology (Cheng & Lin, 2002). The rationale behind this omission is the fact that relationship exists between behavioural intention and perceived usefulness. Also, the was a weak relationship between behavioural intention and attitude (Davies, 1989). Therefore, it was argued that behavioural intention affects actual usage of information system or technology and was directly influenced by both perceived ease of use and perceived usefulness but not behavioural intention. Therefore, Davies et al. (1989) proposed the need to remove the attitude construct.

Despite this argument, the technology acceptance model has made tremendous impact and achievement in research, information system and technology development with the aid of the technology acceptance model, business owners and researchers can ascertain the determinants of individual adoption or usage of a particular information system or technology in an organisation (Tarhini et al., 2015; Lee & Lehto, 2013). In addition, it helps in determining how ease a given information system or technology is based on users' perceptions (Alhawari & Mouakket, 2010).

Finally, the technology acceptance model is useful to this PhD research study in the sense that it will enable the researcher to ascertain the perceptions of construction workers on the adoption of AI in construction projects in the United Kingdom. Therefore, providing basis for further technological development in construction industry in the country. It will also assist the government in formulating policies and guidelines towards improving the adoption and usage of AI in construction projects across the country.

4.1.5.1 Technology Acceptance Model's Relevance to AIMM Principles

Perceived Ease of Use (PEU) in AI Adoption

In the context of AIMM, which serves as a maturity model for evaluating AI adoption in the construction sector, the concept of perceived ease of use becomes pivotal. AIMM aims to gauge how construction organisations can seamlessly integrate and implement AI technologies. The model assesses the readiness and capabilities of these organisations to embrace AI advancements. Perceived ease of use, as highlighted by TAM, directly corresponds to AIMM's evaluation of how user-friendly and accessible AI solutions are within the construction sector. Construction organisations navigating AI adoption face challenges related to the ease with which their workforce can engage with and incorporate these technologies into their daily operations. AIMM, by integrating TAM principles, can delve into the user experience aspect, exploring the perceptions of construction professionals regarding the ease of using AI applications. This assessment is not only about the technical intricacies of AI systems but also about the overall user interface, training requirements, and the adaptability of AI tools to the existing workflow. AIMM, drawing inspiration from TAM, can employ surveys, interviews, and usability assessments to measure the perceived ease of use among stakeholders in the construction industry. This alignment ensures that the maturity model considers not only the technological aspects of AI but also the human factors influencing its adoption. By exploring and addressing perceived ease of use, AIMM contributes to a comprehensive understanding of AI readiness in the construction sector, providing valuable insights for organisations aiming to advance in their AI adoption journey.

Perceived Usefulness (PU) for Construction Industry

The Technology Acceptance Model (TAM) formulated emphasises the critical role of perceived usefulness (PU) in the acceptance and adoption of technology. According to TAM, individuals are more likely to adopt a particular technology if they perceive it as useful and capable of enhancing their job performance. This principle holds profound implications for the integration of artificial intelligence (AI) in the construction industry and linking it to the Artificial Intelligence Maturity Model (AIMM) enhances the model's assessment of AI adoption. In the context of AIMM, a maturity model designed to evaluate AI adoption in the construction sector, the concept of perceived usefulness becomes central. AIMM seeks to understand how AI applications contribute to and enhance job performance within construction organisations. By aligning with TAM's perceived usefulness construct, AIMM can systematically evaluate the impact and value that AI technologies bring to construction professionals.

Furthermore, AIMM's assessment involves probing the perceived usefulness of AI tools, addressing questions related to their practical utility, efficiency, and overall contribution to job roles within the construction industry. This evaluation goes beyond the technical capabilities of AI systems and delves into their real-world applications. For instance, AIMM can explore how AI-driven insights improve decision-making processes, streamline project management, enhance safety protocols, or optimise resource allocation in construction projects. To operationalise this alignment, AIMM can employ surveys, interviews, and case studies to gather feedback from construction professionals regarding their perceptions of AI's usefulness. This user-centric approach ensures that AIMM goes beyond technological functionalities and considers the practical implications of AI adoption in construction workflows.

TAM Stance Towards AI Adoption

The Technology Acceptance Model (TAM) introduces the construct of attitude which represents an individual's positive or negative perception towards using a particular technology. This construct plays a crucial role in shaping behavioral intention and, subsequently, the actual usage of the technology. AIMM, designed to evaluate AI adoption maturity in the construction industry, can incorporate the assessment of stakeholders' attitudes towards AI technologies. Understanding the attitudes of various stakeholders, including construction professionals, project managers, and decision-makers, is essential for anticipating potential barriers or facilitators in the adoption process. To operationalise this link, AIMM can utilise surveys, interviews, or focus groups to gather qualitative and quantitative data on stakeholders' perceptions of AI in construction. Questions may focus on aspects such as trust in AI technologies, perceived risks, benefits, and expectations. This data can then be mapped onto AIMM's maturity levels to identify patterns and correlations between attitudes and the stages of AI adoption maturity. By integrating the assessment of attitudes, AIMM adds a human-centric dimension to its evaluation of AI adoption. This dimension goes beyond technical considerations and acknowledges the role of human perceptions in shaping the trajectory of AI integration in construction projects. AIMM, as a maturity model, aims to guide organisations through progressive stages of AI adoption, and understanding attitudes becomes instrumental in tailoring strategies that resonate with the sentiments of the construction industry stakeholders.

Behavioural Intention and Actual Use in Construction Projects

The constructs of behavioral intention and actual use, introduced by the Technology Acceptance Model (TAM), hold significant implications for the adoption of AI technologies in the construction industry. When linked to the Artificial Intelligence Maturity Model (AIMM), these constructs become instrumental in assessing the readiness, intentions, and real-world implementation of AI within construction projects. In TAM, behavioral intention represents the user's plan or intent to continue or cease using a particular technology in the future. This construct is influenced by perceived ease of use and perceived usefulness. Actual use, on the other hand, measures the degree to which users apply a specific technology in terms of measured value and frequency. When applying these constructs to AIMM, it provides a dynamic perspective on how construction organisations plan, execute, and sustain AI adoption. AIMM's goal is to guide construction organisations through maturity levels of AI adoption, reflecting progressive stages of sophistication and integration. By incorporating behavioral intention and actual use, AIMM gains insights into the human dimension of AI adoption. Surveys, interviews, or observational data collection methods can be employed to understand organisations' intentions, plans, and the practical application of AI technologies in construction projects. This link between TAM's behavioral intention and actual use constructs and AIMM enhances the maturity model's ability to capture not only the strategic intentions of organisations but also the tangible implementation of AI technologies in the construction sector. It bridges the gap between planning and execution, offering a comprehensive understanding of AI adoption dynamics within the industry. Ultimately, this linkage supports AIMM's overarching aim of facilitating a structured and informed journey for construction organisations in adopting and maturing their AI capabilities.

4.1.6 The Technological-Organisational-Environmental (TOE): This framework offers a robust theoretical foundation for understanding how organizations adopt and integrate new technologies, such as artificial intelligence (AI) (Prakasa and Fauzan, 2024). The model was initially proposed by Tornatzky and Fleischer in 1990; it examines three critical dimensions: technological factors, organisational characteristics, and external environmental influences. Within the technological dimension, the TOE framework assesses the specific attributes and capabilities of AI technologies available to organizations (Baker, 2012). This includes evaluating the sophistication of AI algorithms, the accessibility of AI tools and platforms, and the scalability of AI solutions. For the Artificial Intelligence Maturity Model (AIMM), integrating the TOE framework allows for a comprehensive evaluation of an organization's technological readiness and capacity to adopt AI, crucial for determining its maturity level in AI implementation. Moving to the organisational dimension, the TOE framework explores internal factors within organizations that impact AI adoption. This encompasses organisational structure, leadership support for AI initiatives, existing IT governance frameworks, and the organisational culture surrounding technological innovation. Understanding these organisational dynamics is vital for the AIMM framework to assess how well AI strategies align with organisational goals and how effectively AI projects are managed across departments. The environmental dimension of the TOE framework considers external influences that affect AI adoption, including regulatory environments, industry standards, market dynamics, and economic conditions (Awa et al., 2017). These factors shape the external pressures and opportunities organizations face in adopting AI technologies. For AIMM, integrating the environmental dimension helps evaluate how external factors impact the implementation and sustainability of AI initiatives, ensuring alignment with regulatory compliance and adapting to market demands.

The incorporation of the TOE framework into AIMM enables organizations gain a holistic perspective on AI maturity assessment. This approach enhances the AIMM's capability to identify readiness levels, barriers, and strategic alignment opportunities related to AI adoption. Moreover, it supports organizations in mitigating risks associated with AI implementation, fostering continuous improvement through adaptive learning, and positioning AI as a driver of competitive advantage and innovation in their respective industries.

Chapter Summary

This chapter explores six (6) key theories that contribute to the understanding of Artificial Intelligence (AI) adoption within the construction industry. These theories are the Diffusion of Innovation, Stage Theory, Decision Theory, Core Competency Theory, the Technology Acceptance Model (TAM), and the Technological-Organisational-Environmental (TOE). The Diffusion of Innovation theory, developed by Everett Rogers, examines how new ideas and technologies spread through societies. Applied to the context of AI adoption in construction, this theory helps to comprehend the processes through which innovative AI practices permeate the industry. It guides the Artificial Intelligence Maturity Model (AIMM) in understanding the factors influencing the rate and extent of AI adoption among construction organizations. By identifying innovators, early adopters, and laggards, AIMM gains insights into the dynamics of AI diffusion within the construction sector. The Stage Theory presents a framework for comprehending the gradual evolution of organizations through distinct maturity stages. Applied to AI adoption, the Stage Theory aligns seamlessly with AIMM, which is designed to evaluate the maturity levels of AI implementation in construction. The theory guides AIMM in categorizing construction organizations into different stages of AI adoption maturity, facilitating a structured and informed approach to AI integration. The Decision Theory, attributed to Leonard Savage, is a crucial framework that aids in understanding how individuals and organizations make choices. In the context of AIMM, Decision Theory, particularly the normative aspect, contributes significantly. It aligns with AIMM's mission to guide construction entities through optimal decision-making processes at various maturity levels of AI adoption. By exploring elements such as acts, events, outcomes, and payoffs, Decision Theory enriches AIMM's assessment framework, ensuring that decisions align with organisational objectives and contribute to the optimization of AI adoption. The Core Competency Theory, proposed by C.K. Prahalad and Gary Hamel, is another foundational theory that focuses on an organization's ability to coordinate technologies and skills to deliver superior value. Integrated into AIMM, Core Competency Theory emphasizes the importance of identifying and leveraging strengths within construction organizations. It aligns with AIMM's objective of evaluating AI maturity within the construction industry by assessing how organizations strategically manage resources and enhance capabilities. Finally, the Technology Acceptance Model (TAM), developed by Davis, sheds light on how individuals accept and use technology. In the context of AIMM, TAM principles enrich the model's evaluation by focusing on user-centric aspects of AI adoption within the construction industry. By addressing perceived ease of use, perceived usefulness, attitudes, behavioral intentions, and actual use, TAM ensures that AIMM's assessment considers not only technological aspects but also the human factors influencing AI adoption. This chapter serves as a theoretical foundation for AIMM by integrating five key theories that collectively contribute to a holistic understanding of AI adoption within the construction industry. The Technological-Organisational-Environmental (TOE) model, which was proposed by Tornatzky and Fleischer in 1990, examines three critical dimensions: technological factors, organisational characteristics, and external environmental influences. The incorporation of the TOE framework into AIMM enables organizations gain a holistic perspective on AI maturity assessment. This approach enhances the AIMM's capability to identify readiness levels, barriers, and strategic alignment opportunities related to AI adoption. These theories guide AIMM in assessing maturity levels, decision-making processes, and user acceptance, providing a comprehensive framework for organizations navigating the complex landscape of AI integration.

5 CHAPTER FIVE: RESEARCH METHODOLOGY

Chapter Overview

The specific definition of 'research' varies from one academic discipline to another but, there is a common agreement that the function of research is to answer questions, establish facts and acquire new knowledge (Bahr et al., 1984). Whilst the entire systematic process involved in carrying out research is the research methodology (Kumar, 2002). The term research methodology is also very loose in terms of its definition and usage between studies. However, in the general sense and thus, within this study, the concept of research methodology encompasses a study's research philosophy framework, procedure, activities within the procedure, data gathering methods, and data analysis approaches used in the process of theory verification and conclusion (Singh, 2006). As such, the researcher's choice of methodology informs the validation, accuracy and further ensues a justification of the study Crotty (1998). The subsequent sections further discuss the research process that informs a methodological approach for this study. As such, Table 5.1 outlines the elements considered under research methodology and summarises the justification for selecting the options chosen for this study under each element. Furthermore, Figure 1 demonstrates the hierarchy of the elements which are as follows; Ontological and philosophical study of a research philosophy, research paradigms, strategy, choice as well as the methods used in conducting and analysing the study.

Table 5.1. Identified Research Choice

Research Methodology	Existing Approach	Chosen Approach	Justification
Ontology Philosophy	Realist Relativism	Realist Ontology	This study seeks to validate or falsify the existence of the reality with the notion that the subject cannot be dissociated from the object which further justifies the

			use of a mixed-method approach in conjunction with a pragmatic paradigm.
Epistemological Philosophy	Subjectivism Objectivism Constructionism Pluralism	Epistemological Pluralism	Allows the use of both subjectivism and objectivism in a single study. This approach triangulates the strengths and weakness from both philosophical stance in a bid to ensure an even rigorous study.
Research paradigm	Positivism/Post-positivist Critical realism Interpretivism Pragmatism	Pragmatism	This paradigm is termed as goal-driven which ensures that research findings satisfy the research question irrespective of what approach it takes.
Research Approach	Inductive Deductive Abductive	Abductive	The chosen approach in this research is selected to address the limitations between inductive and deductive reasoning
Research choice	Qualitative Quantitative Mixed methods	Mixed methods	Mixed method in this research used a qualitative approach to gain an in-depth understanding of the research to ensure relativity. However, the quantitative research in this study is used

			to validate and ensure generalizability.
Research Strategy	Phenomenology Case study Experimental Research Grounded Theory Survey Research Ethnography	Case study Survey research	The research strategy employs both case study and survey research. The case study prompts the use of investigative methods like interview and observations while the survey research is conducted to sure research validity through targeting a large audience with the use of questionnaire surveys.
Research Methods	Interviews Focus Groups Interviews (FGI) Historical data Experimental Questionnaire Survey Observations	Focus Groups Interviews (FGI) Questionnaire Survey	The methods used in this research encompasses both qualitative and quantitative research methods. Therefore, the qualitative method is Focus Groups interview and the statistical use of questionnaire survey.
Sampling Techniques	Purposive sampling Systematic sampling Convenience sampling	Purposive Sampling Snowballing sampling	Purposive sampling in this study is used to streamline participants to experts within the industry some of which are mangers, innovative,

	Probability sampling Snowball sampling Cluster sampling Quota sampling		technical mangers in the construction industry
Data Analysis (qualitative and quantitative analysis)	Text interpretation Phenomenological analysis Statistical Analysis Thematic analysis	Thematic Analysis Statistical analysis	To conclude, the research adopts the use of thematic qualitative analysis and statistical analysis to generate and test research theories.

5.1 Research Process

According to Bahr (2014), research is a systematic method for establishing facts and acquiring new information. The systematic process involved in carrying out research is referred to as the research methodology (Kumar, 2002). Therefore, the concept of methodology and interpretation of data and materials used in the process of theory verification and conclusion (Singh, 2006). In correspondence to the approach, Crotty (1998) claimed that the methodological choice of the researcher informs the validation, accuracy and further ensues a justification of study.

The subsequent section further discusses the research process that informs a methodological approach. Based on the researcher's knowledge of research methodology the following interrelated components as shown in Figure 5.1. projects the researcher listed in the following order: Ontological and philosophical study of a research philosophy, research paradigms, strategy, choice as well as the methods used in conducting and analysing the study.

5.2 Research Philosophy

The philosophy behind the researcher's choice of acquiring its knowledge informs and justifies the study. It is the process where the researcher formulates and concludes on the assumptions applied to the research in terms of the belief of nature, existence, and the perception of reality (Žukauskas et al., 2018). These preliminary statements of reasoning shape the methods used throughout the research process as well as how the researcher understands events. As with any concept that has been around for some time, there are established clusters called paradigms that exist based on the combination of assumptions they subject to i.e., their perception on reality and human knowledge (Kuhn, 1972). Any researcher or member that belong to a specific paradigm is said to automatically adopt these set of beliefs and assumptions. This concept of paradigm is used to differentiate between philosophies and is further discussed in succeeding subsections along with some of the types of philosophical assumptions that are made under each paradigm such as the ontological stance, epistemology, and methodology. These philosophical assumptions are used to further differentiate between the existing types of paradigms. The next section discusses two popular philosophical assumption types used to distinguish between philosophies.

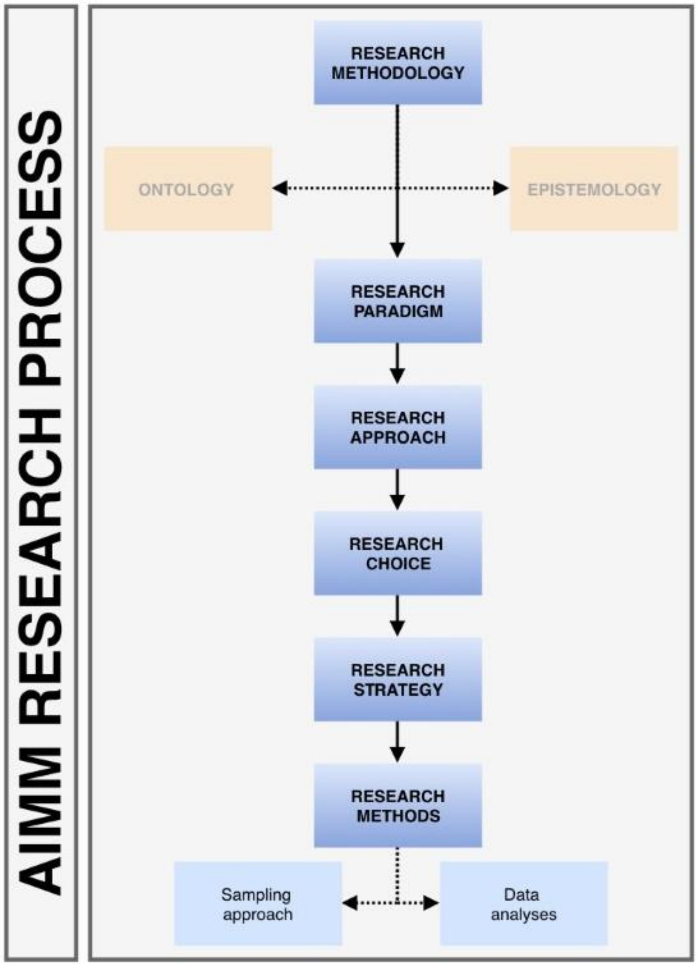


Figure 5.1: Research Process for AI maturity model

5.2.1 Ontology

It follows that the ontological position encompasses of either a realist or relativist perspective. According to Lawson et al. (2013), a realist ontology's belief of truth is either existent or untrue with a practical representation of how things really are in its natural form without any prerogative of how we are aware of what exists, often this notion of study is adopted by objectivists. Contrariwise, the subjective researcher posits in a relativist ontological perspective where it is believed that there is no absolute truth, reiterating that the basis of truth is in accordance with the different perspectives of the subject (Jenkins, 2010).

5.2.1.1 Ontology of the study

The ontological foundation of a research study defines its perspective on the nature of reality and the assumptions about what can be known and how it can be known. In developing an Artificial

Intelligence (AI) Maturity Model for the construction industry, the choice of ontology plays a crucial role in shaping the research approach and framework. Historically, debates in research methodology have centered on whether reality is objective and independent of human perception (realism) or socially constructed and context-dependent (constructivism). Osborne (1996) and Crotty (1998) contribute to these discussions by highlighting the complexities in defining reality and the implications for research methodologies. Crotty, in particular, argues for a commensurable approach to ontology and epistemology, suggesting that the study of being (ontology) and the acquisition of knowledge (epistemology) are intertwined and challenging to separate. For this study, the ontological perspective is grounded in realism, specifically adopting an objectivist outlook. This perspective asserts that there is an objective reality that exists independently of human perception, and this reality can be observed and studied through empirical methods. In the context of developing an AI Maturity Model for the construction industry, realism provides a foundational belief that there are identifiable and measurable attributes of AI adoption and maturity that can be objectively studied and evaluated.

However, modern research paradigms, such as post-positivism, caution against completely dissociating the object from the subject. They acknowledge the complexity of reality and the influence of human perception and interpretation on research findings. Despite these nuances, the realist perspective chosen for this study aligns with the objective of developing a structured and measurable AI Maturity Model that can provide clear insights into the readiness and capabilities of construction firms in adopting AI technologies. Moreover, the research paradigm adopted for this study supports a mixed methods approach, integrating qualitative and quantitative methods to enrich the understanding of AI maturity in the construction industry. This pluralistic epistemology acknowledges the value of both subjective insights and objective measurements in comprehensively assessing AI adoption and maturity levels. Qualitative methods allow for a deeper exploration of contextual factors, stakeholder perspectives, and organisational dynamics, while quantitative data provides statistical validity and generalizability.

In the construction industry, the popularity of this mixed methods approach can be attributed to its ability to capture the multifaceted nature of AI implementation challenges and opportunities. The combination of qualitative insights with quantitative metrics enable researchers to effectively address the complexities of technological adoption within diverse organisational contexts, enhancing the relevance and applicability of the AI Maturity Model.

5.2.2 Epistemology

This strand of research philosophy focuses on "understanding" the depth of the study which expands on the reasoning behind a knowledge i.e. how knowledge is generated and acquired. In a study conducted by Goldman (1999), the epistemological position of a research informs an explanatory reason behind the success and failures of a study. For example, we have constructionism which asserts that reality is socially constructed. Similarly, subjectivism epistemological stance also assumes that worldview is subjective to the social interpretation of reality. Thus, the two aforementioned examples of epistemology agree that the inference of reality is subjective. Alternatively, objectivism basis its view on the external world, asserting that reality exists independently of subjective views and can be measured and tested using mathematical methods (Crotty, 1998). On this basis, this research adopts a subjective-cum-objective in the form of a pluralism epistemology.

5.2.2.1 Epistemology of the study

The idea of epistemological pluralism has seen a surge in construction management research (Dainty, 2008). Although, the objective research process dominates research in the industry. Still, there has been an up rise in arguments about the effects of the objectivism approach (Addis, 2016). In relative terms, the consolidation of quantitative and qualitative methods has been emphasised in current practices engineered to provide complementary insights and effective understanding of the industry. The goal of this research study is to follow the epistemological stance of pluralism in order to gain a thorough understanding of the construction sector. Using a qualitative approach, the study aims to investigate the use of AI application in different industries, business and technological implementation strategies which will inform key process areas and factors influencing the adoption of AI in the construction sector. In addition, the data collected from the subjective inquiry will also be evaluated and tested using quantitative methods to establish a reliable maturity model. Therefore, adopting the pluralism epistemological stance for this study should improve the reliability and validity of this research through the mixed-method methodology.

5.3 Research Paradigm

According to a number of studies, paradigms represent the theoretical framework of a systematic investigation which expands on a researcher's way of how knowledge is studied and interpreted (Guba, 1990; Tuan, 2002; Monahan and Walker, 1988). There have been numerous paradigms adopted across various studies which include positivist, constructionist, postmodernism, pragmatism etc. (Mackenzie and Knipe, 2006). However, when scholars discuss about these paradigms in literature, it is found that the terminology used to define the types of philosophical assumptions such as the ontological and epistemological assumptions sometimes are confusing and "thrown together in grab-bag style as if they were all comparable terms" (Crotty, 1998, pg. 3). These discrepancies can be shown with the likes of a study conducted by Lincoln and Guba and other scholars. Lincoln and Guba (1985) stated that the paradigms consist of epistemology, ontology, methodology and axiology but another notable scholar argued that paradigms consist of Epistemology, ontology, and methodology (Aymer and Okitikpi, 2000). In an array of studies, the notion of the elements of paradigms vary and the meaning of paradigms have been labelled differently amongst researchers. Despite the varying classification of research paradigms, the four elements sub-structured in this study include epistemology, theoretical perspective (paradigms), methodology and methods (Crotty, 1998). The concept dismisses ontology based on Crotty's guidance but expands that each element informs one another i.e., a choice of epistemology informs the choice made in theoretical perspective chosen and so on. But this process could either be a top-down or a bottom-up approach. Figure 2. is a diagram that depicts the stage-by-stage evolution of the research process as demonstrated by Crotty.

The two conventional paradigms adopted across a vast number of studies are positivism or constructionism/Interpretivism (Mackenzie and Knipe, 2006). To further justify the choice of paradigm/theoretical perspective selected for this study, a number of paradigms have been discussed while underlining the preferred paradigm chosen for this study namely pragmatism. Discussion of some of the existing paradigms follows.

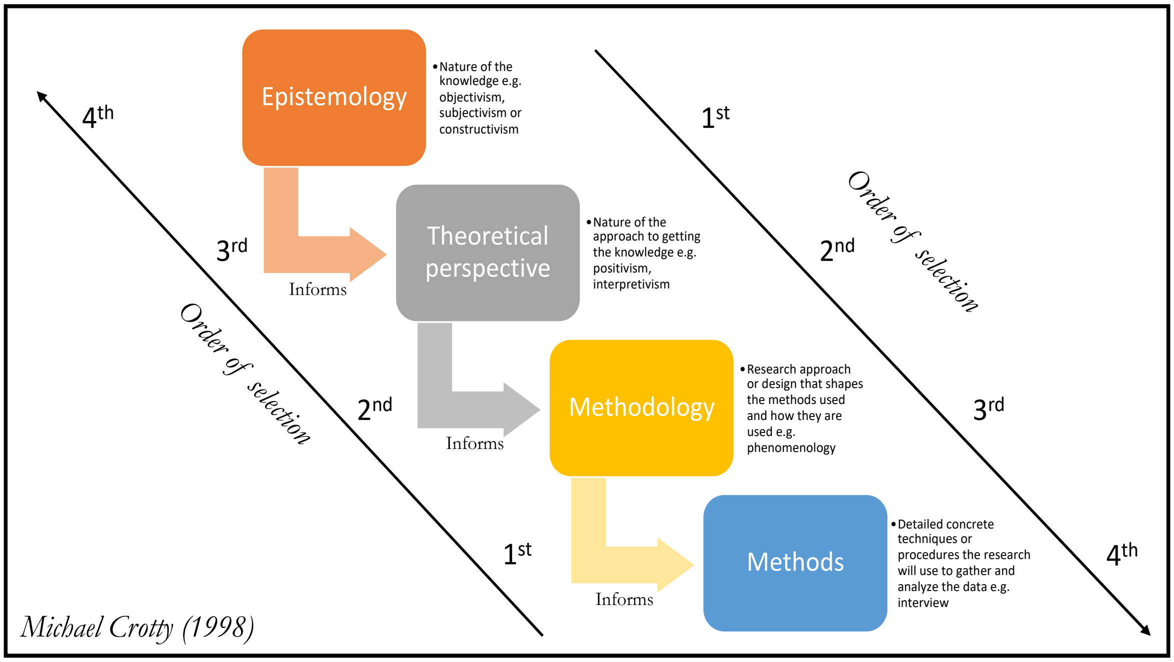


Figure 5.2: Michael Crotty's research process (Crotty,1998)

5.3.1 Positivism

The application of a positivism research paradigm is prevailing in a number of research studies. According to Kaboub (2008), the positivism paradigm proclaims that social reality can be perceived empirically and measured with the use of statistical and scientific methods. In another similar study, it is conferred that the worldview of a positivist is external and presents its facts on reality without any form of subjective view (Liyu et al., 2014). Although, the notion adopted by this study centres on falsifying or revealing the truth through fact validation, prediction, and confirmation. However, the validation of the study lacks in providing in-depth understanding of reality (Asghar, 2013). Based on the above stated, the philosophical stance of the positivism paradigm poses a relativist ontology and an objectivist epistemology.

5.3.2 Interpretivism

The interpretivism research paradigm adopts a qualitative approach toward understanding reality depicting a descriptive investigation. In a study conducted by Goldkuhl (2012), the interpretivist paradigm does not base its focus on reliability but interpretation of the worldview through the lens of the subjects. Thus, the truth behind research can be perceived through multiple views. This paradigm asserts its focus on in-depth understanding which is dependent on researcher's inclusion in the study of reality. On the other hand, one of the main pitfalls in the application of this paradigm is researchers bias which questions its validation (Asghar, 2013). This station the philosophical stance of this research paradigm as a realist ontology and epistemologically subjective.

5.3.3 Critical realism

As per López and Potter (2005), critical realism is a form of post-positivism. The concept of this paradigm reflects the objective and subjective analysis of being in a single study. Hence, the critical realist belief that nature and existence is external and autonomous. However, the study of reality encourages the notion to challenge the researcher's ability to known reality. This paradigm promotes the use of the qualitative approach to research (comprehension) and the quantitative approach to research (validation) within a single study to further explain fact. Therefore, this paradigm explores the shortcomings of the existing practices in a bid to detect limitations and provide alternative tactics.

5.3.4 Paradigm of the study - Pragmatism

Having carried out an extensive review of the various research paradigms (positivist, interpretivism, critical realism, postmodernism amongst others). The study's theoretical perspective falls within a context of pragmatism. According to Mackenzie and Knipe (2006), deconstruction of the role of a paradigm is crucial in research. Thus, the foundation of this theory emerged from the concept of questioning the contention between subjective and objective scholars regarding research validity (Bergman, 2010). In a study conducted by Menand (1997), the pragmatic paradigm called a deconstructive paradigm seeks to verify the reality of a researcher by "what works" in a research question by answering "what" and "why" (Hall, 2012). The pragmatic approach is aim-driven without any dedication to any one system of research philosophy (Posner, 2005). Therefore, the study encompasses both quantitative and qualitative research in one single study to develop a maturity model for AI that works within the construction industry.

This study includes the use of both qualitative and quantitative research methods. However, the research process explores the use of a literature review to gain extensive knowledge of AI implementation expertise across different industries. The study also seeks to conduct in-depth interviews to gain a broad understanding of the nature of the problem of research. This research involves a qualitative approach with a subjective analysis perspective. Nonetheless, in order to generate specific hypotheses, the proposed conclusions from the qualitative method are evaluated. In addition, a questionnaire survey is compiled to check the hypotheses generated which comprehends generalizability to ensure reliability using an analytical point of view. The pragmatist's goal-driven nature ensures that the research finding satisfies the research question irrespective of what approach it takes (Guimaraes et al., 2015).

According to Dewey's "doubly reflective" five-stage pragmatist model depicted in Figure 5.3 visually represents the research process for the chosen paradigm in this study.

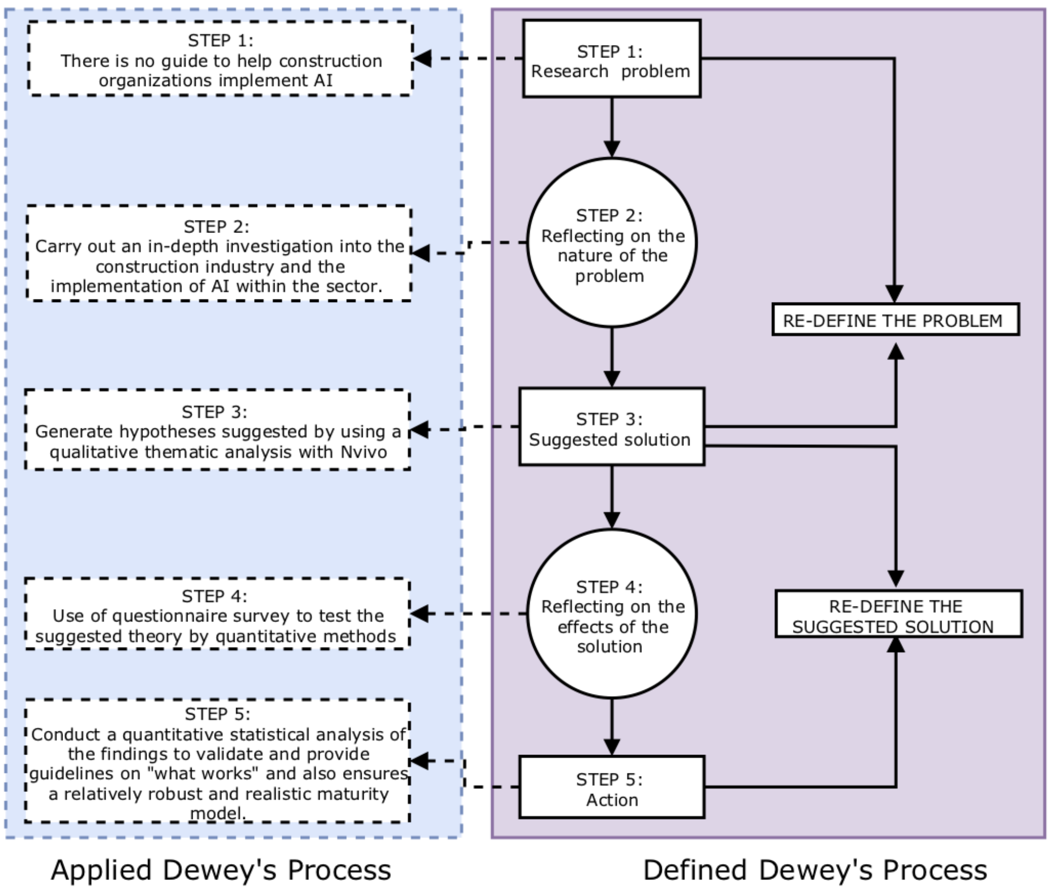


Figure 5.3: Reveals AIMM-research paradigm choice in relation to Dewey's pragmatic method (Farra, 1988)

5.4 Limitations of Research Philosophy

Although the pragmatic approach is widely recognised and used for its 'what works' approach, it promotes the use of mixed approaches in a bid to extract and, most significantly, improve analysis using both qualitative and quantitative methods. In its approach to provide a conclusion that is relevant to the study problem, this method has also been challenged by a number of researchers. The pragmatic approach has also provided a complex research design that, unlike the traditional positivist or interpretivist approach, ensures a lot of resources in the planning and implementation phases. Arguably, this study strongly aims to provide richness in understanding the construction environment and developing a relevant AI maturity model applicable to the construction industry. Relatively, the pragmatic paradigm offers a completely comprehensive understanding of the research problem, addressing the study's reliability, generalizability, and validity. According to Onwuegbuzie and Johnson (2006), Unlike the use of the positivist paradigm that is objectively informed by evidence to show its generalizability and the interpretivist paradigm that focuses solely on the research's validity aspect.

5.5 Research Approach

The research approach that applies to this study is "abductive" reasoning, thereby promoting the hypotheses development and testing while also enabling the use of mixed reasoning. In order to further improve the systematic ingenuity of a research, this method of reasoning adopts both the inductive and deductive definition, which allows triangulation by deriving the strengths and reliability from the qualitative and quantitative methods in a bid to generate a comprehensive result (Flanagan, 1978). It was made known in a study conducted by Kovacs and Spens (2005), that the deductive and inductive justification approach is very distinctive in comparison to the abductive process. This process proceeds from a rule to result to a case phase that generates a result-driven inference that is not inherently logically right (Dubois and Gadde, 2002). Given the above, the abductive reasoning is often adapted in the case of mixed methodology in research design.

5.6 Limitations of Abductive Reasoning

Abductive reasoning is known for its method of critical thinking and delivering the best-case scenario to a research based on known information. In this instance, the hypotheses are generated by exploring data and mapping out a pattern while the deductive approach focuses on deriving logical hypotheses and, lastly, the inductive approach is fixated towards the truth and constructs its hypotheses based on a collection of observations. Nevertheless, some researchers interpret abductive reasoning as an approach that chooses the most economical approach but is believed to be strictly rational. Yet, this study poses to be result-driven and hereby concludes on delivering what works.

5.7 Research Choice

The research choice informs what data is collected and how it is analysed in a study (McCuskey and Guanyin, 2015). However, there has been a recent surge in the adoption of mixed methods in single research.

5.7.1 Quantitative research

The quantitative research employs the use of mathematically based methods i.e., empirical, and statistical methods to explain by testing and analysing the hypotheses in a bid to predict the phenomena (Creswell, 1994). This process is designed to measure the quality and not the quantity of the acquired data. However, evidence shows that quantitative research encompasses two types of study, namely survey and experimental research. The researcher takes an independent stand with the use of the aforementioned quantitative approach which prevents potential bias.

5.7.2 Qualitative Research

On the other hand, the qualitative research is an interpretative approach aimed at describing and gaining an in-depth understanding of the social reality in its natural form (Silverman, 2016). However, unlike the quantitative research, this research basis its data collection method and analysis on the social phenomenon. Some of the qualitative methods uses include observations, focus groups, face-to-face interviews among others (Liamputtong and Ezzy., 2005).

5.7.3 Mixed Methods

The use of mixed methods has seen an increase in research studies (Klassen et al., 2012). According to Graham (2005), the study of mixing methods correlates with the notion of method-triangulation in which two research approaches are implemented in research to test its validity and adversely improve its integrity and accuracy. Though, there has been a number of studies that have spoken against the application of mixed methods in a study (O'Byrne, 2007). For example, Cameron (2011) stressed that a number of researchers had lost their narrative of study with the use of this method because it has given rise to a number of misperceptions, challenging the legitimacy, accuracy, and justification of the study. However, the mixed-method approach promotes a systematic analysis of both paradigms from different perspectives, with the goal of resolving their shortcomings and thus validating and simplifying them into a single study. Notably, the adoption of mixed methods has seen an increase in research studies (Brewer & Hunter, 1989; Cook & Reichardt, 1979; Caracelli & Greene, 1993; Johnson & Onwuegbuzie, 2004). According to Driscoll et al. (2007), in current research, streamlining and defining a quantitative method for objective research and a qualitative method for a subjective approach has taken a new shape. Thus, studies were carried out in a manner in which techniques such as surveys, experimental research, which is categorised as quantitative, were incorporated in qualitative research. Nevertheless, a number of prominent scholars ensued in the debate, by following an abductive logic, to justify the use of both philosophical stances in a single study. Without further ado, the grounded theory has proven to justify the use of multi- research methods in single research (Charmaz and Belgrave, 2007).

5.7.4 Justification of mixed-methods approach

To further justify the use of the mixed-method approach in this study, it is crucial to underline the grounded theory. According to Strauss and Corbin (1997), grounded theory adopts the inductive reasoning notion in conjunction with the deductive reasoning. In corroboration to the given definition, studies have shown that grounded theory underpins the notion to adopt the quantitative and qualitative perspective in thinking and action processes (Glaser et al., 2013). Similarly, the grounded theory is proven to conform relevance in a study which promotes subjective opinion to generate relativist research. However, the theory seeks to conduct reliable research which is tested and verified with the use of mathematical methods.

Given the above, the mixed method approach assumes the development of a maturity model for AI in the construction industry with the use of an exploratory-sequential mixed method. Thus, this study seeks to adopt the qualitative and quantitative method in a single study. To further address differing views from specialist in the construction sector on the complex nature of the construction firm. However, the data gathered from the interviews are evaluated, and hypotheses are created in the form of these results. Also, quantitative research is carried out to further validate the study by testing the hypotheses using statistical methods and generate verified, which in effect will guide the development of a robust maturity model.

5.8 Research Strategy

There are several existing research techniques that are intended to provide guidance during the study of research. Some of these are ethnography, phenomenology, experimental research, case study, grounded theory amongst others (Phillips, 1966). After careful conduction of an extensive review on the various types of research technique, this study will adopt two strategies, i.e., the case study strategy and survey strategy.

5.8.1 Case Study Strategy

In several research studies, the case study approach promotes a thorough investigation of social topics using interviews, observations, and other qualitative methods (Harrison et al., 2017). Though, social subjects may vary from people, cities, religion, and culture; nevertheless, an understanding of the research problem is derived from multiple views that inherently strengthens the study. The case study approach is a widely recognized methodology for conducting in-depth investigations of complex social phenomena. According to Yin (2012), case study research allows for a comprehensive examination of a contemporary issue within its real-life context, particularly when the boundaries between the phenomenon and its context are not clearly evident. This approach is particularly useful in exploratory research, where the aim is to gain insights and generate new ideas through detailed and contextual analysis. Yin (2012) emphasizes on several strategies to improve the internal validity of case study research. One key strategy is the use of multiple sources of evidence, which enables the triangulation of data. By collecting data through interviews, observations, document analysis, and other qualitative methods, researchers can cross-verify information, thereby increasing the credibility and reliability of the findings (Yin, 2012). This multi-faceted approach not only strengthens the study's validity but also provides a better understanding of the research problem. In this study, the case study approach facilitates an in-depth exploration of AI implementation within UK construction firms. The analysis of specific instances of AI adoption enables this research to uncover the factors that influence the process. Interviews with key stakeholders, such as project managers, engineers, and IT specialists, provide valuable insights into the practical challenges and opportunities associated with AI integration.

5.8.2 Survey Strategy

The survey strategy is a structured way to gather data for research through means such as questionnaires distributed to a large populate of respondents (Rea and Parker, 2014). Therefore, this technique allows for generalizability in the study finding which strengthens the validation for research. As a result, this study will adopt survey research to encourage wider adaptability of large populations to the results from a subjective perspective.

5.9 Research Design Methods

Research methods represent a collection of procedures, strategies and instruments used to collect and analyse data (Hennink et al., 2020). There are two distinctive types of research methods used, namely the quantitative and qualitative research process. The use of literature review focus groups and Questionnaire survey will be adopted in this study.

5.9.1 Literature Review

Literature review involves a study of the research topic with the use of scholarly journals, books, and relevant resources (Snyder, 2019). Furthermore, the literature review gives he researcher a good understanding of the chosen topic. Often, it helps to reinforce the principle of a thesis among a variety of advantages included in conducting a literature (Blummer and Kenton, 2020).

5.9.2 Focus Groups interviews

Given the complex and dynamic nature of the construction sector, this study seeks to explore practical opinions of construction practitioners of the selected UK construction industry. (i.e., Balfour Beatty and Costain). The study seeks to conduct semi- structured interviews with the use of Focus Group Interviews (FGIs). This approach informs a wider range of information and allows research clarification. Although, this method of enquiry as compared to individual interviews are not as sufficient in covering the depth on a particular issue (Longhurst, 2003). However, this research seeks to identify the process requirement addressed by the construction experts in a wider range to ensure a descriptive and prescriptive understanding of the measurement of AI applications in construction.

5.9.3 Questionnaire survey

This study is carried out using a systematic method to cover a broad spectrum of participants. According to Hinkin (1998), the questionnaire is an evaluation of a structured and unstructured survey carried out in research for data collection. The questions put in succinct are used to advise or respond to research theory. Hence, Therefore, this study seeks to adopt the use of this method of collecting data for generalizability and validation use. Although, questionnaire surveys can reach a wide number of people the reliability of this survey data is however questioned based on accuracy, number of responses received and misinterpretation amongst other factors. This research seeks to use this mode of enquiry to validate the qualitative generated theory from the focus group interviews.

5.10 Maturity Model Development Process:

The maturity model development process is as shown in Table 5.2.

Table 5.2: Maturity Model Development Process

MM Development steps	**AIMM Framework Components/ AIMM Activity steps/ Characteristics**
Maturity model Framework	Peffers et al., (2007) *1.Problem identification and Motivation* *2.Objectives of a solution* *3.Design and Development* *5.Demonstration* *6.Evaluation* *7.Communication*
Maturity Model key groups	Organisational Maturity Model
Maturity Level	Five Levels adopted from Capability Maturity Model (CMM) framework: *Level 1(Initial); Level 2(Assessing); Level 3(Determined); Level 4(Managed); Level 5(Optimised)*
Maturity Model Name	AIMM in Construction
Focus of the Model	Domain Specific MM (Construction Sector)
Entity of the Model	People, process, and technology
Stakeholder	Construction Industry and UK Government
Domain Focus (Unit of analysis)	Organisation
Target of the Model (Audience)	Construction practitioners and UK Government
Structure of the Model	CMM-Like
Model Flow	Continuous Model
Purpose of use	Prescriptive and Descriptive Purpose

Improvement Roadmaps	Process Recommendation Guidelines
Dimensions	The identification of common themes will be derived from the consolidation of critical success factors that have been found for the implementation of artificial intelligence in the construction industry. This has been derived from literature and confirmed by stakeholder experts.
Key Benchmarking Process Areas	The following will be delineated according to the viewpoints of stakeholder experts and a comprehensive examination of academic research, serving as a collection of fundamental benchmarking procedures presented across several dimensions.
Maturity Model Assessment Framework	AIMM Assessment Tool

5.11 Sampling Approach

Sampling plays a key role in research by determining how participants are selected from the broader population of interest, thereby influencing the generalizability and reliability of study findings. Reynolds et al. (2003) define sampling as the method of selecting a subset of individuals or entities from a larger, defined population. This approach ensures that the chosen sample represents the characteristics and diversity of the population, thereby enhancing external validity. Two primary approaches to sampling are commonly employed in research: random sampling and non-random sampling. Random sampling involves the selection of participants purely by chance, ensuring that each member of the population has an equal probability of being included in the sample. This method mitigates bias and allows for statistical inference to the broader population. Examples of random sampling techniques include simple random sampling, stratified sampling, systematic sampling, and cluster sampling (Emerson, 2015). In contrast, non-random sampling methods are based on the subjective judgment of the researcher, focusing on specific characteristics or criteria deemed relevant to the research objectives. Non-random sampling techniques include convenience sampling, purposive sampling, and snowball sampling (Marshall, 1996). These methods are particularly useful when access to the population is limited, or when researchers seek to include participants who possess unique insights or experiences related to the study's focus.

For the development of the AI Maturity Model in the construction industry, this study adopts a multi-case sampling approach to ensure methodological rigor and comprehensive coverage of relevant cases. Purposive sampling is employed both in qualitative and quantitative research components, allowing researchers to select cases that are most informative and representative of different facets of AI adoption and maturity in construction firms. This approach enhances the depth of understanding and enables researchers to capture diverse perspectives and contexts within the industry. Additionally, snowball sampling is utilised specifically in the qualitative research phase. This method involves identifying initial participants who meet the study's criteria and then asking them to refer other potential participants, thereby expanding the sample through referrals. Snowball sampling is particularly effective for accessing hard-to-reach populations or for studying phenomena where participants are interconnected, such as within specialised industry networks or communities of practice. Employing a multi-case sampling strategy that integrates purposive and snowball sampling methods enables this study ensures a comprehensive exploration of AI maturity across different organisational contexts within the construction industry. This methodological approach not only enhances the validity and reliability of findings but also contributes to the richness of qualitative insights and the robustness of quantitative data, supporting a nuanced development of the AI Maturity Model framework.

5.11.1 Purposive and snowball sampling: Qualitative and Quantitative Research

According to Etikan and Alkassim (2016), purposive sampling also known as judgement sampling allows the researcher to cherry pick its participants based on the information, they want from them. The main reason why purposive sampling was selected for this study is because the researcher can sieve through the population using criteria such as knowledge, experience, communication skills or other factors. This type of sampling is very time and cost effective and makes a good case that the research can be generalized because it has adopted this type of sampling. Overall, it makes the study very more effective. This study uses the expert sampling type of purposive sampling for the qualitative sampling approach. Therefore, the chosen process involves a selection of experts from within the construction industry. However, the intended participants are innovation and technical experts and construction managers due to the nature of the research.

The quantitative sampling requires a larger sample size unlike the qualitative approach. Thus, the purposive and snowballing approach has been chosen for selecting participants for the quantitative exercise (i.e., questionnaire survey). According to Etikan and Alkassim (2016), the snowballing sampling method adopts a networking approach to sampling. Whereby, a selective sampling is done, and the selected participants refer other contacts within their network. However, the advance in technology allows the researcher to use social media platforms such as LinkedIn and twitter to perform this exercise. However, researchers have sometimes termed the purposive sampling as judgemental and borderline discriminative while the snowball sampling is said to not guarantee representativeness of the population. Nevertheless, using social media allows the researcher to take control of the selected participant.

5.11.2 Data Analysis

This is the method through which data is measured and analysed using statistical means to produce useful research information (Ramsay, 2004). However, a qualitative or quantitative approach may be used in research analysis. The qualitative analysis is thus a systematic method of identifying and gathering information such as interview transcripts, evaluation notes and other content used during the process of qualitative data collection (Sgier, 2012). For example, text interpretation, phenomenological analysis, grounded theory amongst others are methods of qualitative analysis. The quantitative analysis, on the other hand, focuses on doing a statistical analysis of the data obtained. According to Cramer (2003), the approach of quantitative analysis transforms numerical data into useful information using logical and rational thinking. In accordance with the use of either inferential or descriptive statistics. This research, therefore, aims to apply a thematic qualitative analysis using NVivo to review the transcripts of the interviews and to recognise and interpret recurring themes. Additionally, the use of statistical analysis software (SAS) to extract useful information from a collection of numerical data used was employed to validate this study and create a guideline for this study. Statistical analysis will be applied in this research to establish an objective and empirical pattern of the respondents' responses. Prior to that, different statistical tests will be carried out for data cleaning, description and validation using IBM SPSS software. The reliability of the questionnaire instrument will be tested using Cronbach's Alpha test. The mean, frequency, and standard deviation of the items contained in the questionnaire will be computed. These statistical measures will be computed to elicit the degree of variation in the average mean score value. More so, the One-Way ANOVA, which measures the means of more than two groups to establish whether there is a difference between groups will be used in this research. One-Way ANOVA will be used to determine if there are any significant effects on the factors being studied. The goal is to understand if certain themes have a more significant impact on AI adoption than others.

5.11.3 Validity, Reliability, Rigor and generalisability

The concept of rigor in research as stated by Guba and Lincoln (1989) must ensure application credibility, transferability, dependability, and confirmability during the entire research design phase. Kvale (1995) defined rigour as a notion that ensures precision and transparency in research. This is applied to both quantitative and qualitative research in their distinctive approach. Thus, this study adopts multiple data sources (peer-reviewed journals, company publications, focus groups) which ensure the generalisability (external validity) of the research. Furthermore, the focus groups (purposive sampling) and case study take into account the opinions of multiple participants, thus, improving the generalisability of research findings.

To account for internal validity in the research, the researchers will include a pilot study using a sample of 20 people. These initial responses will be tested for validity (make sure the data is getting what should be gotten) and reliability (the data gotten is consistent) (Lakshmi and Mohideen, 2013). If the collected responses reflect the intended responses, then the questionnaire is rolled out to the wider population. For each survey or questionnaire, an exhaustive exploration of the literature is done to make sure that any other factors are eliminated. Then, at the point of rolling the survey and questionnaire out, pilot studies will be used to secure validity and reliability. In contrast, the appropriateness of the validity and reliability of research is applied to the tools, data and processes used in the quantitative research. Thus, the Likert measurement scale adopted in this study will address the accuracy and ensure validity and reliability in the research. Also, the questionnaire survey in the research

5.12 Ethics Issues

Research ethics is a system used to regulate ethical codes for the analysis of research (Gregory, 2003). Therefore, a number of studies have found that autonomy, equality, confidentiality of disadvantaged participants, beneficence, and privacy, among others, are some of the values guiding research ethics (Zimmer, 2010). In this research, the protection of vulnerable participants is not considered as there is no participation of a vulnerable research group. This research, however, follows the ethical guidelines of UWE. Nonetheless, a plan to submit an ethical proposal to the University's Research Ethics Sub-Committee is underway (RESC). Participants in this study, such as construction experts and other similar participants involved in both the qualitative and quantitative research survey, will also be approached according to the accepted guidelines in an ethical way.

In accordance with UWE ethical research guideline, the approval obtained provides the researcher a cushion which informs that the research adheres to the accepted ethical guidance, the participants are also given a right to access their data and knowledge of how it is being used.

5.12.1 Qualitative Research: Ethical consideration in this study

Given the nature of qualitative research and the close communications taking place between the researcher and the participants. The ethics of this nature of study takes into consideration a number of factors that could impend the ethical guideline of research. Therefore, this research intends to consider ethical concerns, such as the availability of consent forms for all participants before any form of qualitative research (i.e., interviews, focus group interviews) is performed. The consent form will also conform to the participants' choice to partake in the research, maintaining anonymity and confidentiality. However, this study aims to use both video and audio recordings for transparency and data collection purposes. Participants will also be given the option to refuse or withdraw from this data collection mode by opting out at any point in time. However, it will be made clear that the playback of the interview would only be used for the given purpose of this research and confiscated after the study has been completed. In order to avoid plagiarism a sufficient citation will also be given to the literature review.

5.12.2 Quantitative Research: Ethical consideration in this study

In the quantitative process of this research, this study will conform to the use of the informed consent form, data storage, transparency, and anonymization in an ethical manner.

5.13 Data Triangulation

According to Bans-Akutey and Tiimub (2021), data triangulation is a crucial methodological approach that enhances the credibility, reliability, and validity of research findings by using multiple sources of data and analysis approaches to corroborate and validate study results. In developing an AI Maturity Model for the construction industry, data triangulation plays a key role in ensuring comprehensive and robust insights into the complexities of AI adoption and maturity. In this study, data sources include qualitative interviews with industry experts, quantitative surveys of construction firms, and documentary analysis of existing literature and organisational reports. The integration of these diverse sources enabled the researcher to capture a holistic view of AI implementation practices, challenges, and outcomes across different organizations. Qualitative interviews provided rich insights into the stakeholders' perceptions and experiences regarding AI technologies in construction. These interviews allowed the researcher to explore nuanced factors influencing AI adoption. Concurrently, quantitative surveys enabled the collection of structured data on AI maturity levels, adoption rates, and perceived benefits or barriers among a larger sample of construction firms. This quantitative data provided statistical validity and generalizability to the findings to support empirical assertions derived from qualitative analyses. Employing both qualitative and quantitative data triangulation enabled this study to rigorously examination of AI maturity in the construction industry. The complementary nature of these methods allows for a comprehensive exploration of both the depth (qualitative insights) and breadth (quantitative trends) of AI adoption and maturity.

Chapter Summary

Given the thorough evaluation of the research methodology carried out with the aim of justifying the chosen research method, thus engaging in a critical evaluation of the varied research philosophy, paradigms, research strategy, research choice, data collection and analyses. The evaluation thereby justified the selected research method choices for the purpose of this PhD. In a bid to achieve the aim of the study, this research argued against the use of either an objective or subjective way of thinking, stating that either approach will completely answer the research questions. Thus, eliminating the use of a singular way of thinking and adopting an epistemological pluralism driven to triangulate the objective-cum-subjective approach. This study adopts the pragmatic 'what-works-way' of thinking to achieve an exploratory and result-driven Artificial intelligence maturity model in construction. Therefore, the research process appropriately accounted for both the qualitative and quantitative strategy, choice, data collection and analyses used in this study.

6 CHAPTER SIX: QUALITATIVE STUDY

Chapter Overview

This chapter presents the results of the findings that emerged from the qualitative strand of this research study. It started by examining qualitative study. It also examined relevant literature on the basis of the qualitative research method adopted in this study. Also, it presented the type of sampling technique used in the qualitative strand of this study. Furthermore, it elaborates on the method of data analysis adopted for the qualitative part of this study and clearly presents the emergent themes derived from the study. A detailed explanation is presented in the succeeding subheadings.

6.1 Qualitative Study

6.1.1 Literature review

Based on the objective of the study, there was a need to identify the critical success factors of Artificial intelligence specific to the construction industry. However, due to the paucity of literature in this field. This study investigated two distinctive literature perspective aimed at identifying AI success factors in construction by triangulating the various studies on the success factors impacting Artificial intelligence in other complex sectors and other digital technologies specific to the construction industry. The exploration involved an extensive search of literature using key search items. Besides using the key phrase ‘critical success factors’, studying the challenges and barriers to implementation also suggests the critical factors to successful implementation. Therefore, research that studied the success factors, challenges, barriers, or limitations were all included in the exploration. Therefore, the review led to the identification of (54) success factors of AI-powered technologies in various sectors while (44) success factors were derived from other digital technologies specific to the construction industry. Going further, the 98 success factors were deeply analysed using document analysis where similar themes were consolidated and a list of 62 success factors as shown in the Table 6.1 were put up for further confirmation using focus group interviews. The focus group interview involved UK construction and AI experts.

S/N	Success Factors	AI Factor	Sources	Factor Description
1	Shell characteristics	No	, , Damljanovic (2019)	others
2	EMNEs	No	Korrreck (2019), Mckinsey (2018)	others
3	Data Quality	No	Naryan and Tan (2019), Yadav and Singh (2020),	Data
4	Data Availability	Yes	Dora et al. (2021),	Data
5	Data Capability	No	Ngo et al.(2020), Toole et al. (2010)	Data
6	Data Collection	No	Mir et al. (2020), Wolff (201)	Data
7	Data Interpretation	No	Martinez and Fernandez- Rodriguez (2015), Wolff (2021),	Data
8	Data Strategy	No	Gambatese and Hallowell (2011), Perez et al.(2018), Brous et al. (2020)	Data
9	Data Security	Yes	Damljanovic (2019), Bilal et al. (2016), Naryan and Tan (2019), Gbadamosi et al. (2019), Alaloul et al. (2020), Yadav and Singh (2020), Dora et al. (2021)	Data
10	Specific Implementation Requirements	No	Behzad et al. (2020), Wolff (2021)	Organisational
11	Interweave Technology Job roles within Projects	No	Sargent et al. (2012), Rose et al. (2017), Hamma-adama et al. (2020)	Organisational
12	Stakeholder Identification	Yes	Dora et al. (2021), El-Sayegh et al. (2020)	Organisational
13	Benefit Measurement	No	Dora et al. (2021), Woodhead et al. (2018)	Organisational
14	Job relevance	Yes	Dora et al. (2016), Akinradewo et al. (2018)	Organisational

15	Professional image	No	Samek et al. (2017), Wolff (2021)	Organisational
16	Computer anxiety	Yes	Narayan and Tan (2019), Masood and Egger (2019)	Organisational
17	Process Definition and Evaluation	Yes	Ozorhon and Karahan (2017), Ugwu and Kumaraswamy (2007),	Organisational
18	Adoption of Minimal Valuable Products	No	Sharma and Kumar (2020), Yahya et al. (2019),	Organisational
19	Capital structure	No	Furman and Seamans (2018), Perez et al. (2018)	Organisational
20	Governance	Yes	, Narayanan et al. (2020), Cohen et al. (2018), Dora et al. (2021)	Industry
21	Regulatory Policy (government & industry)	Yes	Hamma-adama et al. (2020), Yadav and Singh (2020), Ozorhon and Karahan (2017), Behzad et al. (2020), Abd Rashid et al. (2018), Dora et al. (2021)	Industry
22	Industry Data Standards	No	Bilal et al. (2016), Oke et al. (2021)	Industry
23	Industry Integration Standards	No	Abd Rashid et al. (2018), Ugwu and Kumaraswamy (2007), B47	Industry
24	Industry Usage Standards	No	Makridakis (2017), Brundage et al. (2018)	Industry
25	Industry Evaluation Process & Methods	No	Makridakis (2017), Sun et al.(2018)	Industry
26	Employee Motivation	Yes	Siau and Wang (2018), Marcus et al. (2019),	Resources
27	Employee trust	Yes	Siau and Wang (2018),	Resources
28	Utility	Yes	Emam (2013), Duan et al.(2019)	Resources

29	Process to Data Mapping	No	Nasrollahzadeh et al. (2016), Gebretekie et al. (2021)	Resources
30	AI Technique Selection	Yes	Cai et al. (2020), Al Mansoori et al. (2021)	Resources
31	Resource Optimisation	No	Bilal et al. (2016), Duan et al. (2019),	Resources
32	Multidisciplinary Team (Data Science & Traditional Software Development)	Yes	Ugwu and Kumaraswamy (2007), Zou et al. (2014)	Resources
33	Robust tools	No	Akinade et al. (2018), Damljanovic (2019)	Technology
34	Capital Cost	Yes	Yadav and Singh (2020), Das and cheng (2020), Ozorhon and Karahan (2017),	Technology
35	Operational Cost	Yes	Yadav and Singh (2020), Das and Cheng (2020), Silvero- Fernandez et al. (2019),	Technology
36	Economic Feasibility	Yes	Ellatar (2008), Alinaitwe and Ayesiga (2013), Almarri and Abu Hijleh (2017)	Technology
37	Safety Features	Yes	Ugwu and Kumaraswamy (2007), Oesterreich and Teuteberg (2016)	Technology
38	Hardware Adoption (Availability & Accessibility)	Yes	Ozorhon and Karahan (2017), Ugwu and Kumaraswamy (2007), Kiu et al. (2020),	Technology
39	Software Adoption (Availability & Accessibility)	Yes	Ozorhon and Karahan (2017), Kiu et al. (2020), Midkiff (2008), Wachter et al. (2017)	Technology
40	Technical Solution Development	No	Zhang (2005), Ugwu and Kumaraswamy (2007), Oesterreich and Teuteberg (2016)	Technology

41	Processing Power (GPU)	No	Mir et al. (2020), Grover and Dwivedi (2020), Wolff (2021)	Technology
42	Agile Development	Yes	Lichtenthaler (2020), Yigitcanlar et al. (2020)	Technology
43	Prototype Development	No	Park and Kim (2013), Abir et al. (2020)	Technology
44	Connectivity	No	Azhar (2011), Hardin and McCool (2015), Bilal et al. (2016)	Technology
45	Continuous Iteration of Solution	No	Martinez and Fernandez- Rodriguez (2015), Lockow et al. (2018), Nam et al. (2020)	Technology
46	Consideration of External Elements	No	Alhosani and Alhashmi (2024) , Chen et al. (2021)	Technology
47	Competitive Pressure	Yes	Dora et al. (2021), Tu (2018)	Technology
48	Business Partners	Yes	Damljanovic (2019), Yahya et al.(2019)	Technology
49	Market Trends	Yes	Li et al. (2005), Gavali and Halder (2020)	Technology
50	Technology readiness	Yes	Dora et al. (2021)	Technology
51	Usability (User involvement)	No	Yahya et al. (2019), Yadav and Singh (2020), Das and Cheng (2020), , Kiu et al. (2020), Das et al. (2020)	Others
52	Data Accessibility	Yes	Yadav and Singh (2020), Dora et al. (2021), Mantha and De Soto (2019), Gbadamosi et al. (2019), Woodhead et al. (2018)	Data
53	AI Implementation Strategy	Yes	Abd Rashid et al. (2018), Sun et al. (2018), Ozorhon and Karahan (2017), Ugwu and Kumaraswamy (2007)	Organisational

54	Data Storage	Yes	Provost and Fawcett (2013), Gunduz and Yahya (2018), Naryan and Tan (2019), Choi (2013), Edmondson et al. (2019)	Data
55	Data Standardization	No	Matheny et al. (2019), Choi et al. (2020), Dora et al. (2021), Yadav and Singh (2020), Dora et al. (2021)	Data
56	Awareness & Understanding of the Core of AI	Yes	Kiu et al. (2020), Wang et al. (2017), Hamma-adama et al. (2020), Damljanovic (2019), Behzad et al. (2020)	Organisational
57	Stakeholder Benefit Analysis	Yes	Behzad et al. (2020), Dora et al. (2021), El-sayegh et al. (2020), Abd Rashid et al. (2018),Masood and Egger (2019)	Organisational
58	Top Management sponsorship	Yes	Alhosani and Alhashmi (2024) , Gbadamosi et al. (2019), Yang et al. (2015)	Organisational
59	Investment in Talent Acquisition	Yes	Karacay (2018), Tabesh et al. (2019), Zhou et al. (2020), Abd Rashid et al. (2018), Behzad et al. (2020), Damljanovic (2019),	Resources
60	Adopt Digital Change Management Approach	Yes	Amuda-Yusuf (2018), Behzad et al. (2020), Alhosani and Alhashmi (2024) , Duan et al. (2017), Ugwu and Kumaraswamy (2007), Acquah et al. (2018)	Resources
61	Stakeholder Management	Yes	Ozorhon and Karahan (2017), Dora et al. (2021), Nguyen (2013), Gbadamosi et al. (2019), Martinez and Ferdnandez- Rodriguez (2015)	Resources
62	AI & Construction Domain Experts	Yes	Ugwu and Kumaraswamy (2007), Duan et al. (2017), Masood and Egger (2019), Behzad et al. (2020), Bilal et al. (2016), Hadidi et al. (2017)	Resources

Table 6.1: Exhaustive List of Artificial Intelligence Critical success factors

6.1.2 Focus Groups Interview

Merriam and Tisdell (2015) conceived the focus group interview as a method of collecting data in qualitative research in which an interview will be held on specific topic with group of people or experts who have adequate knowledge about the subject matter. In the same vein, Hennink (2014) opined that the most interesting part of the focus group interview is the interaction that takes place between the interviewer and members of the group will later lead to extraction and generation of valuable information and data in the contrast, this method is not suitable for personal issues or sensitive issues.

In a focus group interview, the interviewer (i.e., researcher) may serve as the focus group interview moderator. As a moderator, he or she must facilitate interaction between group members, draw out differing perspectives and keep the session focused (Franenkel et al., 2015). As a moderator, he or she must be familiar with possible roles and group processes (Krueger & Casey, 2015; Hennik, 2014). Also, the moderator will ask a small group of interviewees (i.e participants or experts) to reflect about some given questions. These interviewee or respondents are usually seated together in a group.so that they can hear the view of one another about a particular question or issue raised (Fraenkel et al., 2015). The moderator will also grant the groups audience to express their views or feelings about any question or issue raised. The focus group interview session is usually recorded by the moderator or researcher using a tape recorder or video recording where applicable. After the recording, the interviewer or researcher will go back to the recording device for further transcription, coding and generating emergent themes from the data obtained.

The focus group interview has a lot of advantages and disadvantages. On its advantages, it enables the researchers to get many views about a particular question. It also gives room for other people to express their views. Its major disadvantage is that it can be messy, if not well coordinated. Therefore, Creswell (2012) urged the moderator to take full control of the interview session in order to get adequate information or data.

Given the aforementioned, the study adopted a focus group interview with 15 UK Construction and AI experts to examine their views on AI adoption within construction firms. Therefore, the exhaustive list of the identified success factors (62) of AI implementation in construction were re-examined and condensed. The expert discussions were both for data collection and validation. To aid research rigor and further validate the stated CSFs, a finalised list of 40 success factors was identified. Therefore, there were 15 experts involved in the qualitative exploration of these factors. The professional demographic of these experts includes:

Table 6.2: Characteristics of Interview Participants

Participant Position	**FG1: Derive additional list of success factors or barriers from experiential knowledge**	**FG2: Confirm results from FG1, validate unique factors & the established categories and establish an importance weighting for each factor**	**FG3: Confirm the most important factors as described by participants**
AI consultant / project managers	2	2	2
Construction project manager	2	2	2
Digital construction experts	2	2	2
Bid Estimator/ manager	1	1	1
Procurement Mangers	1	1	1
AI software developers	3	3	3
Project planners	1	1	1
AI experts such as Machine learning, computer vision, big data analytics and natural language processing experts	3	3	3
Number of Interviewees	15	15	15

The focus group discussion was conducted in (3) iterative approach with the same 15 UK construction and AI experts. Each session had a varied session and lasted between (2-4) hours. The 15 respondents were asked to introduce themselves, communicate their background and professional experience of the AI and construction projects they have irrespectively participated in. Thereafter, the interview session commenced with each construction and AI expert expressing their views on the below questions raised.

- The first focus group discussion to collect data based on experiential knowledge to contrast with the existing success factors from literature review. If the success factor proposed by the experts already existed in the current list, then it was not considered. The list of 62 success factors remained unchanged after the first focus group discussion.

- The second focus group discussion was used to validate the 62 success factors and establish groupings amongst the factors. This session of the interview involved an in-session content analysis with the focus group interviewees. The participants reflected on each factor in the list of success factors to attribute a qualitative importance weight to the factor. This exercise resulted in the elimination of 20 success factors to leave 42 success factors. Additionally, the discussions steered that factors should be grouped and provided the titles for the success factor groups. At the end of the session, the 42 factors were grouped into 7 themes.

- The final focus group was used as a validation exercise which certifies the remaining factors and the groups. Whilst discussing each group, the participants alluded to the removal of two success factors to bring the total of critical success factors to 40. The experts confirmed the seven themes are certified with no need for any changes. A table highlighting the 40 success factors and their groups is found in the data analysis section of this thesis.

6.1.3 Validation of the Thematic Analysis through Expert Judgement

Expert validation was employed in the thematic analysis process to ensure the rigor, credibility, and validity of the results. The fifteen experts were identified and chosen based on their academic qualifications and experience in the UK construction industry. The fifteen experts reviewed the thematic analysis process and the emerging themes, and they provided their insights, critiques, and suggestions. They also assessed whether the identified themes were well-supported by the data and whether they accurately capture the experiences of the respondents. By subjecting the thematic analysis to expert validation, this approach enhanced the trustworthiness of the findings and ensured that the results are robust, reliable, and grounded in the data.

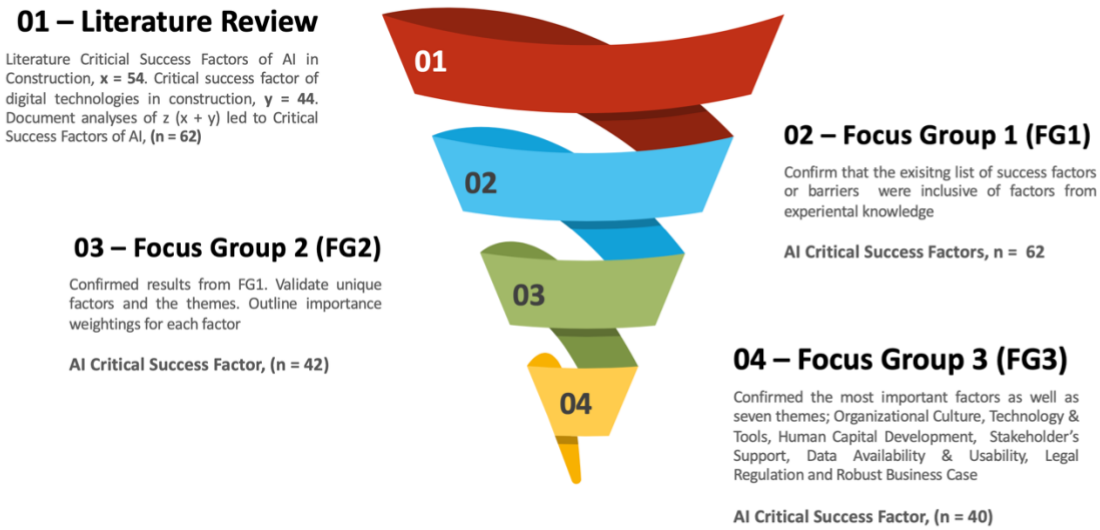


Figure 6.1: demonstrates the process to derive the critical success factors of AI in construction.

6.2 Sampling Approach for Qualitative Data Collections

Fraenkel et al. (2015) conceived sample as a group on which information is obtained. The sampling approach adopted by qualitative data collection is the purposive sampling technique. In this research study, only those who can provide rich and detailed information about AI adoption in construction projects in the United Kingdom were considered. A total of 15 construction experts were contacted to participate in this study. These 15 participants were selected based on the following criteria: ability to apply AI in construction projects, appreciable knowledge of AI application in biding and forecasting process, appreciable year of work experience with different construction companies specific to the United Kingdom, achievement in handling and managing high-impact construction projects in the United Kingdom and involvement in construction projects where NLP and robotics were implemented in the construction process, AI consultants, IoT engineer and big data analytics experts. Only participants that met these criteria were contacted to participate in the focus-group interview due to their experience and involvement in construction projects in the United Kingdom.

Finally, the type of purposeful sampling that was used in this research study is the theory or concept purposeful sampling strategy. It helps the researcher in generating or discovering concepts within AI field by exploring the success factors in adopting AI in construction projects in the United Kingdom.

6.3 Qualitative Data Collection Methods

According to Meriam and Tesdell (2015), the term data refers to ordinary bits and pieces of information found in the environment which can be concrete and measurable. Data conveyed through words are qualitative data. Patton (2015) further conceived qualitative data as a set of data consisting of direct quotations from people about their feelings, knowledge, opinions, and experience which are obtained through direct observation, description of activities, behaviours, interviews, and experts' quotations. Collecting data in a qualitative research study is all about watching, asking, and reviewing (Wolcott, 1992, p. 19). In a nutshell, there are many methods of collecting qualitative research data as described above. In this research study, data that were used for the qualitative strand were collected through interview and documentation. Each of these will be discussed in the next sub-heading.

6.4 Interviews and Documentation

6.4.1 Interview

Interview has become an important source of collecting data in every sphere of human endeavour. Media houses used interview as a means of obtaining information and constructing stories (Merriam & Tesdell, 2015; Fontana & Frey, 2005, p. 695). Interview is one of the methods adopted by qualitative researchers in collecting data or information from individuals. Fraenkel et al. (2015) conceived interviewing as a measure used by researchers in checking the accuracy of or to verify or refute an impression gained through observation. Similarly, Patton (2015) argued that qualitative researchers used interview to solicit other people's perception about a particular issue. In that takes place between the researcher and participants (Brinkmann & Kvale, 2015, p. 5). Also, Creswell (2012) argued that interview occurs in a qualitative research study when researchers ask one or more participants general, open-ended questions and record their answers. In this research, the focus group interview is used to solicit information from construction experts on adoption of AI in construct projects in the United Kingdom.

6.4.2 Documentation

Document is another tool used by qualitative researchers in obtaining and analysing information. Merriam and Tisdell (2015) stressed that document is often used as an umbrella word for a wide range of written, physical, digital, and visual materials related to the research study. Documents are often used by qualitative researchers in their research studies (Pink, 2013). They refer to things that cannot be observed or things that have taken place before the commencement of the research study but are relevant to the claims of the study (Patton, 2015, p. 375). Documents in qualitative research may also include autobiographies, letters, diaries, official records, poems, newspaper accounts, corporate records, historical accounts, organisational promotional materials, blogs, government documents and others. Merriam and Tisdell (2015) argued that most documents are available before the commencement of the research study. These documents can be available physically, on video, online, through blogs, photographs which can be used as data sources (Lee, 2000)

In this research, the researcher explored some past studies on artificial intelligence implementation across different fields and industries. Among these are the study of Awwad et al. (2020) on critical success factors influencing BIM level 2 implementation in UK construction industry. on critical success factors for integrating AI and robotics. Winkler and Zinsmeister (2019) on the trends in digitalization of intralogistics and the critical success factors of its implementation. Duan et al. (2019) on AI for decision making in the era of big data evolution. Also, this research study will be backed with the study of Lee et al (2018) on industrial AI for industry 4.0 based manufacturing systems. It also examined the study of Makridakis (2017) on the forthcoming AI revolution and the study of Martinez and Fernandez (2015) on AI applied to project success. A close look at some of these past research documents revealed that these documents are recent. In addition, this research study will explore some magazines and construct reports relevant to AI application in construction industry. They will able be used to back the findings in this research study.

6.5 Qualitative Data Analysis

This section presents the demographic information of construction experts interviewed in this qualitative strand of this research study for better understanding. A detailed report of this is presented below:

Table 6.3: Demographic information of construction experts

S/N	ITEMS	FREQUENCY	PERCENTAGE
1	Gender: Male	10	66.7
	Female	5	33.3

	Total	15	100
2.	Experience: 1 -5 years	2	13.3
	6 – 10 years	5	33.3
	11 and Above	8	53.4
	Total	15	100
3	Qualification: B.Sc.	5	33.3
	M.Sc.	4	26.7
	PhD	3	20.0
	Others	3	20.0
	Total	15	100
4.	Nationality: EU	4	26.6
	UK	8	53.4
	Others	3	20.0
	Total	15	100

As indicated in Table 6.3 above, it was found that 10 (66.7%) of the respondents are male construction experts while the remaining 5 (33.3%) are female construction experts working with different construction companies in the United Kingdom. On the years of work experience of these construction experts, it was found that 2 (13.3%) had worked as construction experts with their construction companies for 1 to 5 years, 5 (33.3%) of theses construction experts had worked with construction companies for 6 to 10 years while the remaining 8 (53.4%) had worked with different construction companies in United Kingdom for 11 years and above. This shows that more than a half of the construction experts interviewed in the qualitative strand of this research study had worked with different construction companies and had gained substantial experience in the United Kingdom.

Furthermore, 5 (33.3%) of the interviewed construction experts had Bachelor of Science Degree as their highest academic qualification, 4 (26.7%) had Masters' Degree as their highest academic qualification while 3 (20%) have attained a PhD and the remaining 3 (20%) had other professional certifications in construction and environmental sciences. This is an indication that these construction experts are learned and are aware of the issues relating to construction work in the United Kingdom. Lastly, the table examined the nationality of these construction experts and found that 4 (26.6%) of these construction experts interviewed in this research study are citizens of European Union countries, 8 (53.4 %) are citizens of United Kingdom while the remaining 3 (20 %) are from other countries but working as construction experts in the United Kingdom.

From the information provided in the Table 6.3, it is evident that all the sampled participants have substantial knowledge about the field and are experienced enough to provide detailed information on the adoption of AI by construction workers in the United Kingdom.

6.6 Thematic Analysis

In this section, the researcher presents the result of emergent themes that originated from the focus group interview held with the construction experts in United Kingdom. Before, presenting the thematic analysis result, it is important to shed light of the meaning of the concept for better understanding. Creswell (2012) argued that thematic data analysis consists of distilling how things work and naming essential features in themes in the cultural setting. In order to do this, the researcher describes and develops themes from the gathered information or data, codes the data and formulate a set of non-overlapping themes. Also, in generating emergent theme, Creswell (2012) further argue that researchers must single out some detail to include and exclude others that are repeating. This involves describing events or activities without deviating too far from the actual scene. However, the thematic analysis on the data derived from the interviews were explored using NVivo 10 software to transcribe the interview to textual data. In the pantheon of qualitative analysis tools, NVivo stands out as an invaluable tool for navigating the intricate landscape of thematic analysis. NVivo is a widely recognised software tool that was used to uncover the latent narratives, patterns, and themes within the qualitative data collected. Before coding, the researcher became familiar with the data. This involved transcribing the interviews and reviewing the content to gain a comprehensive understanding of the information provided by the participants. Explicitly stated ideas directly articulated by participants, were identified during this initial familiarization phase. During the initial coding phase, the researcher begins to systematically label and categorize segments of the data. This involved assigning codes to specific sections of the transcripts that capture the essence of the information. In-vivo coding involved using participants' own words or phrases as codes. This method captured the richness and authenticity of participants' language. Implicit ideas, which may be embedded in participants' expressions, attitudes, or subtle nuances, were identified during in-vivo coding. This approach allows for the exploration of underlying meanings. Furthermore, open coding enabled breaking down the data into smaller units and assigning descriptive codes to these units. It involved a more detailed examination of the content. Throughout the coding process, the researcher engaged in constant comparison, revisiting previously coded data to ensure consistency and coherence in the emerging themes.

NVivo software facilitated the organisation and management of coded data. It allowed for the systematic arrangement of codes into themes and provides a visual representation of the data structure. NVivo assisted in coding both explicitly stated and implicit ideas. Firstly, NVivo enabled the seamless transcription of interview data into textual formats, laying the groundwork for subsequent analysis. The software's intuitive interface allowed the researcher to manage the large qualitative data effectively, and ensured that no details were overlooked during the initial familiarization phase. During the coding phase, NVivo supported the application of various coding techniques essential for thematic analysis. Initial coding involved systematically labeling and categorizing segments of data, capturing participants' explicit statements and implicit meanings. In-vivo coding, a technique where participants' own words or phrases are used as codes, preserved the authenticity and richness of their contributions, reflecting their perspectives accurately. Additionally, NVivo facilitated open coding, which involved breaking down data into smaller units to explore and assign descriptive codes. This process allowed for a detailed examination of the content, to uncover themes that emerged from the interviews. Throughout these coding stages, NVivo's functionalities ensured consistency by enabling constant comparison of coded data.

6.6.1 Theme One: Organisational Culture

The thematic analysis of experts’ responses highlighted the significance of organisational culture as a driving force behind the successful adoption of AI in the UK construction industry. Organisational culture encompasses various factors that contribute to the integration of AI technologies and practices into construction projects. The experts emphasised that construction companies investing in talent acquisition and skill development are better positioned to adopt AI in their projects. Skilled workers and experts equipped with professional ethics and practices play a key role in implementing AI effectively. This finding is in line with existing literature that focuses on the impact of skilled experts on the use of AI. According to Casalino et al. (2021), a competent workforce is a cornerstone for successful AI adoption in various industries, and this includes the construction industry. In addition, the acquisition of specialized skills enhances the implementation of an insight-driven approach and results in improved decision-making processes. In line with this, Nda and Fard (2013) highlighted that organisations that invest in employee training and development usually end up with employees who are more adaptable to continuous learning and technological changes. This demonstrates the importance of having a competent workforce capable of harnessing AI's potential.

Strategic communication also emerged as a vital element of organisational culture that fosters the adoption of AI. Clear and effective communication channels across the organisation facilitate the free flow of information. This, in turn, encourages individuals to share innovative ideas that enhance construction project quality. Strategic communication not only promotes trust but also encourages the exchange of valuable insights. It also serves as a conduit for promoting cooperation among leaders and staff, thereby fostering an environment conducive for the integration of AI. Many studies have identified that an organisation’s culture plays a significant role in its adoption of AI (Behl et al., 2022; Dabbous et al., 2022).

The experts also highlighted the necessity of digital change management practices for the successful adoption of AI. According to Maali et al. (2020), with regards to the adoption of AI in the construction industry, change management is a blueprint that guides organisations to anticipate potential challenges and ensures that they can fully leverage the benefits of AI technology. This implies that a construction organisation’s ability to embrace digital change management policies significantly influences its compliance with AI technologies and innovative practices. Organisations that are digitally compliant can seamlessly integrate AI into their projects. This adoption of AI is facilitated by the integration of digital technology through well-structured change management strategies and policies.

Furthermore, the bottom-up approach to decision-making emerged as a significant catalyst to successful adoption of AI. Most construction companies that encourage input from all levels of their teams foster an environment where every member's perspective is valued. Encouraging bottom-up decision-making is consistent with studies promoting employee engagement and empowerment

(Bailey et al., 2017; Björk et al., 2021; Corbeanu and Iliescu, 2023). This approach not only boosts morale but also empowers team members and creates a sense of ownership in the projects. More so, this approach positively impacts employee motivation by making them feel valued and engaged in the decision-making process (Park et al., 2014).

In conclusion, an organisational culture that prioritises talent acquisition, strategic communication, digital change management, and bottom-up decision-making empowers construction companies to successfully integrate AI into their projects. By creating an environment that values skill development, fosters cooperation, embraces digital transformation, and encourages diverse perspectives, construction companies in the UK can pave the way for effective AI adoption and innovation in their projects.

Table 6.4: Construction Experts Feedback

Theme One: Organisational culture **Description:** This was considered as an essential factor influencing adoption artificial intelligence in construction projects in the United Kingdom. These are factors relating to the construction companies as an entity.		
Context: Organisational culture includes the ability of a construction company to invest its resources in talent acquisition		
S/No	**Quotation**	**Source**
1.	"Companies that invest their resources in talent acquisition will definitely adopt artificial intelligence in their construction projects because they will have sufficient skilled workers and experts who can implement professional ethics and practices in the construction projects"	R1
2.	"Whenever any construction organisation invest in skill acquisition, this will encourage insight driven approach and enhance decision making process"	R4
3.	"Yes, I absolutely agreed that encouragement of skill or talent acquisition will promote the adoption of artificial intelligence in construction projects"	R13
Context: Organisational culture connotes the ability of the company to establish strategic communication that will promote cooperation among leaders and staff.		

4.	"This is essential ingredient in promoting artificial intelligence adoption in any construction project. Strategic communication ensures free and healthy flow of information across the organisation"	R6
5.	"…not only that, but it will also encourage people to share valuable ideas and innovations that will improve the quality of the construction project"	R7
6.	"---we need to be strategic in the way we communicate. It will not only promote trust but will enable exchange of meaningful and productive development which will later impact positively on the construction work"	R2
Context: Organisational culture refers to the ability of the construction company to adopt digital change management approach		
7.	"...sometimes adopting artificial intelligence in construction projects depends on the ability of the concern organisation to imbibe digital change management policy. This will go a long way in ensuring compliance and accepting meaningful innovations"	R15
8.	"Yeah, construction companies must be digital compliant for them to adopt artificial intelligence in their construction plans and projects"	R11
9.	"With digital change management approach, the construction company will implore digital technology in its construction projects. Therefore, adopting artificial intelligence in construction projects will be easier"	R14
10.	"I think the success occurs as a result of the policy or management approach adopted by many construction companies. Here, some construction companies are adopting artificial intelligence in their construction projects simply because they imbibe digital change management approach"	R3
11.	"We welcome innovations and digital change management strategy. With these we can easily adopt artificial intelligence in our projects"	R10
12.	'…working with organisations that enhance digital management policies and plans will enable construction teams. It will also help in ensuring artificial intelligence in construction projects"	R5
Context: Organisational culture includes the ability of construction companies to ensure bottom-up approach in communication and decision-making processes		

<table>
<tr><td>13.</td><td>“Sure, the kind of communication strategy and decision-making policies adopted by different construction companies’ matters. In my organisation, we adopt bottom-up policy in communication and decision making. It contributed to our success in delivering quality projects”</td><td>R8</td></tr>
<tr><td>14.</td><td>“…using this approach will enable management of the organisation to learn from and take valuable suggestions and ideas from subordinates. Thereby making the views of others relevant”</td><td>R9</td></tr>
<tr><td>15.</td><td>“You see in this construction work; a member of the construction team can come up with a meaningful solution to a problem regardless of the status or level of the person. Taking vital suggestions contributed to our adoption of artificial intelligence in our construction projects”</td><td>R11</td></tr>
<tr><td colspan="3">On this point, two respondents argued that the bottom-up approach boost morale of the construction team members as reported in the statement below:</td></tr>
<tr><td>16.</td><td>“…whenever we seek their ideas and views, they feel excited. Therefore, they are ready to give their best and useful solutions towards improving quality of our construction works”</td><td>R3</td></tr>
<tr><td>17.</td><td>“As a project manager, I observed that the bottom-up method helps our company a lot. It makes every member of the construction team relevant and allows them see the project as theirs. This drive enhances our adoption of artificial intelligence in construction works”</td><td>R10</td></tr>
<tr><td colspan="3">Context: Organisational culture allows employee motivation within the organisation as reported below:</td></tr>
<tr><td>18.</td><td>“In my organisation, we used this approach or method in motivating our staff and soliciting their commitment”</td><td>R4</td></tr>
<tr><td>19.</td><td>“….it helps a lot. My team members prefer because it allows them to express their views and concern”</td><td>R8</td></tr>
<tr><td>20.</td><td>…. including them in decision making, seeking their ideas and communicating effectively with them will serve as a form of motivation to members of construction team. These will enable them to contribute towards adopting artificial intelligence in construction projects.”</td><td>R15</td></tr>
<tr><td colspan="3">Conclusion: Organisational culture in form of communication strategy, policy on talent acquisition, digital change management practices and strategic management practices will enable members of the construction team in adopting artificial intelligence in construction projects.</td></tr>
</table>

6.6.2 Theme Two: Technology and Tools

The insights gained from the thematic analysis highlight the role played by technology and sophisticated tools in driving the adoption of artificial intelligence (AI) in the UK construction industry. The responses from the construction experts indicated the significance of technology advancement and modern equipment in shaping the landscape of construction projects. They emphasised the indispensability of technology in modern construction endeavors and underlined that the contemporary construction environment relies heavily on technology across all phases of projects. This finding is in congruent with existing literature which underscores the crucial role played by technology in shaping modern construction practices (Lota et al., 2022; Tetik et al., 2019). According to McCoyand Yeganeh (2021), the contemporary construction industry relies heavily on technology at every phase of a project, from initial design to project execution. This implies that from design to execution, modern construction processes are intricately intertwined with technology and its innovations. The implication of the responses by the respondents is that the integration of technology is not merely an option but a necessity in the construction industry. By embracing cutting-edge equipment and technology, construction companies position themselves to incorporate AI seamlessly into their operations. This technological stance enables them to align with industry trends and stay competitive. The integration of technology is described as a pathway that naturally leads to the adoption of AI tools and contributes to the enhanced efficacy and distinction of projects.

Furthermore, several respondents underscored the correlation between technology adoption and the reputation of construction companies. The experts asserted that companies known for their consistent use of quality technology-driven solutions are more likely to secure contracts and build a positive reputation. This aligns with findings by Hollebeek et al. (2019), who suggested that clients are increasingly inclined to engage with organisations recognised for their commitment to technological advancement. This implies that the ability to leverage modern technology and AI tools sets these companies apart in the eyes of clients, thereby establishing a competitive edge that attracts contracts and fosters client loyalty.

More so, the experts emphasised that technology and AI adoption entail a commitment to continuous improvement. Beyond the immediate application of sophisticated tools, the adoption of AI involves ongoing iterations and enhancements of AI solutions. According to Jöhnk et al. (2021), AI adoption is not limited to the initial implementation phase; it involves iterative processes that enhance AI solutions over time. This iterative process occurs not only during the construction phase but also after the implementation of projects. This iterative approach ensures that AI solutions remain relevant, effective, and aligned with the changing needs of the construction industry.

In conclusion, this theme highlights the significant influence of technology and sophisticated tools on the adoption of artificial intelligence in the UK construction industry. The majority of construction companies recognise that technology is a fundamental driver of modern construction processes and that embracing it is essential for remaining competitive. The integration of advanced technology acts as a gateway to adopting AI tools, enhancing project efficiency and quality. Moreover, the reputation-building effect of technology adoption contributes to attracting contracts and client loyalty.

Theme Two: Technology and tools **Description:** The use of technology and sophisticated tools in construction work accounts for artificial intelligence adoption by construction companies in the United Kingdom		
1	"Technology is the key/ Today, we are in the era of technology advancement. Technology is required in all facets of human endeavour. Therefore, the construction process is not left out"	R12
2	"Construction work currently depend on modern technologies. That is the reason why construction companies rely on sophisticated tools and equipment in their construction works"	R7
Context: Some respondents argued that the need for modern technology has helped their companies in adopting artificial intelligence as presented below:		
3	"The use of modern equipment and technology has bragged some companies to adopt artificial intelligence in their construction works"	R13

<table>
<tr><td>4</td><td>“…we need to be compliant and move with trend in the industry, Therefore, imbibing technology is a necessity. This enables us to apply artificial intelligence in our projects”</td><td>R6</td></tr>
<tr><td>5</td><td>“By applying modern technology in construction projects, we tend towards adopting artificial intelligence tools which make us stand-out in the industry”</td><td>R9</td></tr>
<tr><td>6</td><td>“Yes, we need technology. Classy equipment, tools and technology in construction are what some clients look for. Therefore, we must adopt technology and ensure usage of artificial intelligence tools”</td><td>R2</td></tr>
<tr><td colspan="3">Similarly, two respondents claimed that their companies were able to attract or win more contracts because of their reputation of adopting technology as reported below:</td></tr>
<tr><td>7</td><td>“Let me state the case of my company here. We won many contracts because of our adoption of technology and artificial intelligence in construction projects”</td><td>R5</td></tr>
<tr><td>8</td><td>Once clients know you for your consistent quality technology-driven projects, they will continue to patronize you and even refer more clients to your office….”</td><td>R11</td></tr>
<tr><td colspan="3">Context: Technology and tools involve continuous iteration of artificial intelligence solution after implementation of build technology maturity within the organisation as expressed by these respondents below:</td></tr>
<tr><td>9</td><td>“… technology is not limited to immediate use of sophisticated tool alone; it entails continuous iteration of artificial intelligence solution after implementing the construction projects”</td><td>R1</td></tr>
<tr><td>1</td><td>“… also, there is need for regular and systemic repetition of artificial intelligence solution after the completion of the construction work”</td><td>R10</td></tr>
<tr><td colspan="3">Conclusion: In essence, the use of modern-day technology and sophisticated tools account for the success recorded by construction companies in the area of artificial intelligence adoption in construction projects in the United Kingdom.</td></tr>
</table>

6.6.3 Theme Three: Human Capital Development

This theme provided valuable insights into the critical role of human capital development in driving the successful adoption of artificial intelligence (AI) in the UK construction industry. The construction experts unanimously emphasised that the adoption of AI in construction projects is not only about technological implementation but also a means to cultivate and nurture the competencies of the workforce. According to Jarrahi et al. (2023), AI adoption is instrumental in cultivating skills and knowledge management among employees. As employees engage with AI tools, they naturally enhance their capabilities and become more proficient in AI applications. This implies that AI adoption in construction projects fosters the development of in-house competency.

Furthermore, the experts signified that the integration of AI also encourages the acquisition of skills and knowledge among construction team members. The concept of upskilling in the context of AI adoption resonates with findings of Olan et al. (2019), who highlighted that AI adoption encourages employees to embrace broader technological trends and stay technologically adaptable. As individuals engage with AI tools, they naturally enhance their capabilities, making them more proficient in both AI applications and broader construction practices. The newfound skills position team members to contribute meaningfully to national development, making them more marketable and capable contributors.

In addition, the experts highlighted the emergence of collaborative partnerships between construction companies and AI solution providers. AI adoption fosters collaborations that not only reduce costs but also enhance the quality of construction projects. Companies that leverage external AI expertise to optimise their processes usually increase efficiency and deliver superior results (Enholm et al., 2022; Sjödin et al., 2021). These partnerships underscore the strategic approach taken by construction organisations to leverage external expertise for mutual benefit.

Furthermore, AI adoption prompts construction companies to prioritise employee upskilling and knowledge transfer. Training programmes are initiated to ensure that the workforce is well-versed in AI tools and applications. The transfer of knowledge from AI-savvy team members to their peers enhances the overall skill set within the organisation. This approach promotes a culture of continuous learning and skill enhancement, resulting in a workforce better equipped to address complex challenges and drive innovation.

The adoption of AI also necessitates staff training and retraining to maximize the potential of AI applications (Arslan et al., 2022; Zirar et al., 2023). Construction companies in the UK recognise that training is essential to unlock the full benefits of AI technology. Whether through in-service or external training, construction companies ensure that team members are up-to-date with the latest technology trends. This training not only bolsters employee capabilities but also contributes to their readiness towards the ever-changing business landscape (Morandini et al., 2023). The experts also pointed out that AI adoption encourages companies to enlist the expertise of both AI specialists and construction domain experts. By collaborating with individuals proficient in AI and construction practices, these companies can strengthen their capabilities and deliver projects that meet international standards. This multidisciplinary approach accelerates project completion, ensuring that companies remain competitive and capable of delivering high-quality, sustainable outcomes.

In conclusion, this theme signifies the profound impact of human capital development on the successful adoption of artificial intelligence in the construction industry. Beyond technology implementation, AI adoption serves as a catalyst for cultivating in-house competency, broadening technological readiness, forming collaborative partnerships, facilitating knowledge transfer, maximizing AI application potential, and engaging with AI and construction domain experts. This holistic approach not only enhances project efficiency and quality but also empowers the workforce to thrive in an increasingly technology-driven landscape. By prioritizing human capital development and harnessing the capabilities of AI, construction companies in the United Kingdom can position themselves as leaders in innovation, collaboration, and sustainable project delivery. The integration of AI becomes a transformative journey that enriches both the workforce and the industry as a whole.

Theme Three: Human capital development **Description:** This is another important success factor expressed by the construction experts. They argued that adopting artificial intelligence in construction projects will develop in-house competency in artificial intelligence as stated below:		
1.	"To be frank with you, the adoption of artificial intelligence in construction projects will aid the production and development of in-house competency among construction team"	R5
2.	"People working on the project will definitely increase their skills and knowledge about usage of artificial intelligence"	R1
3.	"…with this knowledge they will be marketable and contribute to national development"	R12
4.	"…the more you engage in the usage of artificial intelligence in construction projects, the better your knowledge and skill"	R8

5.	"When we started adopting artificial intelligence in our construction projects, we had appreciable number of in-house experts in my organisation which yield a lot of profits for my organisation"	R2
Context: Adopting artificial intelligence construction projects was adjudged to enhance technology readiness of staff beyond artificial intelligence development as presented below:		
6.	"One of the advantages of adopting artificial intelligence in construction work is that it will enable construction team members to develop themselves beyond using artificial intelligence"	R13
7.	... it also enhances technology readiness of construction workers and experts"	R11
8.	"When using artificial intelligence tools, you must be technologically prepared and agree to change to the turn of development. Therefore, it exposed you to many areas and new discoveries"	R9
Context: Adopting artificial intelligence in construction projects will improve the level of technology readiness of members of the construction team beyond AI development as argued below:		
9.	".. their level of technology readiness will improve not only in the area of artificial intelligence but other area of technological advancement"	R10
1(	"…people will learn more and you beyond learning or applying artificial intelligence in construction projects"	R3
1	"As observed in my company, I noticed that since we started adopting artificial intelligence in our construction projects, members of my construction team have been stepping up their technological skills. This is a good signal and indication that we are up to the task"	R7
Context: Adopting artificial intelligence in construction in construction projects encouraged business organisations to collaborate with artificial intelligence solution partners as presented below:		
1	"… through this medium, construction companies can partner with the artificial intelligence solution companies in order to reduce cost and ensure quality service delivery"	R11
1	"Different companies are now collaborating with various AI solution partners. The essence of this collaboration is to improve the quality of construction work and improve performance"	R8

14	"My company signed memorandum of understanding with many artificial intelligence solution partners with the motive of improving the quality of our projects and attracting prospective clients"	R10
15	"...artificial intelligence adoption had dragged many of us into out-sourcing for AI solution companies and working together with them… "	R5
Context: Human capital development enables business organisations to outsource artificial intelligence deployment as argued by the respondents below:		
16	"Another beauty of the artificial intelligent in construction projects is that it enables construction companies to deploy artificial intelligence in their work"	R10
17	"Today construction companies are deploying artificial intelligence in their construction projects in order to meet the needs of the society and promote quality service to their clients"	R13
18	"... they also deploy artificial intelligence as a measure towards ensuring their sustainability in the industry"	R6
19	"This shows the dynamism in the world of work. For construction companies to survive and respond sharply to the needs of this century, they have seen the need to deploy artificial intelligence in construction projects…"	R13
Context: Adopting artificial intelligence in their construction projects has enabled them to promote employee upskilling through knowledge transfer as discussed below:		
20	"Through the adoption of artificial intelligence in construction projects, construction companies are forced to promote skills of their staff"	R1
21	"I share the view of my colleague in this aspect. Like my company, we begin to conduct different training programmemes for our team members"	R9
22	"Also, we ensure transfer of knowledge among our members of staff. Those who have acquired certain knowledge or skill in particular area of artificial intelligence will share what they acquired among their colleague"	R12
23	"… doing this will enable each member of the construction team to share valuable knowledge and contribute towards the development of the team"	R11

<table>
<tr><td colspan="3">Context: Adopting artificial intelligence in construction projects enables construction companies to ensure effective staff training and maximizing artificial application potentials as revealed in the views shared below:</td></tr>
<tr><td>24</td><td>“Once you are adopting artificial intelligence in your construction work, you will be forced to train and re-train your staff on the tools you are using. This will improve the performance of staff and ensure quality service delivery”</td><td>R13</td></tr>
<tr><td>25</td><td>“This training we are talking about can come either as in-service training or external training. The focus is to ensure that the construction team is abreast of latest technology in delivering quality project”</td><td>R8</td></tr>
<tr><td>26</td><td>“…not only that, but companies can also take maximum advantage of the artificial intelligence application potentials in enhancing quality of their projects and attracting more customers”</td><td>R6</td></tr>
<tr><td>27</td><td>“After the training exercise, our company ensure that each member of the team apply whatever you have learnt in your respective area and aspect of the construction project. Doing this has contributed greatly towards our success story”</td><td>R10</td></tr>
<tr><td colspan="3">Context: Adopting artificial intelligence in construction projects has forced companies to solicit the service of artificial intelligence and construction domain experts within the organisation as reported below:</td></tr>
<tr><td>28</td><td>“Another important part of adopting artificial intelligence in construction projects is that it enables construction companies to seek the service of artificial intelligence and construction domain experts as a measure towards ensuring quality and sustainable projects”</td><td>R7</td></tr>
<tr><td>29</td><td>“…we have the need to engage artificial intelligence experts in our company because we need to scale up our team and ensure a quality service”</td><td>R4</td></tr>
<tr><td>30</td><td>“Involving construction domain experts and artificial intelligent experts in a construction project will strengthen an organisation, speed up the task and enable companies to have quality work that can meet international standard”</td><td>R12</td></tr>
<tr><td colspan="3">Conclusion: The position of the construction experts in the focus group interview as presented above shows that adopting artificial intelligence in construction projects will enable business organisations to improve their human capital development and engage skilled personnel to enhance the quality of construction projects.</td></tr>
</table>

6.6.4 Theme Four: Stakeholders' Support

This theme sheds light on the critical role of stakeholders' support in driving the successful adoption of artificial intelligence (AI) in the UK the construction industry. The construction experts emphasised that stakeholders, including management teams, customers, and staff, play a significant role in determining the trajectory of AI integration in construction projects. Stakeholders' support includes multifaceted elements, all of which contribute to the successful integration of AI. Several research aligns with the experts' emphasis on management support as a critical determinant of AI adoption success (Horani et al., 2023; Solaimani and Swaak, 2023). The encouragement and backing provided by stakeholders, including management, customers, and staff, significantly influence the adoption of AI in construction projects. When the management team demonstrates commitment and enthusiasm towards AI integration, it paves the way for successful implementation (Horani et al., 2023).

Trust and transparency also emerged as crucial element of stakeholders' support. When stakeholders, including customers and staff, trust the construction process and are assured of transparency, the road to AI adoption becomes smoother. An atmosphere of trust enables employees to embrace AI technologies with confidence, knowing that their efforts are aligned with stakeholders' expectations (Martínez-Peláez et al., 2023). This trust-driven relationship contributes significantly to the successful implementation of AI in construction projects. The experts also highlighted the significance of stakeholder benefit analysis in ensuring cooperation. By conducting thorough analyses of stakeholders' needs and expectations, construction companies can tailor their AI adoption strategies to align with stakeholder interests. This strategic approach fosters cooperation and collaboration, making stakeholders more receptive to the changes brought about by AI integration. The experts emphasise that this cooperation ultimately drives successful AI adoption.

They also stressed the importance of involving stakeholders at various stages of AI projects. According to Prebanić and Vukomanović (2023), stakeholders' participation, from project conception to completion, is emphasised as a crucial factor in achieving project success. When stakeholders are engaged in the AI project life cycle, their perspectives, feedback, and contributions positively impact the project's trajectory. This inclusive approach not only garners support but also ensures that AI adoption aligns with stakeholders' needs.

In conclusion, this theme underscores the key role of stakeholders' support in driving the successful adoption of artificial intelligence in the construction industry. Stakeholders, including management teams, customers, and staff, collectively determine the direction and outcome of AI integration. A supportive environment characterized by management buy-in, trust, transparency, stakeholder benefit analysis, and involvement ensure that AI adoption is not only feasible but also effective. The collaborative nature of stakeholder engagement contributes to the alignment of AI adoption with stakeholders' interests and expectations. By leveraging stakeholders' insights, construction companies in the United Kingdom can create an environment where AI is embraced and embraced as a solution that adds value to projects. Ultimately, stakeholders' support becomes a driving force that propels the construction industry toward innovation, efficiency, and excellence in AI-enhanced projects.

<table>
<tr><td colspan="3">Theme Four: Stakeholders’ support

Description: This is another factor that account for the successful adoption of artificial intelligence by the construction companies in United Kingdom. Stakeholder’s support refers to the encouragement received by the construction companies from their management team, customers and staff as explained below:</td></tr>
<tr><td>1.</td><td>“Success cannot be achieved in isolation. The support given to the construction team by the company management, staff and other parties go a long way in assisting us to adopting the artificial intelligence in the construction project”</td><td>R5</td></tr>
<tr><td>2.</td><td>“….. the management of our company shows a good commitment and support for artificial intelligence in our construction projects”</td><td>R12</td></tr>
<tr><td>3.</td><td>“The role of this people cannot be denied. They account for success and failure of the construction projects”</td><td>R10</td></tr>
<tr><td>4.</td><td>“Sometimes, the stakeholders can determine the direction and reshape the goal of the project work. Therefore, it is important to carry them along in the process”</td><td>R8</td></tr>
<tr><td colspan="3">Context: Stakeholders’ support includes trust and transparency with stakeholders as expressed below:</td></tr>
<tr><td>5.</td><td>“You see, trust and transparency are very essential in ensuring construction projects completion. When there is trust and openness by stakeholders, adopting artificial intelligence in construction projects will be easier and successful”</td><td>R14</td></tr>
</table>

6.	“When there is trust among stakeholders and construction team, adopting artificial intelligence in construction projects will be superb”	R2
7.	“To me, I think the level of trust counts a lot. This trust will enable the team to achieve a lot and enhance artificial intelligence in construction projects. This is what keeps my company going”	R10
8.	“To me, I think the level of trust counts a lot. This trust will enable the team to achieve a lot and enhance artificial intelligence in construction projects. This is what keeps my company going”	R10
Context: Stakeholders’ support can reflect when management facilitates good initiatives as reported below:		
9.	“Sometimes, to achieve success in construction projects, management team must buy-into and be ready to facilitate meaningful ideas that enhance artificial intelligence adoption. This helps many construction companies here”	R13
1(	“Let me cite an example of my company in this regard. Whenever the management team buy-in or key-into any productive innovation, we always achieve success at the end of our projects. This is one of our motivating factors”	R1
Context: Stakeholders support implies outlining stakeholders’ analysis to ensure stakeholders cooperation as shared below:		
1	“In my company, we usually conduct stakeholder benefit analysis and solicit stakeholders’ cooperation. This accounts for our success in adopting artificial intelligence in our construction projects”	R3
1	“Construction companies that conduct stakeholder benefit analysis usually have stakeholders’ cooperation. This later help them in adopting artificial intelligence in their construction projects”	R11
Context: Stakeholders’ support includes ensuring adequate stakeholders’ involvement in artificial intelligence projects as explained below:		
1	“You see, attaining success in construction projects is a function is many factors which stakeholders’ involvement play a vital role. In my company, we solicit stakeholders’ participation in artificial intelligence project life cycle”	R8
1	“The support received from the stakeholders go a long way in impacting positively in adopting artificial intelligence in our construction works”	R9

Conclusion: Construction experts argued that stakeholders are vital in ensuring success in adopting artificial intelligence in construction projects in the United Kingdom. For any construction company to achieve its set goals and imbibe artificial intelligence meaningfully, it must solicit stakeholders support, participation, and initiatives.

6.6.5 Theme Five: Data Availability and Usability

This theme expounds on the profound impact of data availability and usability on the successful adoption of artificial intelligence (AI) in the UK construction industry. The experts emphasised that AI adoption not only enhances data accessibility but also empowers construction companies to derive valuable insights from available data. They also highlighted the transformative role of AI in providing access to relevant data. AI-driven tools enable construction teams to obtain data that is pertinent to their projects. The experts underlined that the value of AI extends beyond mere data retrieval; it empowers individuals to access data seamlessly, eliminating barriers and enhancing the decision-making process. Similarly, several studies have indicated that improved data accessibility is a fundamental benefit of AI adoption, as it enables organisations to harness data effectively for decision-making and project improvement (El Khatib and Al Falasi, 2021; Li et al., 2023).

Furthermore, the experts emphasised the importance of data security in AI adoption. According to Raimundo and Rosário (2021), AI-powered systems offer enhanced data security measures which ensures that critical project information remains protected. This assurance of data security instills confidence in construction professionals and enables them to harness data without concerns of data breaches. Besides, the convenience of retrieving data at any time and from anywhere further contributes to the practicality of AI adoption.

AI adoption also emerged as a catalyst for improved forecasting and decision-making within construction projects. The experts stated that AI tools facilitate data-driven predictions and informed decisions. Several research has shown that the ability to leverage data analytics and AI algorithms enhances accuracy of predictions and enables organisations to make well-informed choices that influence project outcomes positively (Taboada et al., 2023; Wamba-Taguimdje et al., 2020). The integration of AI in construction projects enhances data storage capabilities; this enables project managers to save and retrieve data effortlessly. This data storage advantage translates into improved project quality and service delivery. The consistency facilitated by AI tools contributes to better performance and client satisfaction. By leveraging stored data, construction teams can achieve continuous improvement in their projects.

The experts emphasised that AI adoption also ensures data standardization across construction projects. Similarly, Kaur et al. (2022) stated that AI tools facilitate the consistent application of standardized practices throughout project implementation. This uniformity enhances collaboration, reduces errors, and streamlines project workflows. The role of AI in enforcing data standardization reinforces its position as a cornerstone of efficient and reliable construction practices. Moreover, AI adoption enables construction teams to extract relevant and actionable data, leading to accurate and reliable results. The experts stated that AI-powered devices provide precision and reliability in data interpretation. This reliability bolsters the confidence of construction professionals in their predictions and decisions, ultimately enhancing the overall quality and sustainability of projects.

In conclusion, this theme underscores the significance of data availability and usability in driving the successful adoption of artificial intelligence within the construction industry. AI-powered tools empower construction professionals to access, analyse, and leverage relevant data with ease. This accessibility enhances forecasting accuracy, decision-making processes, and project outcomes. Moreover, AI's role in data security and storage ensures that critical information remains safeguarded and accessible, contributing to the efficiency of construction operations. The ability to standardize data and derive actionable insights through AI reinforces its transformative impact on the construction landscape.

Theme Five: Data Availability and Usability: **Description:** This is another factor identified by the construction experts. They argued that adopting artificial intelligence in construction projects enhances data accessibility and enable construction companies to leverage on available data as discussed below:		
1.	"Using artificial intelligence in construction work enable us to get relevant data"	R5
2.	"Its value is not just getting relevant data; it assists me a lot because the data needed can be accessed with the aid of the artificial intelligence devices in construction"	R15
3.	"Not only that, but you can also store and retrieve relevant data any day, anytime and anywhere"	R2

4.	"Sometimes, we capitalized on data in forecasting and making relevant construction decision with the help of artificial intelligence tools"	R14
Context: The application of artificial intelligence in construction projects ensure data security while deploying AI as revealed by the respondent below:		
5.	"What I appreciate about the adoption of artificial intelligence in construction project is its ability to secure your data"	R11
6.	"It ensures that your data are well safe and available to you on request"	R8
7.	"Data security is very essential to every user of technology. These devices ensure the safety of your data always. This is another reason why I liked using artificial intelligent devices in construction projects"	R12
8.	"Companies are adopting artificial intelligence devices in construction projects because they are secured. They enable you to make comparison and improve on your projects"	R3
Context: Adopting artificial intelligence in construction projects facilitates data storage and enhance quality service delivery as claimed by the construction experts below:		
9.	"As a project manager, you have the advantage of saving your data using artificial intelligence. This data can help improve the quality of your project"	R1
10	"Applying artificial intelligence helps you in improving your performance and makes your project acceptable to your client"	R9
11	"it helps in ensuring consistency in our performance;"	R4
Context: Adopting artificial intelligence in construction projects helps in confirming data standardization in construction projects as reported below:		
12	"In the course of my practice as a construction engineer, I found that applying artificial intelligence in construction projects assisted me in confirming data standardization throughout the artificial intelligence implementation process"	R10
13	"We can standardize our data with the help of artificial intelligence tools and ensure that standard practices as followed from the begging to the end of the project work"	R13

Context: Adopting artificial intelligence in construction projects enable construction team members to identify relevant and actionable data that can enhance, and reliable result as reported below:		
14	"Construction experts are adopting artificial intelligence in construction projects today because these artificial intelligence tools enable us to get accurate and reliable data that can improve the quality of our projects"	R6
15	"Artificial intelligence devices provide accurate and reliable result which you can count on "	R5
16	"Whenever you have accurate and reliable data, be rest assure that your predictions will be correct. This will assist in facilitating the quality of your construction work"	R7
Conclusion: From the information provided by these construction experts, it was found that adopting artificial intelligence in construction projects assists members of the construction team to derive relevant data, standardize their data, store their data for future use. It also assists them in forecasting and making relevant decision. The utmost goal of data usability and availability in construction project is to enhance sustainable and quality projects.		

6.6.6 Theme Six: Legal Regulations

This theme highlights the role of legal regulations in shaping the successful adoption of artificial intelligence (AI) in the UK construction industry. The construction experts emphasised that legal frameworks, including laws, guidelines, and ethical standards, play a crucial role in guiding construction companies' AI integration efforts. Babuta et al. (2020) stated that regulatory guidelines and directives laid out by UK governmental and oversight bodies serve as fundamental motivators for companies to embrace AI technologies. The experts noted that adherence to these laws and regulations is paramount, as it compels companies to align their practices with legal mandates. The experts also emphasised the role of government agencies in ensuring compliance with construction regulations. These agencies play a crucial role in monitoring construction projects, verifying adherence to guidelines, laws, and standards (Abioye et al., 2021). The presence of regulatory oversight contributes to a culture of compliance and adherence to established norms. Experts note that this oversight fosters consistency in AI adoption across the industry.

Furthermore. legal regulations extend to ethical considerations in AI adoption. The experts emphasised the importance of adhering to ethical standards that govern AI applications in construction projects. According to Díaz-Rodríguez et al. (2023), ethical guidelines governing AI applications are crucial for ensuring the trustworthy and reliable deployment of AI technologies in projects. Construction companies regard these ethical guidelines as essential for building public trust and maintaining industry integrity.

Legal regulations encourage compliance with internationally accepted construction standards. AI tools and devices developed for construction projects adhere to internationally recognised norms, ensuring that they meet rigorous testing and validation criteria. This alignment with global standards instills confidence in construction professionals and assures them of the reliability and effectiveness of AI technologies. The experts outlined the ease and confidence that legal regulations bring to AI adoption. Compliance with guidelines and standards, coupled with ethical considerations, alleviates concerns about the integrity and quality of AI-driven construction projects. Experts note that this stress-free adoption process contributes to the creation of sustainable projects that meet societal needs while upholding industry standards.

In conclusion, this theme underscores the role of legal regulations in shaping the adoption of artificial intelligence within the construction industry. Construction companies in the United Kingdom are driven to adopt AI technologies due to legal mandates, guidelines, and ethical considerations. Governmental agencies ensure compliance through monitoring and enforcement, fostering a culture of adherence to industry standards. By complying with legal regulations and adhering to ethical guidelines, construction companies ensure that AI adoption aligns with internationally recognised norms. This adherence, in turn, engenders trust, confidence, and reliability in AI-driven construction projects. Ultimately, the integration of AI technologies within the construction sector under legal frameworks contributes to the realization of sustainable, high-quality projects that meet the needs of society while upholding ethical and industry standards.

Theme Six: Legal regulations

Description: This refers to the provision of laws on the adoption of artificial intelligence in construction projects. These construction experts maintained that their companies adopted artificial intelligence in construction projects due to the guidelines and directives of the laws of the country as expressed below:

1.	“You see, most companies here are adopting artificial intelligence in their construction projects because it was stipulated by laws of the society. These construction laws guide our operations”	R8
2.	“ Where there is a law, people will definitely comply. This is the key factor. You cannot go outside the directives and guidelines of the construction laws”	R15
3.	“I think the government regulations and laws on construction and environmental development has aided successful adoption of artificial intelligence in construction projects here”	R7
Context: Legal regulations also involve monitoring by concern government agency as expressed below:		
4.	“The effort of the concern agency cannot be over emphasised. They ensure compliance with government directives, laws and guidelines concerning project construction. Therefore, compliance by construction companies is strictly ensured”	R14
5.	“When these bodies visit your site, they ensure you comply with all construction guidelines. With this, everyone key-in into the standard set by the law”	R5
Context: Legal regulations include measuring an ethical and trustworthy artificial intelligence for deployment as revealed below:		
6.	“Another key contributing factor is the ethical standard for artificial intelligence in construction projects. This ethical standard is trustworthy and reliable. Therefore, every construction companies comply”	R8
7.	--- the ethical measures are clearly stipulated for everyone to adopt the artificial intelligence in construction projects. As an expert in the field, I found these measures consistent and convenient”	R10
Context: Legal regulation implies compliance with internationally acceptable construction standard as viewed below:		
8.	“When construction companies adopt artificial intelligence tools and devices in their construction projects, they tend to comply with internationally recognised and acceptable standard…”	R1
9.	… these artificial intelligence tools or devices were developed in line with internationally recognised standard and have passed many tests before applying them. This gives us the confidence”	R13
1(	“Artificial intelligence devices and tools have been constructed or developed in line with international standard. This makes it easier for any construction company to adopt with confidence”	R6

11	"It helped my team a lot. With the aid of artificial intelligence devices or tools, we do not need to worry about whether the standard is attained or not because these devices have taken care of many things for us. Therefore, I found adopting it in construction work as a stress-free exercise"	R12
Conclusion: Based on the position of the construction experts expressed above, it was found that legal regulations in form of laws, guidelines, directives, and enforcement have contributed towards artificial intelligence adoption in construction projects in the United Kingdom. Not only that, It also assisted construction companies to meet up with international standard and providing sustainable projects for the society.		

6.6.7 Theme Seven: Robust Business Care

This theme sheds light on the critical importance of robust business care in driving the adoption of artificial intelligence (AI) in the UK construction industry. According to Gudigantala et al. (2023), AI adoption should be driven by clear business objectives and a well-defined strategy. The responses from the construction experts align with this literature, as they emphasised that AI adoption is not just a technological advancement but a strategic imperative that addresses complex business challenges. The integration of AI tools and techniques enables construction companies to address multifaceted challenges and realise their vision for success.

More so, the experts recognised AI as a versatile solution that empowers business organisations to enhance performance, address inefficiencies, and meet their objectives. The adoption of AI in construction projects enables companies to establish a robust framework that prioritises outcomes over mere outputs. This strategic approach aligns AI-driven objectives with overarching business goals. Studies have shown that AI implementation facilitates the identification of key value drivers and enables organisations to set their priorities and allocate resources effectively (Chowdhury et., 2023; Tominc et al., 2023).

Furthermore, AI adoption assists in identifying and understanding underlying business problem statements. By leveraging AI tools, construction teams can gain insights into operational challenges and areas that require improvement. This understanding enables focused efforts in problem-solving and strategic decision-making. AI adoption also fosters the development and implementation of agile frameworks for project delivery (Tominc et al., 2023). The experts pointed out that AI technologies offer the flexibility to adapt and modify project plans as needed, promoting faster project completion and enhanced efficiency. This adaptability supports dynamic project environments, contributing to the success of construction endeavours. Moreover, the integration of AI into construction projects enhances awareness and understanding of core AI concepts within organisations. As AI becomes more prevalent, employees and teams develop a deeper knowledge of AI tools and their applications. This increased awareness empowers teams to make informed decisions and leverage AI technologies effectively.

AI adoption aids business organisations in conducting economic feasibility analyses and credibility assessments. AI technologies provide the means to evaluate the economic viability of projects and determine their potential success. Construction professionals recognise AI's role in assessing project credibility, contributing to informed decision-making and resource allocation. The experts also emphasised that AI adoption empowers construction companies to ascertain capital costs and operational resources required for project management. By leveraging AI tools, organisations gain insights into the financial implications of projects and the resources needed for their successful execution (Mikalef and Gupta, 2021; Wamba-Taguimdje et al., 2020). This comprehensive understanding supports effective project planning and resource allocation.

In conclusion, this theme underscores the integral role of robust business care in driving the adoption of artificial intelligence within the construction industry. Construction companies in the United Kingdom recognise that AI technologies are not isolated advancements but strategic enablers that address business challenges and drive alignment with organisational goals. The integration of AI in construction projects empowers organisations to solve complex problems, prioritise outcomes, and develop agile frameworks for project delivery. Additionally, AI adoption enhances awareness and understanding of AI concepts, enabling teams to harness these technologies effectively. By conducting economic feasibility analyses and credibility assessments, companies ensure prudent decision-making and project success.

<table>
<tr><td colspan="3">Theme Seven: Robust business care

Description: This is another vital factor identified by the construction experts. They argued that the need to enhance robust business care account for the adoption of artificial intelligence in construction works. One of the points raised here is that application of artificial intelligence will help solve business problems and attain organisational goals as argued below:</td></tr>
<tr><td>1.</td><td>“Business organisations today are in serious need to solve complex business problems and achieve their goals. As a result, there is need for them to adopt artificial intelligence as a solution”</td><td>R6</td></tr>
</table>

2.	"With the adoption of artificial intelligence in business. Organisations can achieve their goals and solve various problems…"	R13
3.	"… apart from solving organisational goals, adopting artificial intelligence in business will help companies improve their performance and business goals"	R3
4.	"There are many problems in the numerous fields that can be resolved with artificial intelligence. In the area of construction, adopting artificial intelligence will enable construction companies solve many problems and achieve their goals"	R14
Context: Adopting artificial intelligence in construction projects can help companies in establishing an artificial intelligence strategy which will prioritise outcomes over outputs as explained below:		
5.	"Adopting artificial intelligence in construction projects will assist construction companies in establishing artificial intelligence implementation strategy. With this, they can set their priority right"	R12
6.	"… with artificial intelligence various business organisations can prioritise their outcome over outputs…"	R4
7.	"… also they can set what should be of utmost value and importance to them and the business"	R8
Context: Adopting artificial intelligence in construction projects will help business organisations in identifying their business problem statement as reported below:		
8.	"We do identify business problems with the aid of artificial intelligence. It helps is solving some of our problems too"	R1
9.	"…our construction team used artificial intelligence in finding some of the problems in our organisations. Thereafter, concise effort will be made towards solving these problems"	R5
Context: Adopting artificial intelligence in construction projects assists in aligning clear artificial intelligence driven objectives with business goals as stated below:		
10	"…it plays a vital role in business development. By adopting artificial intelligence in construction projects, we always align artificial intelligence driven objectives with organisational goals"	R9
11	"This is made possible with the aid of artificial intelligence adoption. It helps our construction team in establishing and merging AI objectives with our goals"	R2
12	"... one can easily bring into line the business objectives with the help of artificial intelligence"	R7

Context: Another way through which adoption of artificial intelligence enhances businesses is by developing and implementing an agile framework for artificial intelligence project delivery as reported below:		
13	"Construction companies today can develop and implement a sustainable framework for artificial intelligence project delivery…"	R10
14	"This is another good part of artificial intelligence. It creates room for implementing and developing a good framework for the project work"	R11
15	"The beauty of this framework is that it will give room for modification and enhances faster delivery of projects"	R15
Context: Adopting artificial intelligence in construction projects will improve awareness and understanding of the core artificial intelligence within the organisation as stated below:		
16	"Using artificial intelligence in construction projects will enhance understanding and promote awareness of the core artificial intelligence in an organisation"	R12
17	"Whenever a construction company adopt artificial intelligence in its construction project, members of the construction team and the company will automatically increase their knowledge and understanding of some artificial intelligence tools"	R15
18	"I also subscribe to that in the sense that the more we use artificial intelligence in construction work, the better we are"	R10
Context: Adopting artificial intelligence in construction projects, assists an organisation in conducting economic feasibility analysis, ensure credibility and enhances success of the artificial intelligence projects as stated by the respondents below:		
19	"Applying artificial intelligence in our construction works helps a lot. With it, our team can establish economic feasibility analysis to determine our economical it is for us to adopt"	R13
20	"Permit me to cite its' benefit in my company. With the artificial intelligence in construction projects, we can ascertain and measure the level of credibility and success attained in our construction projects"	R10
21	"… you can use artificial intelligence to determine the success of your construction projects"	R7
Context: Respondents argued that whenever they adopt artificial intelligence in their construction projects, they will be able to ascertain their capital costs and operational resources required in managing the projects as presented below:		
22	"I think every construction company must adopt artificial intelligence in their projects because it avails you the opportunity to determine your capital costs and determine how successful the project is"	R9

<table>
<tr><td>23</td><td>“To corroborate what my colleague had said, adopting artificial intelligence in construction projects will enable construction experts and the company to ensure a credible project and ascertain their success level”</td><td>R11</td></tr>
<tr><td>24</td><td>“I will stress its value in ensuring that construction companies determine their operational resources which will later assist in proper management and operation of a robust system”</td><td>R15</td></tr>
<tr><td>25</td><td>“… with its business organisations can achieve a robust artificial intelligence system”</td><td>R4</td></tr>
<tr><td colspan="3">Conclusion: From the opinions of these construction experts stated above, it can be deduced that business organisations cannot thrive without applying latest technology and adopting artificial intelligence in their operations. Adopting artificial intelligence will improve performance of business enterprises, enable companies to implement profitable strategies, identify their areas of problems, align their business with their goals, develop viable framework for artificial intelligence framework and ensure sustainable business development.</td></tr>
</table>

6.7 Qualitative Research Findings

The construction industry in the United Kingdom is experiencing a transformative journey marked by the widespread adoption of AI. Through a comprehensive analysis of various themes, it becomes evident that AI adoption in construction is not just a technological shift but a multifaceted endeavour that intertwines innovation, culture, regulations, and strategic foresight. The construction experts assert that a culture of talent acquisition, strategic communication, digital change management, and inclusive decision-making fosters an environment conducive to AI integration. This cultural transformation not only drives adoption but also empowers construction teams to embrace AI technologies and contribute to their successful implementation. In addition, modern technologies and sophisticated tools empower construction companies to harness the capabilities of AI. The experts emphasised that the use of AI not only ensures data accessibility and security but also facilitates its storage, retrieval, and utilisation for accurate decision-making. This technological foundation enables construction firms to remain competitive in an evolving industry landscape.

Human capital development also emerged as a crucial factor in the journey of AI adoption. Through AI integration, construction teams acquire in-house competency and upskill their members. The insights shared by the experts emphasise that AI adoption serves as a catalyst for employee growth, knowledge transfer, and collaboration with AI solution partners. Stakeholder support, equally important, emerges as a driving force that shapes and guides AI adoption strategies. The alignment of stakeholders, including management, staff, and regulatory bodies, reinforces the journey toward successful AI implementation.

In the process of adopting AI, legal regulations play a crucial role. Adherence to construction laws, ethical standards, and international norms propels AI adoption, ensuring compliance and credibility. Additionally, a robust business care strategy proves essential for AI adoption to thrive. By aligning AI with business goals, solving complex problems, and enabling agile frameworks, construction organisations foster an environment that nurtures AI-driven success.

The synthesis of these themes forms a rich tapestry of insights that collectively define the landscape of AI adoption in construction. It is clear that AI adoption is not a singular action but a strategic orchestration involving cultural transformation, technological prowess, skilled human capital, stakeholder alignment, legal compliance, and visionary business care. The construction industry in the United Kingdom is witnessing a paradigm shift where AI transcends mere technology to become an integral part of organisational DNA, propelling construction companies into a future where innovation and excellence converge.

Finally, this chapter addressed the question raised for the qualitative strand of this research study. It clearly explains the research instrument, collection procedure and result that emerged from the focus-group interview. It shows originality of this study by exploring the success factors impacting artificial intelligence adoption by construction companies in the United Kingdom. These factors must be given careful consideration and strategically imbibe by construction companies in the United Kingdom for optimum performance. Out of 42 initial CSF, two factors were identified as replications and removed from the table. These factors include "e*nsuring stakeholders involvement in AI projects*" and "*conduct an economic feasibility analysis*". The finalised Table 6.5. presents the 40 success factors and the 7 emergent themes. The study went further to test these factors quantitatively and examine their effects on construction companies in the United Kingdom. Detail report is presented in the next chapter.

Table 6.5: Finalised Responses for the Critical Success Factor

AI CSF THEMES	S/N	AI SUCCESS FACTORS
Data availability and usability	1	Ensure relevant data is readily accessible to leverage on
	2	Ensure data security
	3	Facilitate the requirement for appropriate data storage
	4	Promote data standardization throughout AI deployment
	5	Provide reliable and actionable data capable to enhance processes
Organisational culture	6	Investment in talent acquisition across multidisciplinary team
	7	Ensure companies adopt insight-driven approach
	8	Establish strategic communication within the organisation
	9	Promote cooperation between leaders and staff
	10	Promote digital change management approach
	11	Encourage bottom-up approach to ensure employee motivation
	12	Encourages continuous iteration of AI solution
Human capital development	13	Upskill inhouse competency in AI
	14	Promote technology readiness beyond AI
	15	Encourage businesses to collaborate with AI solution partners
	16	Embolden businesses to outsource AI deployment
	17	Encourage knowledge transfer and staff training
	18	Encourage businesses to employ AI and construction experts
Stakeholders' support	19	Ensure trust and transparency with stakeholders
	20	Encourage top management commitment and willingness to deliver AI projects
	21	Ensure stakeholders buy-in
	22	Facilitate the need for top-down initiatives
	23	Outline stakeholders benefit analysis and seeks their cooperation
Legal regulations	24	Encourage adoption of governance and policy guidelines
	25	Embolden AI initiatives and enhance trust
	26	Measure an ethical and trustworthy AI for deployment

	27	Encourage compliance with standard
Robust business care	28	Identify business problem statement
	29	Solve business problem statement
	30	Improve and achieve business goals
	31	Establish AI implementation strategy
	32	Align AI driven objectives to the business goals
	33	Develop and implement an agile framework for AI project delivery
	34	Ensure faster project delivery
	35	Increase awareness and understanding of the core of AI within an organisation
	36	Identify capital costs and operational resources required for a project
Technology and tools	37	Enable an organisation to use sophisticated tools in construction projects
	38	Ensure a continuous iteration of AI solution
	39	Ascertain that AI technology is integrated and compatible with existing business process
	40	Prototype development to evaluate the AI application's efficiency on a small scale

Chapter Summary

In this chapter, the 42 critical success factors (CSFs) that underpin the adoption of artificial intelligence (AI) in the United Kingdom's construction industry are explored using qualitative analysis. Prior to the analysis, the 15 construction experts in this study reflected on each of the 62 exhaustive list of artificial intelligence critical success factors and attributed a qualitative importance weight to the factor. This approach resulted in the elimination of 20 success factors, leaving a total of 42 success factors. Using thematic analysis, several themes emerged that draws upon the responses of the construction experts and uncovers a complex landscape where AI integration transcends mere technology and becomes a strategic imperative. A central success factor is Data Availability and Usability. It is emphasised that accessible, secure, standardized, and actionable data forms the bedrock upon which AI-driven decision-making in construction projects is built. Without a robust data foundation, AI's potential cannot be fully harnessed. The chapter also highlights the significance of Organisational Culture. Cultural transformation within construction organisations emerges as a significant factor. This transformation involves various aspects such as investing in talent acquisition across multidisciplinary teams, promoting insight-driven approaches, fostering strategic communication, nurturing cooperation between leadership and staff, and embracing digital change management. These cultural shifts are essential for creating an environment conducive to AI adoption. Human Capital Development is another critical facet of AI adoption. AI serves as a catalyst for employee growth and knowledge transfer. It involves upskilling in-house competencies in AI, expanding technology readiness beyond AI, fostering collaboration with AI solution partners, facilitating knowledge transfer, and recruiting AI and construction experts. A skilled workforce is essential for the successful implementation of AI technologies. The alignment and support of Stakeholders are identified as fundamental drivers for AI adoption. These stakeholders encompass management, staff, regulatory bodies, and external partners. Trust, transparency, top management commitment, and stakeholder buy-in are essential elements that ensure AI initiatives align with organisational objectives. Legal Regulations also play a crucial role in promoting AI adoption. Compliance with construction laws, adherence to ethical standards, and alignment with international norms are vital to ensure that AI adoption is credible and in accordance with established guidelines. Regulatory frameworks provide the necessary structure for AI integration. Robust Business Care strategies are crucial in driving AI adoption. These strategies involve identifying and addressing business problem statements, aligning AI-driven objectives with overarching business goals, developing agile frameworks for AI project delivery, ensuring faster project completion, increasing awareness, and understanding of AI within organisations, and conducting economic feasibility analyses. They form the foundation upon which AI contributes to business success. Finally, the integration of modern Technology and Tools is essential for harnessing AI's capabilities. These tools facilitate data accessibility, security, storage, retrieval, and utilisation. They enable construction companies to remain competitive by leveraging AI to enhance processes and decision-making. In conclusion, this chapter paints a comprehensive picture of the AI adoption journey in the UK construction industry. It underscores that AI adoption transcends technology; it is a strategic transformation that influences culture, data, talent, stakeholder engagement, legal compliance, and overall business care.

Using thematic analysis, this chapter has resolved the research question, which seeks to acknowledge the critical success factors (CSFs) that influence the adoption of artificial intelligence (AI) in the UK construction industry. Through a comprehensive qualitative exploration of the various themes and insights gathered from construction experts, this chapter has provided a comprehensive and holistic understanding of the critical success factors that drive AI adoption in the UK construction industry. The 42 CSFs identified in this chapter collectively highlight the key elements that construction companies and stakeholders must consider when embarking on the AI adoption journey in the UK. These factors encompass data availability and usability, organisational culture, human capital development, stakeholder support, legal regulations, robust business care, and the integration of modern technology and tools. Furthermore, the interplay between the CSFs and their significance AI adoption has been explored. This demonstrates that AI integration is not solely a technological endeavour but a strategic transformation that involves cultural shifts, regulatory compliance, talent development, and the alignment of AI-driven objectives with overarching business goals.

7 CHAPTER SEVEN: QUANTITATIVE STUDY

Chapter Overview

This research utilises a mixed methodological approach – a combination of qualitative and quantitative analysis. While the preceding chapter covered the qualitative part of this research, the overall processes around the quantitative data collection and quantitative analysis of this research are highlighted in this chapter. This includes an in-depth analysis of the sampling strategy utilised in this quantitative study, along with the resulting findings. In addition, the method of data analysis employed for the quantitative aspect of this study is investigated in this chapter. The subsequent subheadings provided a thorough overview of the sample population, sampling technique, questionnaire generation and piloting, final survey distribution, and statistical analysis methodologies. This chapter ends with a comprehensive summary that sums up the quantitative analysis.

7.1 Population and Sampling Techniques

This research sets out to explore the opinions of UK construction experts on the factors affecting the adoption of AI in the UK construction industry, as well as to confirm the wider applicability and generalisability of the research's findings through a large sample survey. The main reason for ascertaining the experts' opinions was to achieve two vital objectives for the research:

(1) To confirm the validity of the 40 theoretical hypotheses generated from the qualitative study

(2) To explore and validate the progressive determinant factors (Identified from the literature) for AI implementation within the UK construction industry through expert views.

To this effect, this research adopted a purposive sampling technique to ascertain the credibility of the information obtained from the respondents, while ensuring the information proved most suitable and pertinent to UK construction companies. The use of the purposive sampling technique allowed for a rich identification of survey respondents based on the established criteria. To ensure the best-fit participants are selected, some criteria used to select the experts' professional demographics include:

- Participants with experience in both Artificial Intelligence and the construction industry expertise i.e., participants must have worked on AI driven construction projects.
- Participants with only UK construction industry experience but some understanding of artificial intelligence.
- Participants with solely Artificial intelligence projects experience

- Participants with vast knowledge and experience working on construction projects.

Given the above criteria, the questionnaire survey was distributed appropriately to suitable stakeholders with varying experience in Artificial Intelligence and in the UK construction industry. The UK's Office of National Statistics (ONS) noted that as of 2021, the UK's construction workforce was estimated to be over 2.2million. This staggering rate also has a strong growth rate of 15.3%, both in the private and public sectors. In line with the research objectives, this study required a specific criteria of employees selected from the UK construction industry with extensive experience in Artificial intelligence and/or the UK construction industry. Given the estimate of over 2.2 million construction workers in both the public and private construction sectors, this study targeted 0.0002% of these workers. These construction workers were targeted for this survey with the aim of leveraging the databases of RIBA, ICE, CIOB, and other construction industry directories.

7.2 Questionnaire Design and Formulation

The results of the qualitative data from Chapter Six were used to develop the questionnaires for this study. The overall aim of this study is to develop a robust Artificial Intelligence Maturity Model (AIMM) that would evaluate and determine the level of AI technology adoption and implementation in UK construction organisations. Four research questions were asked in this study.

7.2.1 Section of the Questionnaire

The questionnaire for this study is divided into three (3) sections. Section A is on the demographics of the respondents and relevant information regarding their various organisations. Section B of the questionnaire contains questions regarding the success factors influencing the adoption of Artificial intelligence (AI) in construction projects while section C contains additional factors that may influence the adoption of AI implementation in construction projects. In section B of the questionnaire, seven (7) themes were identified as Success factors influencing the adoption of Artificial intelligence and forty (40) items were generated from these themes in the questionnaire. The first theme, Data availability and usability contained 5 items; Organisational culture contained 7 items; Human capital development contained 6 items; Stakeholders' support contained 5 items; Legal regulations contained 4 items; Robust business care contained 9 items, while Technology and tools contained 4 items.

7.2.2 Scale Measurement

The scale measurement for the questionnaire was based on the Likert scale. According to Anand (2014), a Likert item is basically a statement that the respondent is asked to evaluate by assigning a numerical value to any either a subjective or objective scale, with the level of agreement/disagreement being the most widely utilised. Respondents define their degree of agreement or disagreement on a symmetric agree-disagree scale for a sequence of items while answering to a Likert item. As a result, the range depicts the intensity of their sentiments for a specific item (Burns and Burns, 2008). Likert is used as a psychometric measuring tool (Wadgave and Khairnar, 2016). Likert rating scale ranges from three to four, five six and seven but the most commonly used is 5-point scale ((Joshi et al., 2015). Therefore, this study will make use of the 5-point scale where 1 = Not Important, 2 = Less Important, 3 = Moderately Important, 4 = Important and 5 = Most Important. This approach provides a platform to sum up the respondents' responses for each of the factors, to establish the overall significance of each factor in the successful AI adoption in the UK construction industry.

7.2.3 Pilot Study and Its Evaluation Technique

A pilot study is used to formulate the design of the full-scale experiment which then can be adjusted. The pilot study is potentially a critical insight to clinical trial design, recruitment and sample size of participants, treatment testing, and statistical analysis to improve the power of testing the hypothesis of the study (Lewis et al., 2021). According to Connelly (2008), extant literature suggests that a pilot study sample should be 10% of the sample projected for the larger parent study. Therefore, 10% of the population is 10% of 285, which is 28. Therefore, 28 respondents were used for Pilot study. In the course of the pilot study, basic descriptive statistics were utilised to analyse the construct validity of the research instrument. By using this approach, the pattern by which similar questions were answered was used to analyse the efficacy of internal constructs. In the end, the results of the pilot study were evaluated, and the feedback was used to better design the questionnaire.

7.3 Data Collection

The questionnaire was designed using Qualtrics and distributed online with 285 respondents filling the online form. Appendix 1 shows a sample of the questionnaire. The online form was beneficial because it allowed wider audiences and enabled a cheaper cost of distribution (Bryman, 2015). The objectives of the study were stated in the introduction section of the questionnaire. Email reminders were sent to the respondents as a reminder and the stage of data collection lasted for about Six (6) months from November 2022 to April 2023. However, a total number of 272 respondents filled the questionnaire appropriately while 13 respondents did not fill it properly.

7.4 Statistical Analysis Techniques

Statistical analysis was applied in this research to establish an objective and empirical pattern of the respondents' responses. Prior to that, different statistical tests were carried out for data cleaning, description and validation using IBM SPSS software. The reliability of the questionnaire instrument was tested using Cronbach's Alpha test. The mean, frequency, and standard deviation of the items contained in the questionnaire were computed. These statistical measures were computed to elicit the degree of variation in the average mean score value. Moreso, the One-Way ANOVA, which measures the means of more than two groups to establish whether there is a difference between groups was used in this research. One-Way ANOVA was used to determine if there were any significant effects on the factors being studied. The goal is to understand if certain themes have a more significant impact on AI adoption than others.

7.5 Preliminary Data Analysis and Screening

While preparing the data for additional statistical analysis, the study conducted some preliminary data screening and cleansing which included identification of unengaged respondents and reliability statistics.

7.5.1 Reliability Analysis

Reliability is the overall internal consistency of a measure (Reynolds and Livingston, 2021). A measure is said to be reliable if it generates consistent results under predictable conditions. This implies that the degree to which a scale gives consistent outcomes when measurements are repeated a number of times is referred to as its reliability. The degree of systematic variations in scale can be evaluated by analysing the correlation between the scores received from various administrations of the scale (Jansen et al., 2003). Consequently, if the correlation in the reliability analysis is strong, the scale produces consistent findings and is thus reliable.

In this research, Cronbach's alpha was used as a measure of the internal consistency or reliability of the questionnaire adopted. According to Tavakol and Dennick (2011), Cronbach's alpha assesses the extent to which all items in a scale or questionnaire are correlated with each other. By a general principle, higher Cronbach's alpha values indicate greater internal consistency. The R statistical software was used to compute the variance-covariance matrix for all the items in the questionnaire.

Cronbach's Alpha formula = $$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum V_i}{V_t}\right)$$

Where:

K =Number of items (questions) in the questionnaire.

V_i =Sum of the variances of all the individual items.

V_t =Variance of the sum of all responses to the items in the scale.

According to Field (2005), the rule of thumb in Cronbach's Alpha (α) coefficient is frequently between 0 and 1. Nevertheless, George and Mallery (2003) suggested that a coefficient value of 0.7 is much more acceptable, whereas a value between 0.7 and 0.8 signifies that the data set has excellent internal consistency. For this study, the values of Cronbach alpha for the seven themes in the questionnaire tested are 0.881, 0.813, 0.894, 0.801, 0.818, 0.874, and 0.946. These values signify an excellent internal consistency of the items in the questionnaire. The purpose of the reliability test in this study was to determine if the identified 40 success factors in the research questionnaire influence AI adoption in the construction industry. The reliability analysis also assisted in determining if the scales used to test the various measures of accountability can consistently and precisely represent the construct being measured (Huang et al., 2006).

7.6 Response Rate

The questionnaire for this research was distributed online. Email reminders were sent to the respondents as a reminder and a total of 285 respondents filled out the online form. The response rate lasted for about Six (6) months from November 2022 to April 2023. However, a total number of 272 respondents filled the questionnaire appropriately while 13 respondents did not fill it properly. Table 7.2 shows the distribution of the 272 respondents whose responses were used for data analysis. These 13 defaulting responses failed preliminary analysis due to incomplete responses or non-responsiveness on several aspects of the questionnaire. For these reasons, the 13 responses were eventually dropped and a total of 272 responses advanced to the next stage for further analysis.

Table 7.1: Socio-demographic Characteristics of Respondents

Gender of Respondents	**Frequency**	**Percentage (%)**
Male	125	46.0
Female	147	54.0
Organisation Type		
Construction	98	36.0
Higher Education Institution (HEI)	118	43.4
Technology Development Organisation	56	20.6
Educational Qualification		
Bachelor's degree	101	37.1
High School/College Graduate, Diploma or Equivalent	6	2.2
Master's degree	126	46.3
Postgraduate Diploma	1	0.4
Others (PhD)	38	13.9
Job Title		
AI Software Developer	17	6.3
Associate Professor/Reader	22	8.1
Big Data Analytics	19	7.0
Lecturer	24	8.8
Machine Learning Expert	7	2.6
Project Manager/Director	97	35.7
Others	78	28.7
Professor	8	2.9
Years of Experience		

0-5 years	117	43.1
6-10 years	96	35.3
11-15 years	30	11.0
16-20 years	19	6.9
21 years and above	10	3.7
Organisation Size		
Small	36	13.2
Medium	93	34.2
Big	143	52.6
Total	**272**	**100.0**

Table 7.2 presents the socio-demographic characteristics of respondents in this research. It provides insights into the composition of the respondent sample. In terms of gender, the sample of the respondents is fairly balanced, with 54% of respondents being female and 46% being male. In terms of organisation type, the majority of respondents (43.4%) come from Higher Education Institutions (HEI), followed by Construction (36%) and Technology Development Organisations (20.6%). This indicates a diverse representation of organisational backgrounds. The educational qualifications show that the largest group of respondents hold master's degrees (46.3%), followed by bachelor's degree holders (37.1%). A smaller percentage holds PhDs (13.9%), while only a few have High School/College Graduate, Diploma, or Equivalent qualifications (2.2%). In terms of job titles, Project Managers/Directors make up the largest group (35.7%), followed by Lecturers (8.8%) and Associate Professors/Readers (8.1%). This suggests a mix of roles within the sample, including academia and project management.

The years of experience among respondents indicate that a significant portion (43.1%) have 0-5 years of experience, while 35.3% have 6-10 years. Only a small percentage (3.7%) have 21 years or more of experience, indicating a relatively young workforce. Lastly, the organisation size reveals that respondents primarily come from big organisations (52.6%), followed by medium-sized (34.2%) and small organisations (13.2%). This information provides context regarding the scale of the organisations represented. In summary, the table's analysis highlights the diversity within the respondent sample in terms of gender, organisational background, educational qualifications, job titles, years of experience, and organisation size. This diversity is crucial for understanding the study's findings and implications within different socio-demographic contexts.

7.7 Descriptive Statistics

According to Kaur et al. (2018), descriptive statistics are used in research to summarise and describe the main attributes of a dataset in order to provide a concise and meaningful representation of the data. This method includes various measures and techniques such as the mean, median, mode, standard deviation, etc. These measures help to either describe where the data tend to cluster or how spread out the data points are from the central tendency. In this research, two measures of the descriptive statistics – the mean and standard deviation – were used to evaluate the success factors that influence the adoption of Artificial intelligence (AI) in construction projects. According to Chakrabarty (2021), the mean, often referred to as the average, measures the central tendency in statistics. It is used to describe where the centre of a dataset is located. In this research, the mean summarised the data by providing a single numerical value that represents the typical or average value in a dataset. The mean was used to determine the top-ranked factors that influence the adoption of Artificial intelligence (AI) in construction projects. Based on success factors influencing the adoption of AI in construction projects, seven (7) themes were considered and the mean score of each of the factors was computed for each theme.

Furthermore, Berry et al. (2021) described the standard deviation as a fundamental measure of variability or dispersion in a dataset. It quantifies how spread out or dispersed the data points are from the mean. In this research, the standard deviation was used to measure how much individual data points deviate from the mean. A higher standard deviation indicates greater variability or spread in the data. Table 7.3 highlights the standard deviation of the success factors that influence the adoption of Artificial intelligence (AI) in construction projects. Based on success factors influencing the adoption of AI in construction projects, seven (7) themes were considered and the standard deviation of each of the factors was computed for each theme.

7.7.1 Descriptive Statistics for Data availability and Usability

Descriptive statistics was carried out to determine the success factors in Data availability and Usability. The IBM SPSS version 22 was used to calculate the mean and standard deviation for each category. The factors were ranked within each group and the overall success factors. Based on the mean computation, the ranking of the success factors is as follows:

1. Facilitate the requirement for appropriate data storage.
2. Provide reliable and actionable data capable to enhance processes.
3. Ensure relevant data is readily accessible to leverage on
4. Ensure data security.
5. Promote data standardization throughout AI deployment.

7.7.2 Descriptive Statistics for Organisational Culture

Descriptive statistics was carried out to determine the success factors in relation to Organisational Culture. Based on the mean computation, the ranking of the success factors within the group is as follows:

1. Encourage bottom-up approach to ensure employee motivation.
2. Promote digital change management approach.
3. Promote cooperation between leaders and staff.
4. Ensure companies adopt insight-driven approach.
5. Promote data standardization throughout AI deployment.
6. Establish strategic communication within the organisation.
7. Encourages continuous iteration of AI solution.

7.7.3 Descriptive Statistics for Human Capital Development

Descriptive statistics was carried out to determine the success factors in relation to Human Capital Development. Based on the mean computation, the ranking of the success factors within the group is as follows:

1. Encourage knowledge transfer and staff training.
2. Promote technology readiness beyond AI.
3. Encourage businesses to collaborate with AI solution partners.
4. Embolden businesses to outsource AI deployment.
5. Encourage businesses to employ AI and construction experts.
6. Upskill in house competency in AI.

7.7.4 Descriptive Statistics for Stakeholders' Support

Descriptive statistics was carried out to determine the success factors in relation to Human Capital Development. Based on the mean computation, the ranking of the success factors within the group is as follows:

1. Ensure stakeholders buy-in
2. Outline stakeholders benefit analysis and seeks their cooperation.
3. Ensure trust and transparency with stakeholders.
4. Encourage top management commitment and willingness to deliver AI projects.
5. Facilitate the need for top-down initiatives.
6. Upskill in house competency in AI.

7.7.5 Descriptive Statistics for Legal Regulations

Descriptive statistics was carried out to determine the success factors in relation to Legal Regulations. Based on the mean computation, the ranking of the success factors within the group is as follows:

1. Encourage compliance with standard.
2. Measure an ethical and trustworthy AI for deployment.
3. Encourage adoption of governance and policy guidelines.
4. Embolden AI initiatives and enhance trust.

7.7.6 Descriptive Statistics for Robust Business Care

Descriptive statistics was carried out to determine the success factors in relation to Robust Business Care. Based on the mean computation, the ranking of the success factors within the group is as follows:

1. Identify business problem statement.
2. Solve business problem statement.
3. Improve and achieve business goals.
4. Align AI driven objectives to the business goals.
5. Identify capital costs and operational resources required for a project.
6. Identify capital costs and operational resources required for a project.
7. Increase awareness and understanding of the core of AI within an organisation.
8. Develop and implement an agile framework for AI project delivery.

9. Establish AI implementation strategy.

7.7.7 Descriptive Statistics for Technology and Tools

Descriptive statistics was computed to determine the success factors in relation to Technology and Tools. Based on the mean computation, the ranking of the success factors within the group is as follows:

1. Enable an organisation to use sophisticated tools in construction projects.
2. Ascertain that AI technology is integrated and compatible with existing business process.
3. Ensure a continuous iteration of AI solution.
4. Prototype development to evaluate the AI application's efficiency on a small scale.

7.8 One-Way Analysis of Variance (ANOVA)

According to Ntumi (2021), the One-Way Analysis of Variance (ANOVA) is a statistical method used to determine whether there are any statistically significant differences between the means of three or more independent (unrelated) groups. When computing One –Way ANOVA, the F-statistic is a test statistic that measures the ratio of the variation between groups to the variation within groups (Mishra et al., 2019). It's used to determine whether the means of the groups are significantly different. A higher F-value suggests greater differences between group means. In addition, the p-value is a measure of the evidence against a null hypothesis. In One-Way ANOVA, a small p-value (α) indicates that there are significant differences between at least two groups. According to Hazra and Gogtay (2016), if the p-value is less than the chosen significance level, the null hypothesis is rejected. This means that there is enough evidence to conclude that at least one group is different from the others. However, a significant ANOVA result does not provide details on specific groups are different; it only indicates that differences exist. On the other hand, If the p-value (α) is not significant, the null hypothesis will be accepted, suggesting that there are no significant differences between the groups (Hazra and Gogtay, 2016).

In this research, One-Way ANOVA was used to compare the means of the different groups of the success factors that influence AI adoption in the construction industry to ascertain if there's enough evidence to conclude that they are not all equal. In other words, One-Way ANOVA was used to determine if there are any significant effects due to the factors being studied. The goal is to understand if certain themes have a more significant impact on AI adoption than others. The chosen p-value (α) for the One-Way ANOVA is 0.05. According to Pereira and Leslie (2009), a significance level of 0.05 (or 5%) is commonly used in hypothesis testing. It represents the threshold at which to decide whether to reject or fail to reject the null hypothesis. Table 7.3 outlines the results of the One-Way ANOVA for each group.

7.8.1 One-Way Analysis of Variance (ANOVA)

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7.8.2 The Results of the One-Way Analysis of Variance (ANOVA)

The p-values for the entire factors under this theme are less than the chosen p-value (0.05). This indicates that within the "Data availability and usability" there is a significant difference in its impact on AI adoption in the construction industry. This suggests that promoting data standardization may have a unique and more substantial influence compared to the other sub-factors within this theme.

For the Organisational culture, the p-values of all the factors are lesser than the chosen significance level of 0.05. Therefore, the null hypothesis is accepted that within the "Organisational culture" theme, all the sub-factors show significant differences in their impact on AI adoption. These findings suggest that all aspects of organisational culture may have a more substantial influence on AI adoption in the context of the UK construction industry.

For Human Capital development, the p-values of the entire factors under this category is less than the chosen significance level of 0.05. An analysis of the One-Way Table indicates that within the "Human capital development" theme, all the factors show a significant difference in its impact on AI adoption. This suggests that encouraging all the factors may have a unique and more substantial influence within this theme.

For Stakeholder's Support, there are 5 factors under this category: Ensure trust and transparency with stakeholders, encourage top management commitment and willingness to deliver AI projects, ensure stakeholders' buy-in, Facilitate the need for top-down initiatives, and Outline stakeholders' benefit analysis and seek their cooperation. The p-values for the 5 factors are lesser than 0.05, the chosen p-value. The null hypothesis is accepted for the 5 factors, indicating that there is a significant difference in Stakeholder's Support on AI adoption.

Furthermore, the analysis of the "Legal regulations" theme indicates that all the factors show significant differences in their impact on AI adoption. The findings suggest that all aspects of legal regulations may have a unique and more substantial influence on AI adoption in the UK construction industry.

Moreso, an analysis of the One-Way ANOVA indicates that within the "Robust business care" theme, all nine factors show significant differences in their impact on AI adoption: The null hypothesis is accepted, indicating that all aspects of robust business care may have a unique and more substantial influence on AI adoption in the UK construction industry.

Lastly, for the "Technology and tools" theme, an analysis of the theme indicates that all the factors show a significant difference in its impact on AI adoption. This suggests that ensuring the integration and compatibility of AI technology with existing business processes and the other three factors have a unique and more substantial influence on AI adoption in the UK construction industry.

Label	AI Success Factor	Mean	SD	Rank within Group	Overall Rank	Cronbach Alpha	One-Way ANOVA
A	**Data availability and usability**						
A1	Ensure relevant data is readily accessible to leverage on	4.2574	0.872	3	14	0.881	0.0345
A2	Ensure data security	3.4321	0.897	4	39		0.0172
A3	Facilitate the requirement for appropriate data storage	4.5468	0.938	1	8		0.1561
A4	Promote data standardization throughout AI deployment	3.2463	0.809	5	40		0.0125
A5	Provide reliable and actionable data capable to enhance processes	4.4412	0.923	2	11		0.0378
B	**Organisational culture**						
B1	Investment in talent acquisition across multidisciplinary team	3.9789	0.984	5	25	0.813	0.0389
B2	Ensure companies adopt insight-driven approach	4.0999	0.927	4	22		0.0442
B3	Establish strategic communication within the organisation	3.8200	0.810	6	31		0.0212
B4	Promote cooperation between leaders and staff	4.1234	0.990	3	20		0.0489
B5	Promote digital change management approach	4.4888	0.814	2	10		0.0234
B6	Encourage bottom-up approach to ensure employee motivation	4.5333	0.798	1	9		0.0123
B7	Encourages continuous iteration of AI solution	3.7654	0.885	7	32		0.0171
C	**Human capital development**						
C1	Upskill in house competency in AI	3.6543	0.965	6	35		0.1798

C2	Promote technology readiness beyond AI	4.1890	0.904	2	18	0.894	0.0425
C3	Encourage businesses to collaborate with AI solution partners	4.1678	0.950	3	19		0.0175
C4	Embolden businesses to outsource AI deployment	3.9012	0.825	4	28		0.0430
C5	Encourage knowledge transfer and staff training	4.2222	0.901	1	16		0.0250
C6	Encourage businesses to employ AI and construction experts	3.6780	0.799	5	34		0.0304
D	**Stakeholders' support**						
D1	Ensure trust and transparency with stakeholders	3.8765	0.959	3	29	0.801	0.133
D2	Encourage top management commitment and willingness to deliver AI projects	3.8760	0.898	4	30		0.0431
D3	Ensure stakeholders buy-in	4.1000	0.920	1	21		0.0182
D4	Facilitate the need for top-down initiatives	3.5432	0.920	5	37		0.0328
D5	Outline stakeholders benefit analysis and seeks their cooperation	3.9321	0.980	2	27		0.0423
E	**Legal regulations**						
E1	Encourage adoption of governance and policy guidelines	4.6542	0.903	3	4	0.818	0.0190
E2	Embolden AI initiatives and enhance trust	4.0001	0.945	4	23		0.0105
E3	Measure an ethical and trustworthy AI for deployment	4.6990	0.881	2	2		0.0485
E4	Encourage compliance with standard	4.7444	0.947	1	1		0.0376
F	**Robust business care**						
F1	Identify business problem statement	4.6543	0.988	1	3		0.0378

F2	Solve business problem statement	4.6342	0.798	2	5	0.874	0.0428
F3	Improve and achieve business goals	4.5678	0.813	3	6		0.0168
F4	Establish AI implementation strategy	3.4901	0.813	9	38		0.0470
F5	Align AI driven objectives to the business goals	4.3765	0.992	4	13		0.0368
F6	Develop and implement an agile framework for AI project delivery	3.5678	0.991	8	36		0.0207
F7	Ensure faster project delivery	4.2432	0.894	5	15		0.0289
F8	Increase awareness and understanding of the core of AI within an organisation	3.7654	0.983	7	33		0.0401
F9	Identify capital costs and operational resources required for a project	4.1987	0.935	6	17		0.0298
G	**Technology and tools**						
G1	Enable an organisation to use sophisticated tools in construction projects	4.5525	0.801	1	7	0.946	0.0335
G2	Ensure a continuous iteration of AI solution	3.9876	0.987	3	24		0.0423
G3	Ascertain that AI technology is integrated and compatible with existing business process	4.4174	0.891	2	12		0.0150
G4	Prototype development to evaluate the AI application's efficiency on a small scale	3.9346	0.828	4	26		0.0315

Table 7.2: Results of One-Way ANOVA

In this study, the mean values were computed to rank the success factors within each thematic category. In the category of "Data Availability and Usability," the mean scores were calculated to prioritize factors like ensuring relevant data accessibility (mean = 4.2574) and promoting data standardization (mean = 3.2463). These means reflect the perceived importance of each factor based on participant responses, with higher means indicating greater influence on AI adoption readiness. The Standard Deviation (SD) measured the dispersion or variability of data points around the mean. A higher SD suggests that data points are more spread out from the mean, indicating greater variability in participant responses regarding the importance of each success factor. In the category of "Organisational Culture," factors like promoting digital change management (SD = 0.814) showed less variability compared to factors like encouraging continuous iteration of AI solutions (SD = 0.885). This variability insight helps in understanding the consensus or divergence among participants' perceptions regarding different success factors. In essence, the use of descriptive statistics, including mean and SD, across thematic categories provided a structured approach to evaluate the factors critical to AI adoption in construction. The rankings derived from these statistical measures offer insights into which factors are perceived as more pivotal and where consensus or divergence exists among respondents. This structured approach not only quantifies the qualitative data but also enhances the reliability and validity of the findings, ensuring a comprehensive understanding of the factors influencing AI adoption readiness in the construction industry.

Chapter Summary

This chapter focused on the quantitative analysis of this research, as it provided a comprehensive overview of the processes and methodologies employed in this phase. This chapter encompassed key quantitative analysis elements such as population and sampling techniques, questionnaire design, data collection, and statistical analysis. The chapter begins by outlining the research objectives, emphasising the need to validate hypotheses and determine determinant factors for AI adoption in the UK construction industry. The purposive sampling technique was used to select suitable respondents based on specific criteria, while targeting a specific fraction of the UK construction workforce. A pilot study with 28 participants was conducted to refine the questionnaire based on feedback. Data collection involved distributing the questionnaire online, with 272 valid responses gathered over six months. Several statistical analysis techniques were employed to evaluate the data collected. Reliability analysis (Cronbach's alpha) was used to assess the questionnaire consistency while descriptive statistics (mean and standard deviation) were used to measure the central tendency of the data, as well as summarise it. The results of the Descriptive

Statistics provided a ranking of the success factors in each in relation to how important they are in the successful AI adoption in the UK Construction Industry. More so, One-Way Analysis of Variance (ANOVA) was used to compare the impact of the success factors on AI adoption. The results of the ANOVA demonstrated significant differences in the influence of the 40 success factors within the seven themes. This implied that all the success factors were significant or played a significant role in the successful AI adoption in the UK construction industry.

8 CHAPTER EIGHT- MATURITY MODEL DEVELOPMENT FOR AI MATURITY MODEL IN CONSTRUCTION

8.1 Chapter Overview

This chapter describes the development of the AIMM-CI Maturity Model using Peffer's Design Science Research Methodology (DRSM) is discussed in detail. The steps of the Maturity Model development, as well as its characteristics are also discussed in this chapter. Moreso, the AIMM-CI Initial Design Framework is evaluated in detail. A pilot study was conducted to with a panel of experts to review and refine the AIMM-CI maturity model. The final AIMM-CI Maturity Model was birthed after undergoing refinement as a result of the feedback and suggestions of the experts in the Pilot Study. For the validation of the final AIMM-CI Maturity Model, a validation survey was formulated which appraised both the content of the maturity model and its usability in the UK construction industry. Furthermore, the AIMM-CI Assessment Framework was discussed. A flowchart that indicates the steps involved in evaluating the AIMM-CI maturity level score was presented alongside a sample evaluation of a construction company using the AIMM-CI Assessment Framework. Finally, this chapter summarises the AIMM-CI Maturity Model and its applicability to the UK Construction industry.

8.2 Maturity Model Design: AIMM Framework using Design Science Research Methodology (DSRM)

The Peffer's design science research methodology framework comprises of six activity steps used in developing the domain specific research, with an aim to address real problems identified in a specific subject. These activity steps provide guidelines for the development of a domain specific model. It provides an end-to-end guideline of the development process which enhances the model by ensuring superiority in its generalisability and standardisation. (1) Problem identification and motivation (2) Define objectives of a solution (3) Design and development of the maturity model (4) Demonstration and evaluate the new maturity model (5) Evaluation of the model through maturity assessment (6) Document design and publish results. Thus, the activities outlined comprises of process requirements used to understand the domain, identify the gap analysis in existing domain specific AIMM, outline the problem present in the AIMM process requirements, analyse and ensure all requirements are met, and lastly evaluate and validate the application of the proposed AIMM domain specific maturity model in construction. Therefore, Table 8.1. outlines Peffers et al. (2007) six activity steps with the defined AIMM domain process requirements.

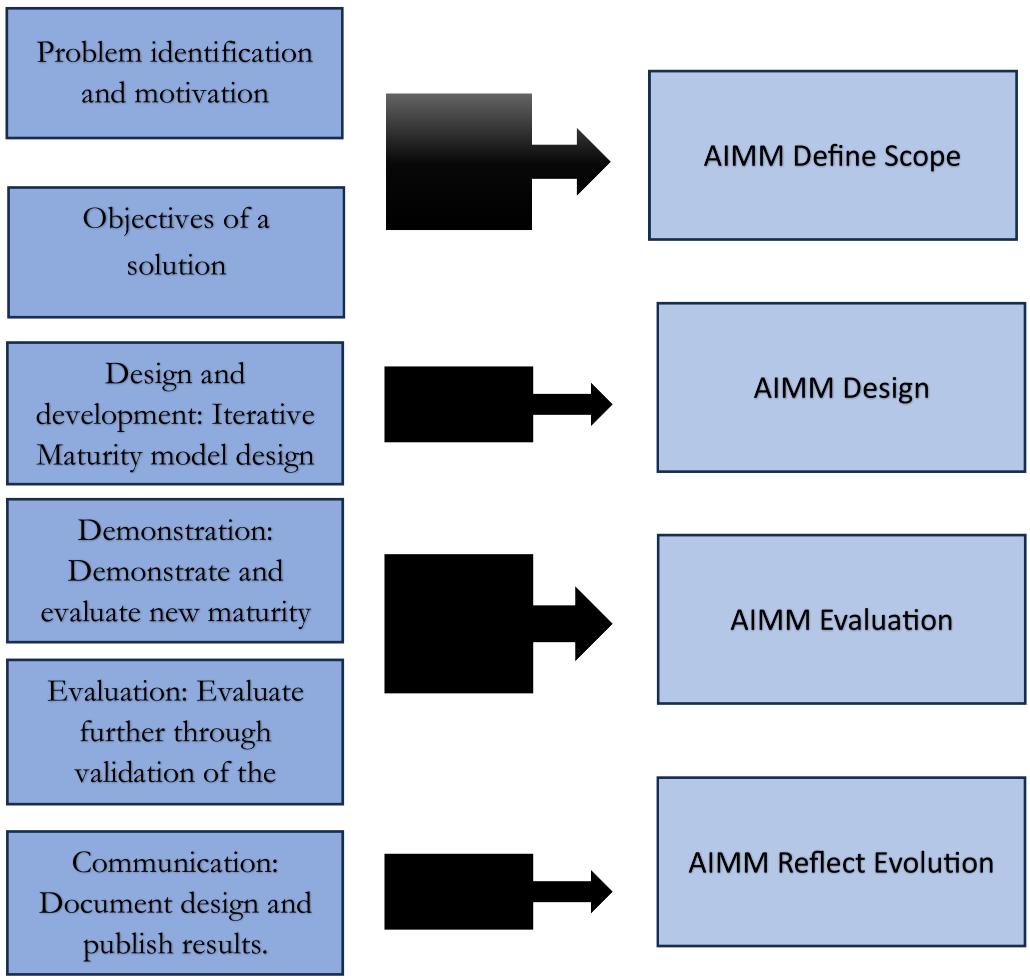


Figure 8.1: AIMM-CI Development Breakdown using Peffer's Design Science Research Methodology (DRSM)

	MM Development steps	AIMM Framework Components/ AIMM Activity steps/ Characteristics
AIMM Define Scope: Problem Identification and Objectives of a solution	Maturity Model Name	AIMM-CI (Artificial Intelligence Maturity model in Construction)
	Purpose of the Model	The primary goal of the AIMM-CI is to encourage the adoption of artificial intelligence (AI) implementation in the UK construction industry. The model simultaneously indicates and evaluates the current level of maturity within the construction industry. Additionally, it sets out a comprehensive roadmap for improvement that outlines the steps between each level of maturity.
	Component of AIMM-CI	The domain of focus for AIMM-CI pertains specifically to the construction sector. The intended audience for this model includes construction practitioners and the UK government. The unit of analysis within this model is the Organisation.
	AIMM-CI Problem Identification/ Gap analysis	As addressed in the Chapter Two of this research, the AIMM-CI Problem Identification/ Gap analysis involves a systematic evaluation of the current state of AI implementation in the construction industry. The first step in building the Maturity model (MM) is to clearly define the problem (Becker et al., 2009). In this research, the first step includes clearly defining the challenges currently faced by the UK construction industry with respect to the adoption of artificial intelligence (AI). Furthermore, a gap analysis will be conducted by comparing the current state of AI adoption in the construction industry with best practices and industry standards. Identify the gaps and deficiencies that hinder the effective implementation of AI technologies.
	AIMM-CI Objective of a solution	As identified in the Chapter Three of this research, the definition of the problem can aid in determining the objectives of a solution. According to Peffers (2007), once the challenges are identified, the model emphasises the importance of defining clear and specific objectives for the AI solution. These objectives serve as guiding principles throughout the AI development and implementation phases. Some of the objectives include: To assess the current level of AI maturity within construction organisations. To provide a structured framework for construction practitioners to understand their AI readiness.

		To provide a structured and purposeful approach to advancing the adoption of artificial intelligence (AI) in the UK construction industry. More so, the AIMM-CI aims to establish clear and actionable objectives that guide construction organisations in their AI adoption journey. To provide clear roadmaps and benchmarks for construction organisations to follow as they progress through the AI maturity levels.
AIMM Design: Design and development: Iterative Maturity model design and development	AIMM-CI Maturity Levels	In chapter Two of this research, five Levels were identified in the literature and adopted from Capability Maturity Model (CMM) framework. They include: Level 1 (Initial); Level 2 (Assessing); Level 3 (Determined); Level 4 (Managed); Level 5 (Optimised)
	AIMM-CI Maturity Levels descriptors	In chapter Two, the Peffers framework introduces the concept of Maturity Levels, drawn from the Capability Maturity Model (CMM). These five levels, ranging from Initial to Optimised, help organisations gauge their progress in AI adoption and identify areas for improvement. Level 1 (Initial): At this stage, organisations in the construction industry are just beginning their journey toward AI adoption. They may have limited awareness of AI technologies and their potential benefits. There is no systematic approach to AI implementation. Level 2 (Assessing): Organisations have started to assess the feasibility and relevance of AI in their operations. They are exploring AI applications and gathering data but haven't implemented AI solutions on a large scale. Level 3 (Determined): Organisations at this level have made a determined commitment to AI adoption. They have established AI strategies and are actively implementing AI solutions in specific areas of their operations. There's a focus on building AI capabilities. Level 4 (Managed): At this stage, organisations have matured in their AI adoption. AI initiatives are well-managed, and there's a structured approach to data collection, analysis, and AI model deployment. The emphasis is on optimizing AI processes.

		Level 5 (Optimised): Organisations at this pinnacle have achieved AI optimisation. AI is deeply integrated into all aspects of their construction operations. Continuous improvement and innovation in AI are part of their culture.
	AIMM-CI Themes	In chapters six and seven, the AIMM-CI themes have been derived from the consolidation of the critical success factors identified to be instrumental in the implementation of Artificial Intelligence in the construction industry. These seven themes have been derived from literature and confirmed by stakeholder experts. The AIMM-CI themes include Data Availability and Usability; Organisational culture; Technology and Tools; Human Capital Development; Stakeholders' Support; Legal Regulations, and Robust Business Care.
	AIMM- CI Key Benchmarking Process Areas	Table 8.7 of chapter eight shows the final completed AIMM-CI table that showcases the key benchmarking process areas identified by comprehensive examination of academic research and the perspectives of the construction experts.
	AIMM-CI Improvement Road map	Figure 8.3 of chapter eight provides a detailed analysis of the AIMM-CI Improvement Road map. A summary of the Improvement Road Map includes:
	AIMM-CI Maturity Assessment Tool	This chapter discusses how the AIMM-CI Assessment Framework was produced in a Microsoft Excel format for ease of usage during assessment. In the framework, there are ten (10) worksheets. Three worksheets focus on the AIMM-CI Guidance; the AIMM-CI Summary; and the AIMM-CI Assessment Levels respectively. The remaining seven (7) worksheets contain the seven (7) AI Adoption Maturity Themes (Data Availability and Usability, Organisational Culture, Technology and Tools, Robust Business Care, Stakeholders' Support, Human Capital Development, and Legal Regulations
AIMM Evaluation: Evaluate further	Validation of the AIMM-CI	Table 8.8 of Chapter eight delves into the validation process of the AIMM-CI Maturity Model. The model underwent evaluation by a panel of 54 experts majoring in construction and artificial intelligence, who are employed in various construction firms in the United Kingdom.

through validation of the maturity assessment	AIMM Evaluation Criteria	Table 8.9 of chapter eight highlights the six criteria evaluation criteria benchmarks. These include Appropriateness, Comprehensiveness of attributes, Relevance of Attributes, Adequacy of Maturity Model levels, Ease of use and level of usefulness and practicability, and Ease of Understanding. These six criteria constitute Section B of the validation questionnaire and have been extensively collaborated by existing literature on its reliability and effectiveness in validating a Maturity Model (Asah-Kissiedu et al., 2021; Salah et al., 2014.).
AIMM Reflect Evolution: Document design and publish results.	AIMM-CI Framework	Figure 8.2 of chapter eight outlines the initial blueprint of the AIMM-CI framework. Table 8.5 highlights the final AIMM-CI maturity framework.

Table 8.1. AIMM-CI Development using Peffer's Design Science Research Methodology (DRSM)

8.3 AIMM-CI Initial Design Framework

The initial blueprint of the AIMM-CI model is presented in Fig. 8.2. Based on the comprehensive model design and maturity model components outlined in Table 8.1, The example AIMM-CI model is designed to encompass five levels of maturity, seven themes, and a compilation of key benchmarking process areas for each identified theme. These process areas have been discovered following a comprehensive examination of relevant literature and have been further validated by qualitative assessment conducted by experts in the field. The progressive characteristics of each maturity level provides a roadmap that the seven themes which constitute the critical success factors of AI adoption in the construction industry undergo from Level 1 (initial) to Level 5 (Optimised). A summary of the AIMM-CI model level descriptors is highlighted below:

8.3.1 Data Availability and Usability

Level 1 (Initial): At this stage, organisations in the construction industry have limited data accessibility and security measures. Data is not readily available, and there is a lack of systematic approaches to data storage and standardization. Data reliability and actionability are notably low, which means that data-driven decision-making is underdeveloped.

Level 2 (Assessing): Organisations at Level 2 are actively assessing their data-related capabilities. They are in the process of identifying critical data sources and evaluating their relevance to AI deployment. Efforts to improve data storage are underway, although they may still be in the early stages. Basic data security measures are being implemented. The organisation has started taking steps toward data standardization, although it might not be well-established yet.

Level 3 (Determined): In Level 3 organisations have made significant progress in enhancing their data capabilities. Data is becoming more accessible with improved security measures in place. Adequate data storage solutions have been implemented, ensuring that data is stored efficiently and securely. Data standardization is actively promoted throughout AI deployment, indicating a mature approach to data management.

Level 4 (Managed): At this stage, organisations have established a well-structured data accessibility framework. Data is readily accessible and highly secure. Data storage solutions are optimised for efficiency and scalability. The organisation invests in appropriate data storage infrastructure. Data standardization is fully integrated into every aspect of AI deployment, indicating a high level of data maturity. Data is extremely reliable and actionable, significantly enhancing processes and decision-making.

Level 5 (Optimised): Level 5 represents the highest level of data maturity within the construction industry. Data is seamlessly accessible, and top-tier security measures are in place to protect it. Cutting-edge data storage technologies are employed for maximum efficiency and scalability. Data standardization is fully automated and integrated into AI processes, reflecting a state of optimisation. Data is exceptionally reliable and actionable, driving continuous process enhancements and innovation. In summary, the progressive characteristics of each maturity level in the "Data" theme reflect the evolution of data-related capabilities within construction organisations as they advance through the AIMM-CI. The model encourages organisations to prioritise data accessibility, security, storage, and standardization as critical factors in their AI adoption journey, ultimately leading to more informed decision-making and improved construction processes.

8.3.2 Organisational Culture

Level 1 (Initial): At this stage, organisations in the construction industry have limited investment in talent acquisition for AI. Data-driven decision-making is not a priority. Communication is ad-hoc and lacks a defined strategy. Collaboration tends to be minimal, with a hierarchical leadership structure. There are minimal efforts to address digital change management, and employee involvement in decision-making is limited. Iteration of AI solutions is infrequent and lacks a structured process.

Level 2 (Assessing): Organisations at Level 2 are actively recognising the importance of AI talent acquisition and are beginning to hire cross-functional AI teams. They are starting to use data for insights but have not fully embraced data-driven decision-making. Communication strategies are being developed. Initiating cross-functional projects is a sign of a growing culture of collaboration. The organisation recognises the need for digital change management and is actively seeking employee feedback. Iterative processes are being implemented, though they are still in the early stages.

Level 3 (Determined): At this stage, organisations make significant investments in acquiring cross-functional AI teams and have integrated them into their operations. Data-driven decision-making is commonplace, and a well-defined communication strategy is in place. Collaboration is actively encouraged and rewarded, indicating a strong culture of teamwork. The organisation has a robust digital change management strategy, and employee feedback actively influences decisions. Iteration is a standard practice, leading to continuous improvements in AI solutions.

Level 4 (Managed): Organisations have reached a level of maturity where they continuously improve their AI talent acquisition efforts. Data insights drive most decisions, and a strong culture of collaboration is ingrained in the organisation's DNA. There's a well-established digital change management framework in place, ensuring that changes are well-managed and embraced by employees. Employees are empowered and motivated to contribute to AI initiatives and drive innovation. Frequent iteration leads to highly optimised AI solutions.

Level 5 (Optimised): At this pinnacle of maturity, AI talent acquisition is a competitive advantage, and the organisation excels in attracting top talent. Data insights are the foundation of all decisions, and exceptional communication fosters innovation and knowledge sharing. Collaboration is not just encouraged but is an inherent component of the organisational blueprint. The organisation sets the gold standard in digital change management, ensuring smooth transitions and adaptations. Employees are highly motivated and drive innovation within the organisation.

In summary, the progressive characteristics of each maturity level in the "Organisational Culture" theme reflect the evolution of cultural factors within construction organisations as they advance through the AIMM-CI. The model emphasises the importance of fostering a culture of collaboration, data-driven decision-making, digital change management, and employee empowerment to support successful AI adoption in the construction industry.

8.3.3 Technology and Tools

Level 1 (Initial): At this stage, organisations in the construction industry have limited or no AI capabilities. They lack a clear understanding of AI technology and its potential benefits. There is no infrastructure or strategy in place to integrate AI into their operations, and any AI projects are in the experimental phase and lack direction.

Level 2 (Assessing): Organisations at Level 2 have recognised the need to assess their AI readiness. They are exploring AI use cases relevant to their industry and beginning to understand AI technology.

Basic infrastructure for data storage and processing is being established to support AI initiatives. Initial pilot projects are underway to evaluate AI feasibility.

Level 3 (Determined): At this stage, organisations have developed a determined AI strategy. They have identified specific AI applications that align with their business goals. Infrastructure and data management capabilities are improved to support AI integration with existing processes. Initial results from AI projects are promising.

Level 4 (Managed): Organisations have effectively integrated AI into their operations at Level 4. AI tools and solutions are being used across various departments. There is a systematic approach to managing AI projects, including monitoring and maintenance. Continuous improvement and optimisation of AI solutions are ongoing.

Level 5 (Optimised): Organisations have achieved optimisation in their use of AI technology at Level 5. AI is deeply ingrained in their business processes and decision-making. Advanced AI solutions are deployed, and they have a competitive edge in their industry. There is a culture of innovation, and they stay at the forefront of AI advancements. In summary, the progressive characteristics of each maturity level in the "Technology Readiness" theme reflect the evolution of technological capabilities within construction organisations as they advance through the AIMM-CI. The model underscores the importance of starting with AI awareness and training, exploring use cases, and investing in infrastructure to support AI initiatives. As organisations mature, they develop clear AI strategies, build dedicated teams, and prioritise projects for maximum business impact. Ultimately, the highest maturity levels are marked by advanced AI adoption, continuous innovation, and a competitive advantage in the industry.

8.3.4 Robust Business Case

Level 1 (Initial): At this stage, organisations in the construction industry have not clearly defined their AI-related business problems. They lack a clear understanding of how AI can address specific challenges. No clear strategy or implementation plan is in place, and there is limited awareness of the potential benefits of AI within the organisation.

Level 2 (Assessing): Organisations at Level 2 are in the process of identifying their AI-related business problems. They are taking initial steps to understand how AI can be applied to solve these problems. A preliminary AI implementation strategy is under development, and awareness within the organisation regarding AI benefits is growing.

Level 3 (Determined): At this stage, organisations have identified their AI-related business problems and challenges. They have developed a clear AI implementation strategy. AI objectives are aligned with broader business goals, indicating a strategic approach to AI adoption. An agile framework for AI project delivery is being established to enhance project management and delivery efficiency. Economic feasibility analysis is conducted to assess the viability of AI projects.

Level 4 (Managed): Organisations effectively solve identified business problems using AI. Business goals are consistently met and improved through AI solutions. AI objectives are well-aligned with business strategies, ensuring that AI investments contribute to overall business success. Projects are delivered efficiently, with a focus on speed and quality, reflecting a mature approach to AI project management. Awareness and understanding of AI are widespread in the organisation.

Level 5 (Optimised): Organisations have optimised their AI-driven business cases. AI solutions contribute significantly to business growth and innovation. AI is seamlessly integrated into all relevant business processes, becoming an integral part of the organisation's operations. Agile frameworks for AI project delivery are continuously improved for maximum efficiency. Capital and operational resources are allocated optimally for AI projects, ensuring maximum returns on investment. In summary, the progressive characteristics of each maturity level in the "Robust Business Case" theme reflect the evolution of organisational readiness to harness the full potential of AI in the construction industry. The model underscores the importance of developing a structured process for identifying and defining specific business problems, aligning AI objectives with broader business goals, and continuously improving project delivery for efficiency. At the highest maturity levels, AI is deeply integrated into all aspects of the organisation, and a culture of innovation and continuous improvement prevails, driving sustained business growth and competitiveness.

8.3.5 Stakeholders' Management

Level 1 (Initial): At this stage, organisations in the construction industry have limited trust and transparency in stakeholder relationships. Top management has not fully committed to delivering AI projects, and stakeholders are not fully bought into the AI initiatives. Efforts to facilitate top-down initiatives related to AI are ineffective, and stakeholders' benefit analysis and cooperation are in the early stages. There is limited involvement of stakeholders in AI projects.

Level 2 (Assessing): Organisations at Level 2 are starting to build trust and transparency in stakeholder relationships. Top management is beginning to show commitment to AI projects, and stakeholders are starting to understand the value of AI initiatives. Efforts are made to facilitate top-down initiatives related to AI, and initial outlines of stakeholders' benefit analysis and cooperation are developed. Stakeholders are becoming more involved in AI projects.

Level 3 (Determined): At this stage, there is a high level of trust and transparency with stakeholders. Top management is fully committed and willing to deliver AI projects, and stakeholders are strongly bought into AI initiatives. Top-down initiatives related to AI are effectively facilitated, and comprehensive strategies for stakeholders' benefit analysis and cooperation are in place. Stakeholders are actively involved in AI projects.

Level 4 (Managed): Trust and transparency with stakeholders are continually reinforced, becoming an integral part of the organisation's culture. Top management consistently demonstrates commitment to AI projects, and stakeholders' support for AI initiatives remains strong. Top-down initiatives related to AI are well-integrated into the organisation, and there are ongoing efforts to optimise stakeholders' benefit analysis and cooperation. Stakeholders play a critical role in the management of AI projects.

Level 5 (Optimised): At the highest maturity level, trust and transparency with stakeholders are ingrained in the organisation's DNA. Top management is fully aligned and dedicated to AI-driven objectives, and stakeholders' support and enthusiasm for AI initiatives are unwavering. Top-down initiatives related to AI are consistently successful, and there is continuous refinement and optimisation of stakeholders' benefit analysis. Stakeholders are actively engaged in shaping the future of AI within the organisation, becoming AI ambassadors.

In summary, the progressive characteristics of each maturity level in the "Stakeholders' Management" theme reflect the evolution of stakeholder engagement and management as organisations advance through the AIMM-CI. The model emphasises the importance of building trust and transparency, garnering top management support, and actively engaging stakeholders throughout the AI journey. At the highest maturity levels, stakeholders become integral to AI project success and actively contribute to shaping the organisation's AI-driven future.

8.3.6 Human Capital Development

Level 1 (Initial): At this stage, organisations in the construction industry are making limited efforts to upskill their in-house competency in AI. There is minimal focus on promoting technology readiness beyond AI, and collaboration with AI solution partners is limited. Businesses are not actively encouraged to outsource AI deployment. Basic knowledge transfers and staff training activities are initiated, and there is occasional hiring of AI and construction experts.

Level 2 (Assessing): Organisations at Level 2 are gradually increasing efforts to upskill their in-house competency in AI. Some initiatives to promote technology readiness beyond AI are underway. Collaboration with AI solution partners is growing. Moderate encouragement for businesses to outsource AI deployment is observed. There is ongoing knowledge transfer and staff training efforts, and occasional hiring of AI and construction experts.

Level 3 (Determined): Significant progress is made in upskilling in-house competency in AI. Technology readiness is actively promoted throughout the organisation. There is strong collaboration with AI solution partners. Encouragement for businesses to strategically outsource AI deployment when appropriate is in place. Well-established knowledge transfers and staff training programmes are implemented, and regular hiring of AI and construction experts occurs.

Level 4 (Managed): In-house competency in AI is consistently strong and continually evolving. Technology readiness becomes an integral part of the organisation's culture. Collaborative partnerships with AI solution partners are highly effective. Businesses strategically optimise AI deployment through a balanced mix of in-house and outsourcing. Cutting-edge knowledge transfers and staff training practices are in place. A dedicated team of AI and construction experts is maintained.

Level 5 (Optimised): In-house competency in AI is considered a core organisational strength. Technology readiness is deeply ingrained in the organisation's culture and operations. AI solution partners are viewed as strategic allies. AI deployment is optimised through the right mix of in-house and outsourcing. The organisation excels in pioneering cutting-edge knowledge transfer and staff training practices. The organisation leads the industry with a world-class team of AI and construction experts, driving innovation.

In summary, the progressive characteristics of each maturity level in the "Human Capital Development" theme underscore the importance of developing human capital to effectively harness AI capabilities. As organisations advance through the AIMM-CI, they evolve from limited efforts and basic knowledge to becoming leaders in human capital development in the context of AI adoption. This evolution includes upskilling, promoting technology readiness, fostering collaboration, optimizing AI deployment, and building a highly proficient team of experts. Human capital development plays a crucial role in achieving AI maturity in the construction industry.

8.3.7 Legal Regulation

Level 1 (Initial): At this stage, organisations in the construction industry are making limited efforts to encourage the adoption of governance and policy guidelines related to AI. There is minimal emphasis on emboldening AI initiatives and enhancing trust. Basic measurement of ethical and trustworthy AI for deployment is conducted, but it is not highly advanced. Minimal emphasis is placed on encouraging compliance with industry standards and regulations.

Level 2 (Assessing): Organisations at Level 2 are gradually increasing efforts to encourage the adoption of governance and policy guidelines related to AI. They are also beginning to put more effort into emboldening AI initiatives and enhancing trust in AI systems. More advanced measures for evaluating the ethics and trustworthiness of AI for deployment are developed. There is a moderate emphasis on encouraging compliance with industry standards and regulations.

Level 3 (Determined): At this stage, organisations actively promote the adoption of governance and policy guidelines related to AI. Strong efforts are made to embolden AI initiatives and enhance trust in AI systems. Well-defined and rigorous measures are in place to ensure the ethical and trustworthy deployment of AI. Organisations actively encourage compliance with industry standards and regulations.

Level 4 (Managed): Governance and policy guidelines related to AI are fully integrated into the organisation's operations and are enforced. AI initiatives are highly emboldened, and trust in AI systems is well-established. Rigorous measures ensure the highest standards of ethical and trustworthy AI deployment. Proactive compliance with industry standards and regulations is maintained.

Level 5 (Optimised): Organisations at this level set industry standard for governance and policy guidelines related to AI. AI initiatives are pioneering and synonymous with trust. Unparalleled measures ensure the highest standards of ethical and trustworthy AI deployment. They lead in compliance with industry standards and regulations, serving as benchmarks for the industry.

In summary, the progressive characteristics of each maturity level in the "Legal Regulation" theme emphasise the importance of navigating legal and regulatory aspects as organisations advance in their AI maturity. This evolution includes promoting governance and policy guidelines, emboldening AI initiatives, enhancing trust, measuring ethics and trustworthiness, and actively complying with industry standards and regulations. As organisations progress through the AIMM-CI, they move from basic awareness and measures to becoming industry leaders in legal and regulatory compliance related to AI adoption in the construction sector. Legal regulation is a critical aspect of ensuring responsible and effective AI deployment.

Figure 8.2 **AIMM-CI Progressive Characteristics for Each Maturity Level**

AIMM Process	AIMM Key Benchamarking Process	Level 1(Initial)	Level 2(Assessing)	Level 3(Determined)	Level 4(Managed)	Level 5(Optimised)
Theme	**Scope**	**PROGRESSIVE CHARACTERISTICS OF EACH MATURITY LEVEL**				
Data	1)Ensure relevant data is readily accesssible to leverage on 2)Ensure data secuirity 3)Facilitate the requirement for appropraite data storage 4)Promote data standardization throughout AI deployement 5)Provide reliable and actionable data capable to enhance processes	• Limited data accessibility and security measures. • The current state of data storage lacks a systematic approach and exhibits limited standardisation. • Data reliability and actionability are notably low.	• Data accessibility and security measures are being assessed. • Efforts to improve data storage are in progress. • Initial steps toward data standardization.	• Data is becoming more accessible with improved security. • Adequate data storage solutions are in place. • Data standardization is actively promoted.	• Data is readily accessible and highly secure. • Data standardization is well-managed throughout AI deployment. • Reliable and actionable data is available for enhancing processes.	• Data is seamlessly accessible and highly secure. • Data standardization is fully integrated into AI deployment. • Data is extremely reliable and actionable, significantly enhancing processes.
Organisational Culture	1)Investment in talent acquisition across multidisciplinary team 2)Ensure companies adopt insight-driven approach 3)Establish strategic communication within the organization 4)Promote cooperation between leaders and staff 5)Promote digital change management approach 6)Encourage bottom-up approach to ensure employee motivation 7)Encourages continuous iteration of AI solution	• Limited investment in talent acquisition • Little emphasis on data-driven decision-making. • Communication is ad-hoc and lacks a defined strategy. • Limited collaboration, hierarchical leadership. • Minimal focus on digital change management. • Limited efforts to involve employees in decision-making. • Iteration is infrequent and lacks a structured process.	• Investment in hiring cross-functional AI teams. • Beginning to use data for insights. • Developing a communication strategy. • Initiating cross-functional projects. • Recognizing the need for digital change management. • Actively soliciting feedback from employees. • Implementing iterative processes.	• Significant investment in cross-functional AI teams. • Data-driven decision-making is commonplace. • Well-defined communication strategy in place. • Collaboration is encouraged and rewarded. • Robust digital change management strategy. • Employee feedback actively influences decisions. • Iteration is a standard practice, leading to improvements.	• Continuous improvement in acquiring AI talent. • Data insights drive most decisions. • Strong collaboration culture is ingrained. • Well-established digital change management framework. • Employees are empowered and motivated. • Frequent iteration leads to highly optimized AI solutions.	• AI talent acquisition is a competitive advantage. • Data insights are the foundation of all decisions. • Exceptional communication fosters innovation. • Collaboration is an inherent component of the organisational blueprint. • Gold standard in digital change management. • Employees are highly motivated and drive innovation.
Technology and Tools	1)Enable an organization to use sophisticated tools in construction projects 2)Ensure a continuous iteration of AI solution 3)Ascertain that AI technology is integrated and compatible with existing business process 4)Prototype development to evaluate the AI application's efficiency on a small scale	• Organizations at this stage have limited or no AI capabilities. • They lack a clear understanding of AI technology and its potential benefits. • There is no infrastructure or strategy in place to integrate AI into their operations. • AI projects, if any, are in the experimental phase and lack direction.	• Organizations have begun assessing their AI readiness. • They are exploring AI use cases relevant to their industry. • Basic infrastructure for data storage and processing is being established. • Initial pilot projects are underway to evaluate AI feasibility.	• Organizations at this stage have a determined AI strategy. • They have identified specific AI applications that align with their business goals. • Infrastructure and data management capabilities are improved. • AI integration with existing processes is in progress, and initial results are promising.	• Organizations have effectively integrated AI into their operations. • AI tools and solutions are being used across various departments. • There is a systematic approach to managing AI projects, including monitoring and maintenance. • Continuous improvement and optimization of AI solutions are ongoing.	• Organizations have achieved optimization in their use of AI technology. • AI is deeply ingrained in their business processes and decision-making. • Advanced AI solutions are deployed, and they have a competitive edge in their industry. • There is a culture of innovation, and they stay at the forefront of AI advancements.
Robust Business Case	1)Identify business problem statement 2)Solve business problem statement 3)Improve and achieve business goals 4)Establish AI implementation strategy 5)Align AI driven objectives to the business goals 6)Develop and implement an agile framework for AI project delivery 7)Ensure faster project delivery 8)Increase awareness and understanding of the core of AI within an organization 9)Identify capital costs and operational resources required for a project	• Organizations at this stage have not clearly defined their AI-related business problems. • There is a lack of understanding of how AI can address specific challenges. • No clear strategy or implementation plan is in place. • Limited awareness of the potential benefits of AI within the organization.	• Organizations are in the process of identifying their AI-related business problems. • Initial steps are taken to understand how AI can be applied to solve these problems. • A preliminary AI implementation strategy is under development. • Awareness within the organization regarding AI benefits is growing.	• Organizations have identified their AI-related business problems and challenges. • They have developed a clear AI implementation strategy. • AI objectives are aligned with broader business goals. • An agile framework for AI project delivery is being established. • Economic feasibility analysis is conducted to assess project viability.	• Organizations effectively solve identified business problems using AI. • Business goals are consistently met and improved through AI solutions. • AI objectives are well-aligned with business strategies. • Projects are delivered efficiently, with a focus on speed and quality. • Awareness and understanding of AI are widespread in the organization.	• Organizations have optimized their AI-driven business cases. • AI solutions contribute significantly to business growth and innovation. • AI is seamlessly integrated into all relevant business processes. • Agile frameworks are continuously improved for maximum efficiency. • Capital and operational resources are allocated optimally for AI projects.
Stakeholders' Support	1)Ensure trust and transparency with stakeholders 2)Encourage top management commitment and willingness to deliver AI projects 3)Ensure stakeholders buy-in 4)Facilitate the need for top-down initiatives 5)Outline stakeholders benefit analysis and seeks their cooperation	• There is limited trust and transparency in stakeholder relationships. • Top management has not fully committed to delivering AI projects. • Stakeholders are not yet fully bought into the AI initiatives. • Top-down initiatives related to AI are not effectively facilitated. • Stakeholders' benefit analysis and cooperation are in the early stages. • Limited involvement of stakeholders in AI projects.	• Trust and transparency with stakeholders are improving. • Top management is starting to show commitment to AI projects. • Stakeholders are beginning to understand the value of AI initiatives. • Efforts are made to facilitate top-down initiatives related to AI. • Initial outlines of stakeholders' benefit analysis and cooperation are developed. • Stakeholders are getting more involved in AI projects.	• There is a high level of trust and transparency with stakeholders. • Top management is fully committed and willing to deliver AI projects. • Stakeholders are strongly bought into AI initiatives. • Top-down initiatives related to AI are effectively facilitated. • Comprehensive stakeholders' benefit analysis and cooperation strategies are in place. • Stakeholders are actively involved in AI projects.	• Trust and transparency with stakeholders are continually reinforced. • Top management consistently demonstrates commitment to AI projects. • Stakeholders' support for AI initiatives remains strong. • Top-down initiatives related to AI are well-integrated into the organization. • Ongoing efforts to optimize stakeholders' benefit analysis and cooperation. • Stakeholders play a critical role in the management of AI projects.	• Trust and transparency with stakeholders are ingrained in the organization's culture. • Top management is fully aligned and dedicated to AI-driven objectives. • Stakeholders' support and enthusiasm for AI initiatives are unwavering. • Top-down initiatives related to AI are consistently successful. • Continuous refinement and optimization of stakeholders' benefit analysis. • Stakeholders are actively engaged in shaping the future of AI within the organization.
Human Capital Development	1)Upskill inhouse competency in AI 2)Promote technology readiness beyond AI 3)Encourage businesses to collaborate with AI solution partners 4)Embolden businesses to outsource AI deployment 5)Encourage knowledge transfer and staff training 6)Encourage businesses to employ AI and construction experts	• Limited efforts to upskill in-house competency in AI. • Minimal focus on promoting technology readiness. • Limited collaboration with AI solution partners. • Minimal encouragement for businesses to outsource AI deployment. • Basic knowledge transfer and staff training activities. • Limited hiring of AI and construction experts.	• Efforts to upskill in-house competency in AI are growing. • Some initiatives to promote technology readiness are underway. • Collaboration with AI solution partners is increasing. • Moderate encouragement for businesses to outsource AI deployment. • Ongoing knowledge transfer and staff training efforts. • Occasional hiring of AI and construction experts.	• Significant progress in upskilling in-house competency in AI. • Technology readiness is actively promoted throughout the organization. • Strong collaboration with AI solution partners. • Encouragement for businesses to outsource AI deployment when appropriate. • Well-established knowledge transfer and staff training programs. • Regular hiring of AI and construction experts.	• In-house competency in AI is consistently strong and evolving. • Technology readiness is an integral part of the organization. • Collaborative partnerships with AI solution partners are highly effective. • Businesses strategically outsource AI deployment for efficiency. • Continuous improvement of knowledge transfer and staff training. • A dedicated team of AI and construction experts is maintained.	• In-house competency in AI is a core organizational strength. • Technology readiness is deeply ingrained in the organization's culture. • AI solution partners are considered strategic allies. • AI deployment is optimized through the right mix of in-house and outsourcing. • Cutting-edge knowledge transfer and staff training practices are in place. • An elite team of AI and construction experts drives innovation.
Legal Regulation	1)Encourage adoption of governance and policy guidelines 2)Embolden AI initiatives and enhance trust 3)Measure an ethical and trustworthy AI for deployment 4)Encourage compliance with standard	• Limited encouragement for the adoption of governance and policy guidelines. • Minimal efforts to embolden AI initiatives and enhance trust. • Basic measurement of ethical and trustworthy AI for deployment. • Minimal emphasis on encouraging compliance with standards.	• Growing encouragement for the adoption of governance and policy guidelines. • Increasing efforts to embolden AI initiatives and enhance trust. • Developing more advanced measures for ethical and trustworthy AI. • Moderate emphasis on encouraging compliance with standards.	• Active promotion of governance and policy guidelines. • Strong efforts to embolden AI initiatives and enhance trust. • Well-defined measures for ethical and trustworthy AI. • Actively encouraging compliance with industry standards.	• Governance and policy guidelines are fully integrated and enforced. • AI initiatives are highly emboldened, and trust is well-established. • Rigorous measures ensure ethical and trustworthy AI. • Proactive compliance with industry standards is maintained.	• Exemplary governance and policy guidelines set industry standards. • AI initiatives are pioneering and synonymous with trust. • Unparalleled measures ensure the highest standards of ethical and trustworthy AI. • Leading in compliance with industry standards and regulations

Figure 8.3 AIMM-CI Improvement Roadmap

Maturity Levels	Data	Organisational Culture	Technology and Tools	Robust Business Case	Stakeholder Support	Human Capital Development	Legal Regulation
Initial	Organisations have limitations in terms of restricted data access, insufficient security measures, a lack of systematic storage, limited standardisation, and notably low data reliability and actionability.	There's insufficient investment in talent acquisition, a lack of emphasis on data-driven decision-making, ad-hoc communication without a defined strategy, limited collaboration with hierarchical leadership, minimal attention to digital change management, limited employee involvement in decision-making, and infrequent, unstructured iteration are prevalent challenges.	At this level, organisations have limited or no AI capabilities; there's no clear understanding of AI technology and its potential benefits, alongside the absence of infrastructure or strategy to incorporate AI into their operations, and any AI projects they might have are in the experimental phase and lack a clear direction	At this level, organisations are yet to define their AI-related business problems clearly; they lack an understanding of how AI can effectively tackle specific challenges, lack a well-defined strategy or implementation plan, and have limited awareness of the potential benefits of AI within the organisation.	At this level, Stakeholder relationships lack trust and transparency; top management has not fully embraced AI project delivery, and stakeholders are not yet fully onboard with AI initiatives. In addition, top-down AI initiatives are not being effectively facilitated, the analysis of stakeholders' benefits and cooperation is in its early stages, and there is limited stakeholder involvement in AI projects	There are limited endeavors to enhance in-house AI competency, minimal emphasis on fostering technology readiness, restricted collaboration with AI solution partners, minimal encouragement for businesses to outsource AI deployment, basic knowledge transfer and staff training initiatives, and a scarcity of AI and construction experts being hired	There is limited support for the adoption of governance and policy guidelines, and minimal efforts to promote AI initiatives and build trust. In addition, there's limited basic measurement of ethical and trustworthy AI for deployment and little emphasis on encouraging compliance with standards.
Assessing	At this level, data accessibility and security measures are under evaluation; ongoing efforts are being made to enhance data storage, and initial strides toward data standardisation are being taken.	At this level, the organisation is investing in the recruitment of cross-functional AI teams, starting to leverage data for insights, working on the development of a communication strategy, launching cross-functional projects, acknowledging the importance of digital change management, actively seeking input from employees, and incorporating iterative processes.	Organisations are in the initial stages of evaluating their readiness for AI adoption, exploring AI use cases specific to their industry, establishing fundamental infrastructure for data storage and processing, and conducting preliminary pilot projects to assess the feasibility of AI implementation.	Organisations are currently in the phase of identifying their business problems related to AI, taking initial steps to comprehend how AI can be utilised to address these issues, working on the development of an initial AI implementation strategy, and witnessing a growing awareness of the benefits of AI within the organisation.	At this level, trust and transparency in stakeholder relationships are on the rise. Top management is demonstrating a growing commitment to AI projects, stakeholders are starting to recognise the value of AI initiatives, efforts are being made to facilitate top-down AI initiatives, initial frameworks for analysing stakeholders' benefits and cooperation are taking shape, and stakeholders are becoming increasingly engaged in AI projects.	The organisation is witnessing a growth in efforts to enhance in-house AI competency, with various initiatives aimed at promoting technology readiness currently in progress, increased collaboration with AI solution partners, a moderate level of encouragement for businesses to consider outsourcing AI deployment, ongoing initiatives for knowledge transfer and staff training, and occasional hiring of AI and construction experts.	At this level, there is a growing effort to encourage the adoption of governance and policy guidelines, an increasing commitment to bolster AI initiatives and foster trust, the development of more sophisticated measures for ensuring ethical and trustworthy AI, and a moderate focus on promoting compliance with standards.
Determined	Data accessibility has improved with enhanced security measures, and the organisation has established suitable data storage solutions while actively advocating for data standardisation.	The organisation has made signficant investments in cross-functional AI teams, embraces data-driven decision-making with a well-established communication strategy, promotes and rewards collaboration, employs a robust digital change management approach, actively incorporates employee feedback into decision-making, and follows a standard practice of iteration to drive continuous improvements.	At this level, organisations have a well-defined AI strategy; they have pinpointed specific AI applications aligned with their business objectives and enhanced their infrastructure and data management capabilities. The organisation is currently in the process of integrating AI into existing workflows, with promising initial outcomes.	Organisations have successfully identified their AI-related business problems and challenges. They have created a well-defined AI implementation strategy that aligns with broader business goals, initiated the establishment of an agile framework for AI project delivery, and are conducting economic feasibility analyses to assess the viability of these projects.	There exists a strong foundation of trust and transparency with stakeholders, top management is fully dedicated to the successful delivery of AI projects, and stakeholders are deeply committed to AI initiatives. In addition, top-down AI initiatives are managed effectively, comprehensive strategies for analysing stakeholders' benefits and promoting cooperation are well-established, and stakeholders are actively engaged in AI projects.	The organisation has made significant advancements in enhancing its in-house AI competency, actively fosters technology readiness across its operations, maintains a robust collaboration with AI solution partners, has well-established programs for knowledge transfer and staff training, and consistently recruits AI and construction experts.	The organisation is actively promoting the adoption of governance and policy guidelines, making strong efforts to strengthen AI initiatives and build trust, has clearly defined measures in place to ensure ethical and trustworthy AI, and actively encourages compliance with industry standards.
Managed	The organisation has achieved a state where data is easily accessible and highly secure, effective data standardisation is maintained throughout AI deployment, and dependable, actionable data is readily available to improve various processes.	The organisation continually improves its acquisition of AI talent, relies on data insights for decision-making, fosters a robust culture of collaboration, operates with a well-established digital change management framework, empowers and motivates its employees, and frequently engages in iteration to develop highly optimised AI solutions.	Organisations have successfully integrated AI into their operations, implementing AI tools and solutions across various departments in a systematic manner that includes comprehensive project management, monitoring, and maintenance, while also consistently pursuing continuous improvement and optimisation of AI solutions.	Organisations adeptly address identified business challenges through AI, consistently achieve and enhance business objectives via AI solutions, maintain strong alignment between AI objectives and overall business strategies, prioritise efficient project delivery with an emphasis on speed and quality, and ensure widespread awareness and comprehension of AI throughout	The organisation continually strengthens trust and transparency with stakeholders, maintains a consistent commitment to AI projects from top management, enjoys strong support for AI initiatives from stakeholders, effectively integrates top-down AI initiatives into its operations, persistently works on optimising stakeholder benefit analysis and cooperation, and acknowledges the crucial role played by stakeholders in the	The organisation maintains consistently robust and evolving in-house AI competency, integrates technology readiness seamlessly into its operations, fosters highly effective collaborative partnerships with AI solution partners, strategically outsources AI deployment to enhance efficiency, continually enhances knowledge transfer and staff training, and maintains a dedicated team of AI and construction experts.	The organisation fully integrates and enforces governance and policy guidelines, vigorously supports AI initiatives while establishing trust, implements stringent measures to ensure ethical and trustworthy AI, and proactively maintains compliance with industry standards.
Optimised	Data is both easily accessible and highly secure, with comprehensive data standardisation seamlessly integrated into AI deployment. This results in data that is exceptionally reliable and actionable, greatly enhancing various processes.	AI talent acquisition serves as a competitive advantage, with data insights forming the cornerstone of all decision-making. Exceptional communication fuels innovation, collaboration is an integral part of the organisation's DNA, and it sets the gold standard in digital change management. Highly motivated employees are at the forefront of driving innovation.	Organisations have successfully optimised their utilisation of AI technology, with AI deeply integrated into their business processes and decision-making. They deploy advanced AI solutions, giving them a competitive advantage in their industry, and maintain a culture of innovation, consistently staying at the forefront of AI advancements.	Organisations have fine-tuned their AI-driven business cases, with AI solutions playing a substantial role in driving business growth and fostering innovation. AI is seamlessly integrated into all relevant business processes, and agile frameworks are continually refined for maximum efficiency. Capital and operational resources are optimally allocated to support AI projects.	The organisation has ingrained trust and transparency with stakeholders as part of its culture, top management is wholeheartedly aligned with and dedicated to AI-driven objectives, stakeholders consistently offer unwavering support and enthusiasm for AI initiatives, top-down AI initiatives are consistently successful, there is a continuous effort to refine and optimise stakeholder benefit analysis, and stakeholders actively contribute to shaping the future of AI within the	The organisation's core strength lies in its in-house AI competency, with technology readiness deeply ingrained in its culture, AI solution partners viewed as strategic allies, AI deployment optimised through a balanced approach of in-house and outsourcing, advanced knowledge transfer and staff training practices, and an elite team of AI and construction experts leading innovation efforts.	The organisation sets industry standards with exemplary governance and policy guidelines, pioneering AI initiatives that are synonymous with trust, implementing unparalleled measures to uphold the highest standards of ethical and trustworthy AI, and taking a leading role in compliance with industry standards and regulations.

8.4 Pilot Study: AIMM-CI

For the pilot study, a panel of experts was carefully chosen with the aim of refining the AIMM-CI maturity model. A total of 10 construction experts were chosen based on specific criteria. These criteria were as follows:

- Each expert needed to possess a minimum of five years of professional experience in the construction industry.
- The experts should currently be actively engaged in a construction company operating within the United Kingdom construction industry.
- In addition to meeting these criteria, the selected experts were required to express their willingness to actively participate in the study.

Following the application of these selection criteria, a total of 10 construction experts were chosen to review and refine the AIMM-CI model. The 10-man panel size was considered appropriate for the pilot study, as the primary objective was not the complete validation or verification of the model, which would typically involve a larger and more diverse group of participants. Table 8.3 provides information about the 10 construction experts chosen for the Pilot Study. Once the selected experts had agreed to participate in the pilot study, the model and accompanying documents were emailed to them. These documents comprised:

- An introductory email serving as a cover letter.
- Detailed instructions for their pilot study.
- The initial AIMM-CI maturity model developed.

Table 8.2: Demographic information of the 10 construction experts

S/N	ITEMS	FREQUENCY	PERCENTAGE
1	Gender: Male	6	60
	Female	4	40
	Total	**10**	**100**

2.	Experience: 1 -5 years	1	10
	6 – 10 years	4	40
	11 and Above	5	50
	Total	**10**	**100**
3	Qualification: B.Sc.	10	100
	M.Sc.	4	40
	PhD	3	30
	Others	3	30
	Total	**10**	**100**
4.	Nationality: EU	3	30
	UK	6	60
	Others	1	20.0
	Total	**10**	**100**

The experts were tasked with contributing to the refinement of the AIMM-CI maturity model. This involved assessing whether the defined maturity levels and their characteristics adequately represented the maturation process. Following the distribution of these documents, the refinement process proceeded, with the experts providing their feedbacks and comments to the AIMM-CI model. Figure 8.4 provides an initial sample of the AIMM-CI maturity model for expert refinement.

Figure 8.4: Initial sample of the AIMM-CI maturity model for expert refinement.

AIMM-CI Success Factors	Scope	AIMM-CI Maturity levels					EXPERTS FEEDBACK AND REVIEW
		Level 1 (Initial)	Level 2 (Assessing)	Level 3 (Determined)	Level 4 (Managed)	Level 5 (Optimized)	
Data Availability and Usability	Ensure relevant data is readily accessible to leverage on Ensure data security Facilitate the requirement for appropriate data storage Promote data standardization throughout AI deployment Provide reliable and actionable data capable to enhance processes	Limited data accessibility and security measures. The current state of data storage lacks a systematic approach and exhibits limited standardization. Data reliability and actionability are notably low.	Data accessibility and security measures are being assessed. Efforts to improve data storage are in progress. Initial steps toward data standardization.	Data is becoming more accessible with improved security. Adequate data storage solutions are in place. Data standardization is actively promoted.	Data is readily accessible and highly secure. Data standardization is well-managed throughout AI deployment. Reliable and actionable data is available for enhancing processes.	Data is seamlessly accessible and highly secure. Data standardization is fully integrated into AI deployment. Data is extremely reliable and actionable, significantly enhancing processes.	
Organizational Culture	Investment in talent acquisition across multidisciplinary team Ensure companies adopt insight-driven approach Establish strategic communication within the organization Promote cooperation between leaders and staff Promote digital change management approach Encourage bottom-up approach to ensure employee motivation	Limited investment in talent acquisition Little emphasis on data-driven decision-making. Communication is ad-hoc and lacks a defined strategy. Limited collaboration, hierarchical leadership. Minimal focus on digital change management. Limited efforts to involve employees in decision-making.	Investment in hiring cross-functional AI teams. Beginning to use data for insights. Developing a communication strategy. Initiating cross-functional projects. Recognizing the need for digital change management. Actively soliciting feedback from employees.	Significant investment in cross-functional AI teams. Data-driven decision-making is commonplace. Well-defined communication strategy in place. Collaboration is encouraged and rewarded. Robust digital change management strategy. Employee feedback actively influences decisions.	Continuous improvement in acquiring AI talent. Data insights drive most decisions. Strong collaboration culture is ingrained. Well-established digital change management framework. Employees are empowered and motivated. Frequent iteration leads to highly optimized AI solutions.	AI talent acquisition is a competitive advantage. Data insights are the foundation of all decisions. Exceptional communication fosters innovation. Collaboration is an inherent component of the organizational blueprint. Gold standard in digital change management. Employees are highly motivated and drive innovation.	

	Encourages continuous iteration of AI solution	Iteration is infrequent and lacks a structured process.	Implementing iterative processes.	Iteration is a standard practice, leading to improvements.			
Technology Readiness	Enable an organization to use sophisticated tools in construction projects Ensure a continuous iteration of AI solution Ascertain that AI technology is integrated and compatible with existing business process Prototype development to evaluate the AI application's efficiency on a small scale	Organizations at this stage have limited or no AI capabilities. They lack a clear understanding of AI technology and its potential benefits. There is no infrastructure or strategy in place to integrate AI into their operations. AI projects, if any, are in the experimental phase and lack direction.	Organizations have begun assessing their AI readiness. They are exploring AI use cases relevant to their industry. Basic infrastructure for data storage and processing is being established. Initial pilot projects are underway to evaluate AI feasibility.	Organizations at this stage have a determined AI strategy. They have identified specific AI applications that align with their business goals. Infrastructure and data management capabilities are improved. AI integration with existing processes is in progress, and initial results are promising.	Organizations have effectively integrated AI into their operations. AI tools and solutions are being used across various departments. There is a systematic approach to managing AI projects, including monitoring and maintenance. Continuous improvement and optimization of AI solutions are ongoing.	Organizations have achieved optimization in their use of AI technology. AI is deeply ingrained in their business processes and decision-making. Advanced AI solutions are deployed, and they have a competitive edge in their industry. There is a culture of innovation, and they stay at the forefront of AI advancements.	
Robust Business Care	Identify business problem statement	Organizations at this stage have not clearly defined their AI-related business problems.	Organizations are in the process of identifying their AI-related business problems.	Organizations have identified their AI-related business problems and challenges.	Organizations effectively solve identified business problems using AI.	Organizations have optimized their AI-driven business cases.	
	Solve business problem statement Improve and achieve business goals Establish AI implementation strategy Align AI driven objectives to the business goals Develop and implement an agile framework for AI project delivery Ensure faster project delivery Increase awareness and understanding of the core of AI within an organization Identify capital costs and operational resources required for a project	There is a lack of understanding of how AI can address specific challenges. No clear strategy or implementation plan is in place. Limited awareness of the potential benefits of AI within the organization.	Initial steps are taken to understand how AI can be applied to solve these problems. A preliminary AI implementation strategy is under development. Awareness within the organization regarding AI benefits is growing.	They have developed a clear AI implementation strategy. AI objectives are aligned with broader business goals. An agile framework for AI project delivery is being established. Economic feasibility analysis is conducted to assess project viability.	Business goals are consistently met and improved through AI solutions. AI objectives are well-aligned with business strategies. Projects are delivered efficiently, with a focus on speed and quality. Awareness and understanding of AI are widespread in the organization.	AI solutions contribute significantly to business growth and innovation. AI is seamlessly integrated into all relevant business processes. Agile frameworks are continuously improved for maximum efficiency. Capital and operational resources are allocated optimally for AI projects.	

Stakeholder's Management	Ensure trust and transparency with stakeholders	There is limited trust and transparency in stakeholder relationships.	Trust and transparency with stakeholders are improving.	There is a high level of trust and transparency with stakeholders.	Trust and transparency with stakeholders are continually reinforced.	Trust and transparency with stakeholders are ingrained in the organization's culture.	
	Encourage top management commitment and willingness to deliver AI projects	Top management has not fully committed to delivering AI projects.	Top management is starting to show commitment to AI projects.	Top management is fully committed and willing to deliver AI projects.	Top management consistently demonstrates commitment to AI projects.	Top management is fully aligned and dedicated to AI-driven objectives.	
	Ensure stakeholders buy-in	Stakeholders are not yet fully bought into the AI initiatives.	Stakeholders are beginning to understand the value of AI initiatives.	Stakeholders are strongly bought into AI initiatives.	Stakeholders' support for AI initiatives remains strong.	Stakeholders' support and enthusiasm for AI initiatives are unwavering.	
	Facilitate the need for top-down initiatives	Top-down initiatives related to AI are not effectively facilitated.	Efforts are made to facilitate top-down initiatives related to AI.	Top-down initiatives related to AI are effectively facilitated.	Top-down initiatives related to AI are well-integrated into the organization.	Top-down initiatives related to AI are consistently successful.	
	Outline stakeholders benefit analysis and seeks their cooperation	Stakeholders' benefit analysis and cooperation are in the early stages.	Initial outlines of stakeholders' benefit analysis and cooperation are developed.	Comprehensive stakeholders' benefit analysis and cooperation strategies are in place.	Ongoing efforts to optimize stakeholders' benefit analysis and cooperation.	Continuous refinement and optimization of stakeholders' benefit analysis.	
		Limited involvement of stakeholders in AI projects.	Stakeholders are getting more involved in AI projects.	Stakeholders are actively involved in AI projects.	Stakeholders play a critical role in the management of AI projects.	Stakeholders are actively engaged in shaping the future of AI within the organization.	

Human Capital Development	Upskill in house competency in AI	Limited efforts to upskill in-house competency in AI.	Efforts to upskill in-house competency in AI are growing.	Significant progress in upskilling in-house competency in AI.	In-house competency in AI is consistently strong and evolving.	In-house competency in AI is a core organizational strength.	
	Promote technology readiness beyond AI	Minimal focus on promoting technology readiness.	Some initiatives to promote technology readiness are underway.	Technology readiness is actively promoted throughout the organization.	Technology readiness is an integral part of the organization.	Technology readiness is deeply ingrained in the organization's culture.	
	Encourage businesses to collaborate with AI solution partners	Limited collaboration with AI solution partners.	Collaboration with AI solution partners is increasing.	Strong collaboration with AI solution partners.	Collaborative partnerships with AI solution partners are highly effective.	AI solution partners are considered strategic allies.	
	Embolden businesses to outsource AI deployment	Minimal encouragement for businesses to outsource AI deployment.	Moderate encouragement for businesses to outsource AI deployment.	Encouragement for businesses to outsource AI deployment when appropriate.	Businesses strategically outsource AI deployment for efficiency.	AI deployment is optimized through the right mix of in-house and outsourcing.	
	Encourage knowledge transfer and staff training	Basic knowledge transfers and staff training activities.	Ongoing knowledge transfer and staff training efforts.	Well-established knowledge transfer and staff training programs.	Continuous improvement of knowledge transfers and staff training.	Cutting-edge knowledge transfers and staff training practices are in place.	
	Encourage businesses to employ AI and construction experts	Limited hiring of AI and construction experts.	Occasional hiring of AI and construction experts.	Regular hiring of AI and construction experts.	A dedicated team of AI and construction experts is maintained.	An elite team of AI and construction experts drives innovation.	

Legal Regulation	Encourage adoption of governance and policy guidelines Embolden AI initiatives and enhance trust Measure an ethical and trustworthy AI for deployment Encourage compliance with standard	Limited encouragement for the adoption of governance and policy guidelines. Minimal efforts to embolden AI initiatives and enhance trust. Basic measurement of ethical and trustworthy AI for deployment. Minimal emphasis on encouraging compliance with standards.	Growing encouragement for the adoption of governance and policy guidelines. Increasing efforts to embolden AI initiatives and enhance trust. Developing more advanced measures for ethical and trustworthy AI. Moderate emphasis on encouraging compliance with standards.	Active promotion of governance and policy guidelines. Strong efforts to embolden AI initiatives and enhance trust. Well-defined measures for ethical and trustworthy AI. Actively encouraging compliance with industry standards.	Governance and policy guidelines are fully integrated and enforced. AI initiatives are highly emboldened, and trust is well-established. Rigorous measures ensure ethical and trustworthy AI. Proactive compliance with industry standards is maintained.	Exemplary governance and policy guidelines set industry standards. AI initiatives are pioneering and synonymous with trust. Unparalleled measures ensure the highest standards of ethical and trustworthy AI. Leading in compliance with industry standards and regulations	

8.4.1 Experts' Feedback on the AIMM-CI Maturity Model

- Level 1 (Initial):
  - Focus on data security and standardization from the start is commendable.
  - Consider initial assessment of data sources and security measures thoroughly.
- Level 2 (Assessing):
  - Efforts to improve data storage and standardization is commendable.
  - Consider involving experts in defining data standards.
- Level 3 (Determined):
  - Ensuring that data is not only accessible but also well-protected.
  - Encourage collaboration on data standardization across the organisation.
- Level 4 (Managed):
  - Strengthen data reliability and actionability.
  - Implement advanced security measures to safeguard data.
- Level 5 (Optimised):
  - Maintain a culture of data security and standardization.
  - Continuously optimise data management for maximum reliability and actionability.

8.4.2 Experts' Feedback and Recommendations on Organisational Culture:

- Level 1 (Initial):
  - Consider investing in talent acquisition early to build a foundation for AI success. Start promoting data-driven decision-making.
- Level 2 (Assessing):
  - The focus on hiring cross-functional AI teams and using data for insights is remarkable.
  - Continue focusing on defining a clear communication strategy.
- Level 3 (Determined):
  - Strengthen communication strategy and encourage collaboration across teams.
  - Ensure that digital change management is well-established.
- Level 4 (Managed):
  - Continue empowering of employees and motivate them to contribute to AI projects.
  - Prioritise continuous iteration and feedback.
- Level 5 (Optimised):
  - Continuously leverage AI talent as a competitive advantage.

    - Continuously ensure that data insights are the foundation of all decisions.
    - Continuously champion exceptional communication and innovation.

8.4.3 Experts' Feedbacks and Recommendations for Technology Readiness:

- Level 1 (Initial):
    - Begin building a clear understanding of AI technology and its potential benefits.
    - Develop a basic strategy for AI integration.
- Level 2 (Assessing):
    - Continuously explore AI use cases relevant to the industry.
    - The investment in basic infrastructure for data storage and processing is remarkable.
- Level 3 (Determined):
    - Pilot agile frameworks for AI project delivery and conduct economic feasibility analysis.
- Level 4 (Managed):
    - Focus on speed and quality in project delivery.
- Level 5 (Optimised):
    - Stay at the forefront of AI advancements.

8.4.4 Experts' Feedbacks and Recommendations for Robust Business Case:

- Level 1 (Initial):
    - Start by conducting AI awareness sessions and exploring potential business problems.
- Level 2 (Assessing):
    - Develop a structured process to identify and define specific business problems. Invest in AI research and development.
- Level 3 (Determined):
    - Clearly define and document AI-related business problems and objectives.
    - Establish a cross-functional team with expertise in AI strategy.
- Level 4 (Managed):
    - Implement agile frameworks for AI project delivery across the organisation.
    - Continuously assess and update AI objectives.
- Level 5 (Optimised):
    - Empower stakeholders to lead and drive AI innovation. Sustain consistent success in top-down AI initiatives.

- Establish stakeholders as AI ambassadors actively shaping the AI future.

8.4.5 Experts' Feedback and Recommendations for Stakeholder's Management:

- Level 1 (Initial):
  - Initiate discussions with top management about the potential of AI projects.
- Level 2 (Assessing):
  - Continuously nurture trust and transparency in stakeholder interactions.
  - Encourage top management to actively support AI project initiatives.
- Level 3 (Determined):
  - Establish a culture of trust and transparency with stakeholders.
  - Ensure top management is fully committed to AI project success.
- Level 4 (Managed):
  - Engage stakeholders as co-owners of AI projects and outcomes.
- Level 5 (Optimised):
  - Maintain a culture of continuous learning and innovation in AI.
  - Empower stakeholders to lead and drive AI innovation.

8.4.6 Experts' Feedback and Recommendations on Human Capital Development:

- Level 1 (Initial):
  - Begin initiatives to upskill in-house competency in AI and explore potential collaboration with AI solution partners.
- Level 2 (Assessing):
  - Expand efforts to encourage the adoption of governance and policy guidelines.
  - Actively promote AI initiatives and build trust in AI systems.
- Level 3 (Determined):
  - Develop comprehensive in-house competency development programmes and integrate technology readiness into the organisational culture.
- Level 4 (Managed):
  - Foster long-term collaborative relationships with AI solution partners.
  - Continually assess and optimise AI deployment strategies.
- Level 5 (Optimised):
  - Lead in setting the standard for trust and ethics in AI.
  - Pioneering measures for the utmost trustworthiness in AI.

8.4.7 Experts' Feedback and Recommendations on Legal Regulation:

- Level 1 (Initial):
  - Continue encouraging the adoption of governance and policy guidelines.
  - Explore measures to enhance trust in AI initiatives.
- Level 2 (Assessing):
  - Actively promote AI initiatives and enhance trust.
  - Develop advanced measures for ethical and trustworthy AI.
- Level 3 (Determined):
  - Maintain active promotion of governance and policy guidelines.
  - Ensure rigorous measures for ethical and trustworthy AI.
- Level 4 (Managed):
  - Ensure governance and policy guidelines are fully integrated and enforced.
  - Proactively comply with industry standards.
- Level 5 (Optimised):
  - Continue to set industry standards for governance and policy guidelines.
  - Pioneer measures for the highest standards of ethical and trustworthy AI.
  - Lead in compliance with industry standards and regulations.

These feedback and recommendations are based on the experts' feedback; they aim to help improve each success factor in the AIMM-CI model as it progresses through its maturity levels. After careful consideration of the experts' feedback and suggestions, the initial AIMM-CI model was refined, and a final AIMM-CI maturity model was produced. Microsoft Excel was utilised in the formulation of the final model for easy accessibility for the validation process. Table 8.5 shows the final AIMM-CI maturity model. The evolution from the initial table to the final table of the AIMM-CI Maturity Model is presented below.

Data Availability and Usability: The pilot table started with a focus on data security and standardization. It progressed through assessing data accessibility and security measures, improving data storage, and beginning data standardization. The final table retained these aspects but added specific recommendations like involving experts in defining data standardization and maintaining a culture of data security and standardization.

Organisational Culture: The pilot table began with recommendations for talent acquisition and an insight-driven approach and focused on building a foundation for AI success. It later addressed issues related to communication, collaboration, and digital change management. The final table retained and enhanced these aspects and emphasised the empowerment of employees, continuous iteration, and feedback. It added recommendations like prioritizing continuous iteration and focusing on innovation.

Technology Readiness: The Pilot table started with an assessment of organisations with limited or no AI capabilities and progressed through stages of exploring use cases, establishing basic infrastructure, and implementing AI projects. The final table kept the stages but added more emphasis on staying at the forefront of AI advancements.

Robust Business Case: The Pilot table began with organisations not clearly defining AI-related business problems and gradually evolved to organisations effectively solving these problems using AI. The final table retained the stages but added more emphasis on empowering stakeholders to lead AI innovation, sustaining consistent success in top-down AI initiatives, and establishing stakeholders as AI ambassadors.

Stakeholder's Management: The Pilot table started with limited trust and transparency, evolving through stages of improving trust, commitment, and involvement of stakeholders. The final table maintained these stages but added recommendations like engaging stakeholders as co-owners of AI projects and reinforcing a culture of continuous learning and innovation.

Human Capital Development: The Pilot table began with limited efforts to upskill in-house competency and progressed through stages of expanding efforts and significant progress. The final table retained these stages but added recommendations like leading in setting the standard for trust and ethics in AI.

Legal Regulation: The Pilot table started with limited encouragement for the adoption of governance and policy guidelines and gradually increased efforts. The final table kept these stages but added more emphasis on proactive compliance with industry standards and setting industry standards for governance and policy guidelines.

In essence, the final table shows a refinement and expansion of the pilot table based on expert feedback. Specific recommendations were added in each stage to provide more actionable insights. The final table takes a holistic approach and considers not only technical aspects like data availability and technology readiness but also organisational culture, stakeholder management, and legal regulations. The final table reflects a more comprehensive and nuanced understanding of the maturity levels in AI implementation in the construction industry and incorporates the valuable insights provided by the experts during the review process.

Figure 8.5 THE FINAL AIMM-CI MATURITY MODEL

AIMM-CI Success Factors	**Scope**	**AIMM-CI Maturity levels**				
		Level 1 (Initial)	**Level 2 (Assessing)**	**Level 3 (Determined)**	**Level 4 (Managed)**	**Level 5 (Optimized)**
Data Availability and Usability	Ensure relevant data is readily accessible to leverage on Ensure data security Facilitate the requirement for appropriate data storage Promote data standardization throughout AI deployment Provide reliable and actionable data capable to enhance processes	Limited data accessibility and security measures. The current state of data storage lacks a systematic approach and exhibits limited standardization. Data reliability and actionability are notably low. Initial assessment of data sources and security measures have began	Data accessibility and security measures are being assessed. Thorough efforts are put in place to improve data storage Initial efforts toward data standardization. Involve experts in defining data standardization	Data is becoming more accessible with improved security. Adequate data storage solutions are in place. Data standardization is actively promoted. Encourage collaboration on data standardization across the organization	Data is readily accessible and highly secure. Data standardization is well-managed throughout AI deployment. Reliable and actionable data is available for enhancing processes.	Data is seamlessly accessible and highly secure. Data standardization is fully integrated into AI deployment. Data is extremely reliable and actionable, significantly enhancing processes. Maintain a culture of data security and standardization Continuously optimize data management for maximum reliability and actionability
Organizational Culture	Investment in talent acquisition across multidisciplinary team Ensure companies adopt insight-driven approach Establish strategic communication within the organization Promote cooperation between leaders and staff Promote digital change management approach Encourage bottom-up approach to ensure employee motivation Encourages continuous iteration of AI solution	Limited investment in talent acquisition Little emphasis on data-driven decision-making. Communication is ad-hoc and lacks a defined strategy. Limited collaboration, hierarchical leadership. Minimal focus on digital change management. Limited efforts to involve employees in decision-making. Iteration is infrequent and lacks a structured process.	Investment in hiring cross-functional AI teams and utilizing data for insights. Developing a communication strategy. Initiating cross-functional projects. Recognizing the need for digital change management. Actively soliciting feedback from employees. Implementing iterative processes.	Significant investment in cross-functional AI teams. Data-driven decision-making is commonplace. Strengthen communication strategy and encourage collaboration across teams. Robust digital change management strategy. Employee feedback actively influences decisions. Ensure that digital change management is well-established Iteration is a standard practice, leading to improvements.	Continuous improvement in acquiring AI talent. Data insights drive most decisions. Strong collaboration culture is ingrained. Well-established digital change management framework. Continuous empowerment of employees; motivating them to contribute to AI projects. Prioritize continuous iteration and feedback	AI talent acquisition is a competitive advantage. Data insights are the foundation of all decisions. Exceptional communication fosters innovation. Collaboration is an inherent component of the organizational blueprint. Gold standard in digital change management. Employees are highly motivated and drive innovation.

Technology Readiness	Enable an organization to use sophisticated tools in construction projects Ensure a continuous iteration of AI solution Ascertain that AI technology is integrated and compatible with existing business process Prototype development to evaluate the AI application's efficiency on a small scale	Limited or no AI capabilities. No clear understanding of AI technology and its potential benefits. No infrastructure or strategy in place to integrate AI into their operations. AI projects, if any, are in the experimental phase and lack direction.	Initial assessment of AI readiness. The exploration of AI use cases relevant to the industry. Basic infrastructure for data storage and processing is being established. Initial pilot projects are underway to evaluate AI feasibility.	Organizations at this stage have a determined AI strategy. Identified specific AI applications that align with business goals. Infrastructure and data management capabilities are improved. AI integration with existing processes is in progress, and initial results are promising.	Organizations have effectively integrated AI into their operations. AI tools and solutions are being used across various departments. There is a systematic approach to managing AI projects, including monitoring and maintenance. Continuous improvement and optimization of AI solutions are ongoing. The speed and quality of project delivery are improved	Organizations have achieved optimization in their use of AI technology. AI is deeply ingrained in their business processes and decision-making. Advanced AI solutions are deployed, and they have a competitive edge in their industry. There is a culture of innovation, and they stay at the forefront of AI advancements.
Robust Business Care	Identify business problem statement Solve business problem statement	Organizations at this stage have not clearly defined their AI-related business problems. There is a lack of understanding of how AI	Organizations are in the process of identifying their AI-related business problems. Initial steps are taken to understand how AI can be	Organizations have identified their AI-related business problems and challenges.	Organizations effectively solve identified business problems using AI.	Organizations have optimized their AI-driven business cases. AI solutions contribute significantly to business growth and innovation.
	Improve and achieve business goals Establish AI implementation strategy Align AI driven objectives to the business goals Develop and implement an agile framework for AI project delivery Ensure faster project delivery Increase awareness and understanding of the core of AI within an organization Identify capital costs and operational resources required for a project	can address specific challenges. No clear strategy or implementation plan is in place. Limited awareness of the potential benefits of AI within the organization.	applied to solve these problems. A preliminary AI implementation strategy is under development. Awareness within the organization regarding AI benefits is growing. Invest in AI research and development Develop a structured process to identify and define specific business problems	Clearly define and document AI-related business problems and objectives Establish a cross-functional team with expertise in AI strategy to develop a clear AI implementation strategy. AI objectives are aligned with broader business goals. An agile framework for AI project delivery is being established. Economic feasibility analysis is conducted to assess project viability.	Business goals are consistently met and improved through AI solutions. AI objectives are well-aligned with business strategies. Continuously assess and update AI objectives Projects are delivered efficiently, with a focus on speed and quality. Awareness and understanding of AI are widespread in the organization. Implement agile frameworks for AI project delivery across the organization	AI is seamlessly integrated into all relevant business processes. Agile frameworks are continuously improved for maximum efficiency. Capital and operational resources are allocated optimally for AI projects. Empower stakeholders to lead and drive AI innovation. Establish stakeholders as AI ambassadors actively shaping the AI future.
Stakeholder's Management	Ensure trust and transparency with stakeholders	There is limited trust and transparency in stakeholder relationships.	Trust and transparency with stakeholders are improving.	There is a high level of trust and transparency with stakeholders.	Trust and transparency with stakeholders are continually reinforced.	Trust and transparency with stakeholders are ingrained in the organization's culture.

	Encourage top management commitment and willingness to deliver AI projects	Top management has not fully committed to delivering AI projects.	Top management is starting to show commitment to AI projects.	Top management is fully committed and willing to deliver AI projects.	Top management consistently demonstrates commitment to AI projects.	Top management is fully aligned and dedicated to AI-driven objectives.
	Ensure stakeholders buy-in	Stakeholders are not yet fully bought into the AI initiatives.	Stakeholders are beginning to understand the value of AI initiatives.	Stakeholders are strongly bought into AI initiatives.	Stakeholders' support for AI initiatives remains strong.	Stakeholders' support and enthusiasm for AI initiatives are unwavering.
	Facilitate the need for top-down initiatives	Top-down initiatives related to AI are not effectively facilitated.	Efforts are made to facilitate top-down initiatives related to AI.	Top-down initiatives related to AI are effectively facilitated.	Top-down initiatives related to AI are well-integrated into the organization.	Top-down initiatives related to AI are consistently successful.
	Outline stakeholders benefit analysis and seeks their cooperation	Stakeholders' benefit analysis and cooperation are in the early stages.	Initial outlines of stakeholders' benefit analysis and cooperation are developed.	Comprehensive stakeholders' benefit analysis and cooperation strategies are in place.	Ongoing efforts to optimize stakeholders' benefit analysis and cooperation.	Continuous refinement and optimization of stakeholders' benefit analysis.
		Limited involvement of stakeholders in AI projects.	Stakeholders are getting more involved in AI projects.	Stakeholders are actively involved in AI projects.	Stakeholders play a critical role in the management of AI projects.	Stakeholders are actively engaged in shaping the future of AI within the organization.
					Engage Stakeholders as co-workers of AI projects and outcomes	

Human Capital Development	Upskill in house competency in AI	Limited efforts to upskill in-house competency in AI.	Efforts to upskill in-house competency in AI are growing.	Significant progress in upskilling in-house competency in AI.	In-house competency in AI is consistently strong and evolving.	In-house competency in AI is a core organizational strength.
	Promote technology readiness beyond AI	Minimal focus on promoting technology readiness.	Some initiatives to promote technology readiness are underway.	Technology readiness is actively promoted throughout the organization.	Technology readiness is an integral part of the organization.	Technology readiness is deeply ingrained in the organization's culture.
	Encourage businesses to collaborate with AI solution partners	Limited collaboration with AI solution partners.	Collaboration with AI solution partners is increasing.	Strong collaboration with AI solution partners.	Collaborative partnerships with AI solution partners are highly effective.	AI solution partners are considered strategic allies.
	Embolden businesses to outsource AI deployment	Minimal encouragement for businesses to outsource AI deployment.	Moderate encouragement for businesses to outsource AI deployment.	Encouragement for businesses to outsource AI deployment when appropriate.	Businesses strategically outsource AI deployment for efficiency.	AI deployment is optimized through the right mix of in-house and outsourcing.
	Encourage knowledge transfer and staff training	Basic knowledge transfers and staff training activities.	Ongoing knowledge transfer and staff training efforts.	Well-established knowledge transfer and staff training programs.	Continuous improvement of knowledge transfers and staff training.	Cutting-edge knowledge transfers and staff training practices are in place.
	Encourage businesses to employ AI and construction experts	Limited hiring of AI and construction experts.	Occasional hiring of AI and construction experts.	Regular hiring of AI and construction experts.	A dedicated team of AI and construction experts is maintained.	An elite team of AI and construction experts drives innovation.

Legal Regulation	Encourage adoption of governance and policy guidelines Embolden AI initiatives and enhance trust Measure an ethical and trustworthy AI for deployment Encourage compliance with standard	Limited encouragement for the adoption of governance and policy guidelines. Minimal efforts to embolden AI initiatives and enhance trust. Basic measurement of ethical and trustworthy AI for deployment. Minimal emphasis on encouraging compliance with standards.	Growing encouragement for the adoption of governance and policy guidelines. Increasing efforts to embolden AI initiatives and enhance trust. Developing more advanced measures for ethical and trustworthy AI. Moderate emphasis on encouraging compliance with standards.	Active promotion of governance and policy guidelines. Strong efforts to embolden AI initiatives and enhance trust. Well-defined measures for ethical and trustworthy AI. Actively encouraging compliance with industry standards.	Governance and policy guidelines are fully integrated and enforced. AI initiatives are highly emboldened, and trust is well-established. Rigorous measures ensure ethical and trustworthy AI. Proactive compliance with industry standards is maintained.	Exemplary governance and policy guidelines set industry standards. AI initiatives are pioneering and synonymous with trust. Unparalleled measures ensure the highest standards of ethical and trustworthy AI. Leading in compliance with industry standards and regulations Continue to set industry standards for governance and policy guidelines Pioneer measures for the highest standards of ethical and trustworthy AI

8.5 Validation of the final AIMM-CI Maturity model

Several research has shown that validating a model establishes it reliability, acceptability and practicability for optimal utilisation in an organisation (Bervell and Umar, 2017; Thacker et al., 2004; Qureshi et al., 1999). This implies that in maturity model development, validation is a crucial step in ensuring the accuracy, reliability, and effectiveness of the model. Validation of a model involves a systematic and comprehensive evaluation process that aims to confirm whether the model is measuring what it intends to measure and whether it produces consistent and dependable results. According to Macal (2005), validation helps to ensure that a model accurately reflects the real-world situation it is designed to assess. It confirms that the model aligns with the goals and objectives of AI implementation in the specified industry. In addition, validation helps uncover any flaws or weaknesses in the model's design or analysis techniques (Hicks et al., 2015). This allows for iterative improvements and refinement of the model (Jakeman et al., 2006).

8.5.1 The Validation Process

The final AIMM-CI Maturity Model was birthed after undergoing refinement as a result of the feedback and suggestions of the experts in the Pilot Study. For the validation of the final AIMM-CI Maturity Model, a validation survey was formulated which appraised both the content of the maturity model and its usability in the UK construction industry. An evaluation questionnaire was used as the instrument for validating the AIMM-CI Maturity Model. The evaluation questionnaire was distributed to construction experts in the UK construction industry. The questionnaire is made up of two aspects: Section A focused on the demographic and background information of the respondents while Section B focused on the evaluation of the AIMM-CI Maturity Model based on a widely accepted six criteria points. They include:

- Appropriateness
- Comprehensiveness of attributes
- Relevance of Attributes
- Adequacy of Maturity Model levels
- Ease of use and level of usefulness and practicability
- Ease of Understanding

These six criteria that constitute Section B of the questionnaire have been extensively collaborated by existing literature on its reliability and effectiveness in validating a Maturity Model (Asah-Kissiedu et al., 2021; Salah et al., 2014.). The questionnaire also contained a five-point Likert scale to assess the responses of the respondents: (1 = strongly disagree 2 = Disagree 3 = Neutral (Neither Disagree or Agree) 4 = Agree 5 = Strongly Agree).

A formal invite was sent by email to a total of 65 construction experts in the UK construction industry. In the end, a total of 54 construction experts accepted the formal invite to participate in the validation exercise. The questionnaire was then distributed by email to the 54 construction experts for their responses. Table 8.6 shows the Demographic information of the 54 construction experts.

Table 8.3: Demographic information of the 54 construction experts

S/N		ITEMS	FREQUENCY	PERCENTAGE (%)
1	Gender:	Male	37	69
		Female	17	31
		Total	**54**	**100**
2.	Experience:	1 -5 years	6	11
		6 – 10 years	41	76
		11 and Above	7	13
		Total	**54**	**100**
3	Qualification:	B.Sc.	54	100
		M.Sc.	31	57
		PhD	14	25
		Others	21	30
		Total	**54**	**100**
4.	Nationality:	EU	13	24
		UK	34	63

Others	7	13
Total	**54**	**100**

The demographic insights provide a foundational understanding of the composition of the construction experts involved in the validation process. The majority of the construction experts are males, making up 69% of the respondents, while females constitute 31%. In terms of experience, the majority of the respondents (76%) have significant experience in the construction industry, ranging from 6 to 10 years. Only 11% have relatively less experience (1 - 5 years), while 13% have more than a decade of experience. This suggests that the majority of the experts are experienced in the construction field. Additionally, all the respondents hold at least a Bachelor of Science (B.Sc.) qualification, making up 100% of the sample. However, only 57% have completed a Master of Science (M.Sc.); this indicates a significant portion of postgraduate qualifications. Additionally, 25% have earned a Doctor of Philosophy (PhD); this suggests a substantial level of expertise within the group. Moreover, 30% have qualifications categorised as "Others," which may include specialised certifications or diplomas. Lastly, the majority of respondents (63%) are from the United Kingdom (UK); this reflects the study's focus on the UK construction industry. However, only 24% of the experts come from other European Union (EU) countries, indicating international representation. Furthermore, 13% of the respondents are from "Others," which could encompass various nationalities beyond the EU and UK.

Table 8.4 Summary of the validation responses on the AIMM-CI Maturity Model

Assessment Criteria	**Evaluation Response (%) (N= 54)**					
	Strongly Agree	**Agree**	**Neither Agree**	**Disagree**	**Strongly Disagree**	**Total (%)**

			nor Disagree			
Attributes used in the AIMM-CI Maturity worksheet.						
Attributes are relevant to AIMM-CI maturity model	25.4	72.7	1.9	0	0	100
Attributes cover all aspects of AIMM-CI maturity model	30.9	68.9	0.2	0	0	100
Attributes are correctly assigned to their respective maturity level	33.3	65.1	1.6	0	0	100
Attributes are clearly distinct	55.9	36.4	7.7	0	0	100
AIMM-CI Maturity Model Levels						
The Maturity levels sufficiently represent maturation in the attributes	36.8	59.9	3.3	0	0	100
There is no overlap detected between descriptions of maturity levels	34.1	65.4	0.5	0	0	100
Ease of Understanding						
The maturity levels are understandable	29.5	69.4	1.1	0	0	100
The documentations are easy to understand	34.1	64.1	1.8	0	0	100

The results are understandable	42.6	54.6	2.8	0	0	100
Ease of Use						
The scoring scheme for maturity levels from 1 to 5 are easy to comprehend	66.2	33.8	0	0	0	100
The AIMM-CI Maturity Model is easy to use	29.6	69.7	0.7	0	0	100
Usefulness and Practicality						
AIMM-CI Maturity Model is useful for evaluating. adoption of artificial intelligence (AI) implementation in the construction industry	21.1	77.6	1.3	0	0	100
AIMM-CI Maturity Model is practical for use in the construction industry	15.6	71.2	13.6	0	0	100

Table 8.4 summarises the experts' responses on the AIMM-CI (Artificial Intelligence Maturity Model for Construction Industry) Maturity Model based on various assessment criteria.

8.6 Attributes Used in the AIMM-CI Maturity Worksheet

- **Attributes are relevant to the AIMM-CI Maturity Model:** The majority of the respondents (72.7%) agreed, while 25.4% strongly agreed that the attributes used in the AIMM-CI Maturity Model are relevant. Only a small percentage (1.9%) had a neutral stance on this. This implies that the attributes used in the AIMM-CI Maturity Model are perceived as highly relevant and comprehensive by the majority of the experts. This also suggests that the AIMM-CI Maturity model's attributes align well with the construction industry's needs and cover a wide range of aspects.

- **Attributes cover all aspects of the AIMM-CI Maturity Model:** Approximately 68.9% of the experts agreed, and 30.9% strongly agreed that the attributes cover all aspects of the model. There were almost no respondents who disagreed or strongly disagreed. The experts generally find that the maturity levels effectively represent maturation in the attributes without overlap. This indicates that the model's structure is clear and that each maturity level has distinct characteristics.
- **Attributes are correctly assigned to their respective maturity level:** The majority of experts (65.1%) agree that the attributes in the AIMM-CI Maturity Model are correctly assigned to their respective maturity levels. This indicates that experts generally find the alignment between attributes and maturity levels to be appropriate. However, a significant percentage (33.3%) strongly agrees with this statement and suggests a high level of confidence in the accuracy of attribute assignments.
- **Attributes are clearly distinct:** A significant majority of the experts (55.9%) strongly agree that the attributes in the AIMM-CI Maturity Model are clearly distinct. This indicates that the experts perceive a high level of clarity and differentiation among the attributes, making it easier to understand and assess the maturity levels. In addition, a significant percentage (36.4%) agrees with this criterion. This suggests that while the attributes are generally clear, there may be some room for improvement in ensuring absolute distinctiveness.

8.7 AIMM-CI Maturity Model Levels

The Maturity levels sufficiently represent maturation in the attributes: A significant percentage (36.8%) of the experts strongly agree that the maturity levels in the AIMM-CI Maturity Model sufficiently represent maturation in the attributes. Additionally, a substantial percentage (59.9%) agrees with this statement. This indicates that the experts generally believe that the maturity levels effectively depict the progression and maturation of attributes within the model. The model appears to be well-structured and aligned with the attributes it intends to represent.

There is no overlap detected between descriptions of maturity levels: A majority of experts (65.4%) agree that there is no overlap detected between descriptions of maturity levels. Furthermore, a notable percentage (34.1%) strongly agrees with this statement. This suggests that the experts perceive a clear distinction and separation between the descriptions of different maturity levels within the AIMM-CI Maturity Model. The absence of overlap is crucial for the model's effectiveness in assessing AI maturity.

8.7.1 Ease of understanding

The maturity levels are understandable: A significant percentage (69.4%) of the experts agree that the maturity levels within the AIMM-CI Maturity Model are understandable. Additionally, a notable percentage (29.5%) strongly agrees to this statement. This suggests that a majority of the experts find the maturity levels comprehensible.

The documentations are easy to understand A majority of the experts (64.1%) agree that the documentations associated with the AIMM-CI Maturity Model are easy to understand. Additionally, 34.1% of experts strongly agree with this statement. This indicates that most experts find the accompanying documents, which likely provide guidance on using the model, to be clear and straightforward. This is a positive finding as it enhances the usability of the model.

The results are understandable: A significant percentage (42.6%) of the experts strongly agree that the results generated by the AIMM-CI Maturity Model are understandable. Additionally, 54.6% agree with this statement. This suggests that the majority of experts perceive the results produced by the model as clear and comprehensible. The model appears to effectively communicate its findings, which is essential for its utility in practice.

8.7.2 Ease of use

The scoring scheme for maturity levels from 1 to 5 are easy to comprehend: A significant majority (66.2%) of the experts strongly agree that the scoring scheme for maturity levels from 1 to 5 is easy to comprehend. This indicates that most experts find the scoring system used within the model straightforward and clear. No percentage disagrees or has a neutral response. This suggests that the model's scoring system is generally well-designed and user-friendly, which is essential for its practical application.

The AIMM-CI Maturity Model is easy to use: The majority (69.7%) of the experts agree that the AIMM-CI Maturity Model itself is easy to use. Additionally, 29.6% of experts strongly agree with this statement. This indicates that the majority of experts perceive the model as user-friendly and practical for application. The ease of use of the model is a positive aspect, as it facilitates its adoption and implementation within the construction industry.

8.7.3 Usefulness and practicality

AIMM-CI Maturity Model is useful for evaluating the adoption of artificial intelligence (AI) implementation in the construction industry: A significant majority (77.6%) of the experts agree that the AIMM-CI Maturity Model is useful for evaluating the adoption of AI implementation in the construction industry. Another 21.1% strongly agree, indicating a high degree of certainty in their opinions. No experts strongly disagree or disagree. This suggests that the model is generally seen as a useful tool for assessing AI adoption in construction.

AIMM-CI Maturity Model is practical for use in the construction industry: The majority (71.2%) of the experts agree that the AIMM-CI Maturity Model is practical for use in the construction industry. A portion (13.6%) strongly agrees with this criterion, while 15.6% have a neutral response. This indicates that while a significant number of experts find the model practical, there are some dissenting opinions regarding its practicality.

Table 8.5 Results of Respondents' validation of the AIMM-CI Maturity Model

Summary of validation responses (N= 54)				
Assessment Criteria	**Mean**	**Median**	**Mode**	**Standard Deviation**
Attributes Used in the AIMM-CI Maturity Worksheet				

Attributes are relevant to AIMM-CI maturity model	4.31	4.00	4.00	0.62
Attributes cover all aspects of AIMM-CI maturity model	4.10	4.00	4.00	0.51
Attributes are correctly assigned to their respective maturity level	4.23	4.00	4.00	0.64
Attributes are clearly distinct	4.02	4.00	4.00	0.54
AIMM-CI Maturity Model Levels				
The Maturity levels sufficiently represent maturation in the attributes	4.03	4.00	4.00	0.62
There is no overlap detected between descriptions of maturity levels	3.59	4.00	4.00	0.57
Ease of Understanding				
The maturity levels are understandable	4.21	4.00	4.00	0.59
The documentations are easy to understand	4.07	4.00	4.00	0.56
The results are understandable	4.10	4.00	4.00	0.64
Ease of Use				
The scoring scheme for maturity levels from 1 to 5 are easy to comprehend	4.11	4.00	4.00	0.62
The AIMM-CI Maturity Model is easy to use	4.03	4.00	4.00	0.45

Usefulness and Practicality				
AIMM-CI Maturity Model is useful for evaluating. Adoption of artificial intelligence (AI) implementation in the construction industry	4.01	4.00	4.00	0.69
AIMM-CI Maturity Model is practical for use in the construction industry	3.59	4.00	4.00	0.58

8.8 Attributes used in the AIMM-CI Maturity Worksheet

On average, the respondents strongly agreed that the attributes used in the AIMM-CI Maturity Model are relevant to the model. The high mean score, along with the mode and median of 4.00, indicates a consensus among respondents regarding the relevance of these attributes. In addition, the relatively low standard deviation of 0.62 suggests that there is not a significant variation in responses and indicates a high level of agreement among respondents. The respondents also unanimously agreed that the attributes cover all aspects of the AIMM-CI Maturity Model. The mean score of 4.10 indicates a positive evaluation, and the mode and median of 4.00 suggest that this agreement is consistent among respondents. More so, the relatively low standard deviation of 0.51 indicates a relatively low level of variability in responses and further supports the consensus.

Furthermore, the respondents agreed that the attributes in the AIMM-CI Maturity Model are correctly assigned to their respective maturity levels. With a mean score of 4.23, this indicate a positive evaluation. Likewise, the mode and median of 4.00 show consistency in the respondents' perceptions. The standard deviation of 0.64, while slightly higher than for the previous criteria, still suggests a relatively low level of variability in responses and indicates a reasonable level of agreement. In terms of attributes clearly distinct, the respondents agreed that the attributes in the AIMM-CI Maturity Model are clearly distinct. The mean score of 4.02 indicates a positive evaluation; the mode and median of 4.00 demonstrate consistency among the respondents' perceptions. The standard deviation of 0.54 also suggests a relatively low level of variability in responses and signifies a considerable level of agreement regarding the distinctiveness of the attributes.

8.9 AIMM-CI Maturity Model Levels

The respondents agreed that the Maturity levels in the AIMM-CI Maturity Model sufficiently represent maturation in the attributes. The mean score of 4.03 indicates a positive evaluation, and the mode and median of 4.00 suggest that this agreement is consistent among the respondents. The standard deviation of 0.62 indicate a moderate level of variability in responses and further suggest a reasonable level of agreement regarding the representation of maturity levels. Furthermore, the respondents agreed that there is no overlap detected between descriptions of maturity levels in the AIMM-CI Maturity Model. The mean score of 3.59 indicates a positive evaluation, but it is slightly lower than the mean for the previous criterion. The mode and median of 4.00 suggest that respondents generally perceive no overlap. The standard deviation of 0.57, similar to the previous criterion, suggests a moderate level of variability in responses but still indicates a reasonable level of agreement regarding the absence of overlap.

8.9.1 Ease of Understanding

In terms of the maturity levels being understandable, the respondents strongly agreed that the maturity levels in the AIMM-CI Maturity Model are understandable. The mean score of 4.21 is well above the neutral point of 3.00 and indicates a high level of agreement. The mode and median of 4.00 suggest that this strong agreement is consistent among the respondents. Besides, the standard deviation of 0.59 indicates some variability in responses and suggests a considerate level of agreement regarding the understandability of maturity levels. More so, the respondents agreed that the documentations related to the AIMM-CI Maturity Model are easy to understand. The mean score of 4.07 is above the neutral point, indicating a positive evaluation. The mode and median of 4.00 suggest that this agreement is consistent among respondents. The standard deviation of 0.56, similar to the previous criterion, suggests a moderate level of variability in responses but still indicates a reasonable level of agreement regarding the ease of understanding of documentation. In terms of results being understandable, the respondents agreed that the results produced by the AIMM-CI Maturity Model are understandable. The mean score of 4.10 is above the neutral point, indicating a positive evaluation. The mode and median of 4.00 suggest that this agreement is consistent among respondents. The standard deviation of 0.64, while indicating some variability in responses, still suggests a reasonable level of agreement regarding the understandability of results.

8.9.2 Ease of Use

The respondents agreed that the scoring scheme for maturity levels from 1 to 5 in the AIMM-CI Maturity Model is easy to comprehend. The mean score of 4.11 is above the neutral point of 3.00, indicating a positive evaluation. The mode and median of 4.00 suggest that this agreement is consistent among respondents. The standard deviation of 0.62 indicates some variability in the experts' responses, but still suggests a reasonable level of agreement regarding the ease of comprehending the scoring scheme. In terms of the AIMM-CI Maturity Model being easy to use, the respondents agreed that the AIMM-CI Maturity Model is easy to use. The mean score of 4.03 is above the neutral point and signifies a positive evaluation. The mode and median of 4.00 suggest that this agreement is consistent among respondents. The standard deviation of 0.45 indicates a relatively low level of variability in responses, further confirming a reasonable level of agreement regarding the model's ease of use.

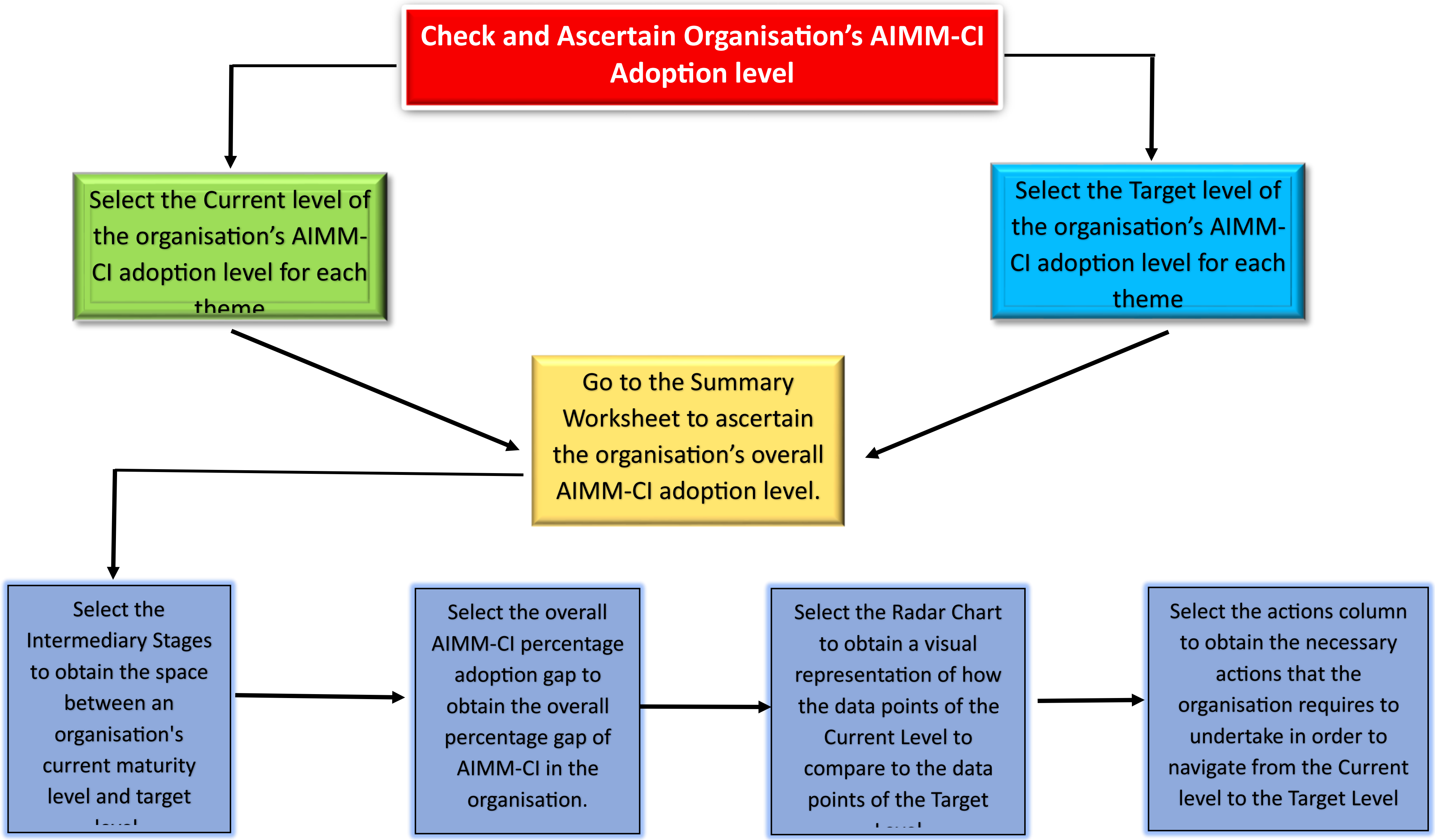
8.9.3 Usefulness and Practicality

The respondents agreed that the AIMM-CI Maturity Model is useful for evaluating the adoption of AI implementation in the construction industry. The mean score of 4.01 is above the neutral point of 3.00, indicating a positive evaluation. The mode and median of 4.00 suggest that this agreement is consistent among respondents. The standard deviation of 0.69, while indicating some variability in responses, still suggests a reasonable level of agreement regarding the model's usefulness for evaluation. Additionally, the experts provided a slightly lower rating for the practicality of the AIMM-CI Maturity Model for use in the construction industry. The mean score of 3.59 is still above the neutral point, but it's lower compared to the usefulness rating. The mode and median of 4.00 suggest that while there is some variability in responses, a substantial portion of respondents found it practical. The standard deviation of 0.58 indicates moderate variability in responses regarding practicality.

8.10 AIMM-CI ASSESSMENT FRAMEWORK

The AIMM-CI Assessment Framework was produced in a Microsoft Excel format for ease of usage during assessment. In the framework, there are ten (10) worksheets; seven (7) worksheets contain the seven (7) AI Adoption Maturity Themes (Data Availability and Usability, Organisational Culture, Technology and Tools, Robust Business Care, Stakeholders' Support, Human Capital Development, and Legal Regulations). Each theme contains a dropdown table with five levels of maturity for Current Level and Target Level (Level 1 Initial, Level 2 Assessing, Level 3 Determined, Level 4 Managed, Level 5 Optimised). For each theme, select the current level of your organisation and a desired Target Level. After completing the selection process for each theme, proceed to the Summary Worksheet. In this worksheet, a summary of the seven (7) themes is outlined, including the AIMM-CI Overall Percentage Gap, Radar Chart, Intermediary Stages and Necessary Actions. Figure 8.6 shows a flowchart that indicates the steps involved in evaluating the AIMM-CI maturity level score. In addition, a sample evaluation of a construction company using the AIMM-CI Assessment Framework is presented below.

Figure 8.6: Flowchart of AIMM-CI Assessment Framework



8.10.1 Sample Assessment of the AIMM-CI Maturity Level of a Construction Company

The steps to be followed in using the AIMM-CI Assessment Framework is as follows:

Step 1:

- For each theme, select the current level of your organisation.
- For each theme, select the desired Target of your organisation.

Note: In this sample, the selected current and target level are Level 1-Initial and Level 2 – Assessing respectively. A sample of the selected response for each success factor is presented below in Figure 8.7:

Figure 8.7: Sample of Selected Success Factors for Analysis

Theme ONE	Data Availability & Usability
Maturity Level	**DATA AVAILABILITY & USABILITY**
Level 1 – Initial	• Limited data accessibility and security measures. • The current state of data storage lacks a systematic approach and exhibits limited standardisation. • Data reliability and actionability are notably low.
Level 2 – Assessing	• Data accessibility and security measures are being assessed. • Efforts to improve data storage are in progress. • Initial steps toward data standardisation.
Level 3 – Determined	• Data is becoming more accessible with improved security. • Adequate data storage solutions are in place. • Data standardisation is actively promoted.
Level 4 – Managed	• Data is readily accessible and highly secure. • Data standardisation is well-managed throughout AI deployment. • Reliable and actionable data is available for enhancing processes.
Level 5 - Optimised	• Data is seamlessly accessible and highly secure. • Data standardisation is fully integrated into AI deployment. • Data is extremely reliable and actionable, significantly enhancing processes.

Current Level	Target Level
Level 1 Initial	**Level 2 Assessing**

ORGANISATIONAL CULTURE

Theme Two	Organisational Culture
Level 1 – Initial	• Limited investment in talent acquisition • Little emphasis on data-driven decision-making. • Communication is ad-hoc and lacks a defined strategy. • Limited collaboration, hierarchical leadership.
Level 2 – Assessing	• Investment in hiring cross-functional AI teams. • Beginning to use data for insights. • Developing a communication strategy. • Initiating cross-functional projects. • Recognising the need for digital change management. • Actively soliciting feedback from employees. • Implementing iterative processes.
Level 3 – Determined	• Significant investment in cross-functional AI teams. • Data-driven decision-making is commonplace. • Well-defined communication strategy in place. • Collaboration is encouraged and rewarded. • Robust digital change management strategy. • Employee feedback actively influences decisions. • Iteration is a standard practice, leading to improvements.
Level 4 – Managed	• Continuous improvement in acquiring AI talent. • Data insights drive most decisions. • Strong collaboration culture is ingrained. • Well-established digital change management framework. • Employees are empowered and motivated. • Frequent iteration leads to highly optimised AI solutions.
Level 5 - Optimised	• AI talent acquisition is a competitive advantage. • Data insights are the foundation of all decisions. • Exceptional communication fosters innovation. • Collaboration is an inherent component of the organisational blueprint. • Gold standard in digital change management. • Employees are highly motivated and drive innovation.

Current Level	Target Level
Level 1 Initial	Level 2 Assessing

TECHNOLOGY AND TOOLS

Theme Three	Technology And Tools
Level 1 – Initial	• Organisations at this stage have limited or no AI capabilities. • They lack a clear understanding of AI technology and its potential benefits. • There is no infrastructure or strategy in place to integrate AI into their operations. • AI projects, if any, are in the experimental phase and lack direction.
Level 2 – Assessing	• Organisations have begun assessing their AI readiness. • They are exploring AI use cases relevant to their industry. • Basic infrastructure for data storage and processing is being established. • Initial pilot projects are underway to evaluate AI feasibility.
Level 3 – Determined	• Organisations at this stage have a determined AI strategy. • They have identified specific AI applications that align with their business goals. • Infrastructure and data management capabilities are improved. • AI integration with existing processes is in progress, and initial results are promising.
Level 4 – Managed	• Organisations have effectively integrated AI into their operations. • AI tools and solutions are being used across various departments. • There is a systematic approach to managing AI projects, including monitoring and maintenance. • Continuous improvement and optimisation of AI solutions are ongoing.
Level 5 - Optimised	• Organisations have achieved optimisation in their use of AI technology. • AI is deeply ingrained in their business processes and decision-making. • Advanced AI solutions are deployed, and they have a competitive edge in their industry. • There is a culture of innovation, and they stay at the forefront of AI advancements.

Current Level	Target Level
Level 1 Initial	Level 3 Determined

ROBUST BUSINESS CASE	
Theme Four	**Robust Business Case**
Level 1 – Initial	• Organisations at this stage have not clearly defined their AI-related business problems. • There is a lack of understanding of how AI can address specific challenges. • No clear strategy or implementation plan is in place. • Limited awareness of the potential benefits of AI within the organisation.
Level 2 – Assessing	• Organisations are in the process of identifying their AI-related business problems. • Initial steps are taken to understand how AI can be applied to solve these problems. • A preliminary AI implementation strategy is under development. • Awareness within the organisation regarding AI benefits is growing.
Level 3 – Determined	• Organisations have identified their AI-related business problems and challenges. • They have developed a clear AI implementation strategy. • AI objectives are aligned with broader business goals. • An agile framework for AI project delivery is being established. • Economic feasibility analysis is conducted to assess project viability.
Level 4 – Managed	• Organisations effectively solve identified business problems using AI. • Business goals are consistently met and improved through AI solutions. • AI objectives are well-aligned with business strategies. • Projects are delivered efficiently, with a focus on speed and quality. • Awareness and understanding of AI are widespread in the organisation.
Level 5 - Optimised	• Organisations have optimised their AI-driven business cases. • AI solutions contribute significantly to business growth and innovation. • AI is seamlessly integrated into all relevant business processes. • Agile frameworks are continuously improved for maximum efficiency. • Capital and operational resources are allocated optimally for AI projects.

Current Level	Target Level
Level 1 Initial	**Level 2 Assessing**

STAKEHOLDER SUPPORT	
Theme Five	**Stakeholder Support**
Level 1 – Initial	• There is limited trust and transparency in stakeholder relationships. • Top management has not fully committed to delivering AI projects. • Stakeholders are not yet fully bought into the AI initiatives. • Top-down initiatives related to AI are not effectively facilitated.
Level 2 – Assessing	• Trust and transparency with stakeholders are improving. • Top management is starting to show commitment to AI projects. • Stakeholders are beginning to understand the value of AI initiatives. • Efforts are made to facilitate top-down initiatives related to AI. • Initial outlines of stakeholders' benefit analysis and cooperation are developed. • Stakeholders are getting more involved in AI projects.
Level 3 – Determined	• There is a high level of trust and transparency with stakeholders. • Top management is fully committed and willing to deliver AI projects. • Stakeholders are strongly bought into AI initiatives. • Top-down initiatives related to AI are effectively facilitated. • Comprehensive stakeholders' benefit analysis and cooperation strategies are in place. • Stakeholders are actively involved in AI projects.
Level 4 – Managed	• Trust and transparency with stakeholders are continually reinforced. • Top management consistently demonstrates commitment to AI projects. • Stakeholders' support for AI initiatives remains strong. • Top-down initiatives related to AI are well-integrated into the organisation. • Ongoing efforts to optimise stakeholders' benefit analysis and cooperation. • Stakeholders play a critical role in the management of AI projects.
Level 5 - Optimised	• Trust and transparency with stakeholders are ingrained in the organisation's culture. • Top management is fully aligned and dedicated to AI-driven objectives. • Stakeholders' support and enthusiasm for AI initiatives are unwavering. • Top-down initiatives related to AI are consistently successful. • Continuous refinement and optimisation of stakeholders' benefit analysis. • Stakeholders are actively engaged in shaping the future of AI within the organisation.

Current Level	Target Level
Level 1 Initial	**Level 2 Assessing**

HUMAN CAPITAL DEVELOPMENT

Theme Six	Human Capital Development
Level 1 – Initial	• Limited efforts to upskill in-house competency in AI. • Minimal focus on promoting technology readiness. • Limited collaboration with AI solution partners. • Minimal encouragement for businesses to outsource AI deployment. • Basic knowledge transfer and staff training activities.
Level 2 – Assessing	• Efforts to upskill in-house competency in AI are growing. • Some initiatives to promote technology readiness are underway. • Collaboration with AI solution partners is increasing. • Moderate encouragement for businesses to outsource AI deployment. • Ongoing knowledge transfer and staff training efforts. • Occasional hiring of AI and construction experts.
Level 3 – Determined	• Significant progress in upskilling in-house competency in AI. • Technology readiness is actively promoted throughout the organisation. • Strong collaboration with AI solution partners. • Encouragement for businesses to outsource AI deployment when appropriate. • Well-established knowledge transfer and staff training programs. • Regular hiring of AI and construction experts.
Level 4 – Managed	• In-house competency in AI is consistently strong and evolving. • Technology readiness is an integral part of the organisation. • Collaborative partnerships with AI solution partners are highly effective. • Businesses strategically outsource AI deployment for efficiency. • Continuous improvement of knowledge transfer and staff training. • A dedicated team of AI and construction experts is maintained.
Level 5 - Optimised	• In-house competency in AI is a core organisational strength. • Technology readiness is deeply ingrained in the organisation's culture. • AI solution partners are considered strategic allies. • AI deployment is optimised through the right mix of in-house and outsourcing. • Cutting-edge knowledge transfer and staff training practices are in place. • An elite team of AI and construction experts drives innovation.

Current Level	Target Level
Level 1 Initial	**Level 2 Assessing**

LEGAL REGULATION

Theme Seven	Legal Regulation
Level 1 – Initial	• Limited encouragement for the adoption of governance and policy guidelines. • Minimal efforts to embolden AI initiatives and enhance trust. • Basic measurement of ethical and trustworthy AI for deployment. • Minimal emphasis on encouraging compliance with standards.
Level 2 – Assessing	• Growing encouragement for the adoption of governance and policy guidelines. • Increasing efforts to embolden AI initiatives and enhance trust. • Developing more advanced measures for ethical and trustworthy AI. • Moderate emphasis on encouraging compliance with standards.
Level 3 – Determined	• Active promotion of governance and policy guidelines. • Strong efforts to embolden AI initiatives and enhance trust. • Well-defined measures for ethical and trustworthy AI. • Actively encouraging compliance with industry standards.
Level 4 – Managed	• Governance and policy guidelines are fully integrated and enforced. • AI initiatives are highly emboldened, and trust is well-established. • Rigorous measures ensure ethical and trustworthy AI. • Proactive compliance with industry standards is maintained.
Level 5 - Optimised	• Exemplary governance and policy guidelines set industry standards. • AI initiatives are pioneering and synonymous with trust. • Unparalleled measures ensure the highest standards of ethical and trustworthy AI. • Leading in compliance with industry standards and regulations

Current Level	Target Level
Level 1 Initial	**Level 2 Assessing**

Step Two:

- After selecting the appropriate current and target levels for the seven (7) themes, proceed to the Summary Worksheet to ascertain the overall maturity level of your organisation.
- Figure 8.8 shows a sample of the Summary Worksheet

Figure 8.8 SAMPLE OF AIMM-CI SUMMARY

Introduction

The AIMM-CI (Artificial Intelligence Maturity model in Construction) Assessment Tool enables construction organisations to self-assess their level of AI Adoption in the UK construction industry. The Assessment Tool indicates and evaluates the current level of maturity within the construction industry. Additionally, it sets out a comprehensive roadmap for improvement that outlines the steps between each level of maturity

The tool presents seven pillars of AI Adoption maturity (Data Availability and Usability, Organisational Culture, Technology and Tools, Robust Business Care, Stakeholders' Support, Human Capital Development, and Legal Regulations) and divides each pillar into 5 levels of maturity - Initial to Optimized. Under each level is listed the characteristics we would expect to find in an organisation that is at that level of AI adoption

How to Use the AIMM-CI Assessment Tool

In this tool, there are ten (10) worksheets; seven (7) worksheets contain the seven (7) AI Adoption Maturity Themes (***Data Availability and Usability, Organisational Culture, Technology and Tools, Robust Business Care, Stakeholders' Support, Human Capital Development, and Legal Regulations***). Each theme contains a dropdown table with five levels of maturity for **Current Level** and **Target Level** (***Level 1 Initial, Level 2 Assessing, Level 3 Determined, Level 4 Managed, Level 5 Optimized***). For each theme, select the current level of your organization and a desired Target Level. After completing the selection process for each theme, proceed to the **Summary Worksheet.** In this worksheet, a summary of the seven (7) themes is outlined, including the **AIMM-CI Overall Percentage Gap, Radar Chart, Intermediary Stages and Necessary Actions.**

The **AIMM-CI Overall Percentage Gap** computes and displays the overall percentage gap of AIMM-CI in your orgnaization.
The **AIMM-CI Radar Chart** provides a pictorial representation of your organization's current and Target level.
The **Intermediary Stages** displays the space between your organization's current maturity level and target level. The **Actions** displays the necessary actions that your organization requires to undertake in order to navigate from the Current level to the Target Level

Step 3:

- Go to the Intermediary Stages column to ascertain the space between your organisation's current maturity level and target level.
- Go to the Actions Column to obtain the necessary actions that your organisation requires to undertake in order to navigate from the Current level to the Target Level.
- Go to the AIMM-CI Overall Percentage Gap Column to display the overall percentage gap of AIMM-CI in your organisation.
- Go to the AIMM-CI Radar Chart to obtain a pictorial representation of your organisation's current and Target level.

Figure 8.9: The Intermediary Levels, Actions, and the Radar Chart.

Themes	Current Level	Target Level	Intermediary Levels	Actions
Data Availability & Usabilit	Level 1 Initial	Level 2 Assessing	Level 1 Initial > Level 2 Assessing	Begin by identifying critical data sources and assess their relevance. Take initial steps to secure sensitive data. Explore data storage options. Raise awareness about data standardisation. Start collecting data for reliability assessment
Organisational Culture	Level 4 Managed	Level 5 Optimised	Level 4 Managed > Level 5 Optimised	• Implement AI governance policies and frameworks. • Encourage employees to actively participate in AI projects. • Continuously innovate and explore emerging AI technologies. • Foster a culture of experimentation and learning.
Technology and Tools	Level 1 Initial	Level 3 Determined	Level 1 Initial > Level 3 Determined	• Start by conducting AI awareness and training sessions for employees. • Begin exploring potential AI use cases in your industry. • Invest in basic data storage and processing capabilities. • Pilot small-scale AI projects to understand its feasibility. • Develop a clear AI strategy aligned with business objectives. • Build a dedicated team with AI expertise. • Assess the compatibility of AI technology with existing processes. • Evaluate AI vendors and tools for your specific needs.
Robust Business Case	Level 2 Assessing	Level 3 Determined	Level 2 Assessing > Level 3 Determined	• Develop a structured process to identify and define specific business problem • Invest in AI research and development to understand its potential impact. • Create a dedicated team responsible for defining AI objectives. • Conduct initial economic feasibility assessments for selected use cases.
Stakeholder Support	Level 4 Managed	Level 5 Optimised	Level 4 Managed > Level 5 Optimised	• Reinforce and institutionalise trust and transparency in stakeholder relationshi • Foster unwavering top management support for AI initiatives. • Engage stakeholders as co-owners of AI projects and outcomes. • Continually refine and optimise top-down AI initiatives. • Implement real-time benefit analysis and cooperation enhancements. • Leverage stakeholder expertise in shaping AI project direction. • Ensure that trust and transparency are deeply embedded in the organisation's DNA. • Celebrate and showcase top management's dedication to AI-driven success.
Human Capital Developmer	Level 3 Determined	Level 4 Managed	Level 3 Determined > Level 4 Managed	• Establish comprehensive in-house competency development programs. • Integrate Technology and Tools into the organisational culture. • Form strategic partnerships with AI solution partners. • Optimise the balance between in-house and outsourced AI deployment. • Continuously refine knowledge transfer and staff training. • Maintain a dedicated team for hiring AI and construction experts.
Legal Regulation	Level 2 Assessing	Level 3 Determined	Level 2 Assessing > Level 3 Determined	• Expand efforts to encourage the adoption of governance and policy guidelines • Actively promote AI initiatives and build trust in AI systems. • Enhance measures for ethics and trustworthiness in AI. • Establish a framework for compliance with industry standards.

Chapter Summary

The chapter discusses the development of the AIMM-CI (Artificial Intelligence Maturity Model for Construction Industry) Maturity Model using the Peffers framework. The model was developed and validated using various assessment criteria. These criteria were assessed by experts in the construction field, and their responses were summarised to evaluate the model's effectiveness. The experts found that the attributes used in the AIMM-CI Maturity Model were highly relevant and comprehensive. They strongly agreed that these attributes covered all aspects of the model, were correctly assigned to their respective maturity levels, and were clearly distinct. This consensus among experts suggests that the AIMM-CI Maturity Model aligns well with the needs of the UK construction industry and has a clear, well-structured attribute framework. The chapter also assessed the AIMM-CI Maturity Model levels, where experts believed that the maturity levels effectively represented the maturation of attributes within the model. They also found no overlap between descriptions of different maturity levels, indicating a clear distinction and separation between them. This clarity is crucial for the model's effectiveness in assessing AI maturity. Under "Ease of Understanding," the experts strongly agreed that the maturity levels in the AIMM-CI Maturity Model were understandable. They also found the associated documentation easy to comprehend, enhancing the model's usability. The results produced by the model were perceived as clear and comprehensible, crucial for practical application. In terms of ease of use, the experts strongly agreed that the scoring scheme for maturity levels (ranging from 1 to 5) was easy to comprehend. They also agreed that the AIMM-CI Maturity Model itself was easy to use, making it practical for application in the construction industry. For the usefulness and practicality, the experts overwhelmingly agreed that the AIMM-CI Maturity Model was a valuable tool for evaluating AI implementation in the construction industry. However, while the majority found it practical, there were some dissenting opinions. Furthermore, the AIMM-CI Assessment Framework, which is designed to help construction companies evaluate their AI adoption maturity was discussed in detail. The process involves selecting current and target levels for the seven (7) AI Adoption Maturity Themes, moving to the Summary Worksheet to determine the overall maturity level, evaluating intermediary stages, necessary actions, and the AIMM-CI Overall Percentage Gap. This Framework provides a structured approach for organisations to assess their AI maturity in different areas and develop a clear understanding of strengths and areas that need improvement. It allows companies to make informed decisions and plans for AI implementation and growth within the construction industry.

9 CHAPTER 9: FINDINGS AND DISCUSSIONS OF RESULTS

Chapter Overview

In this chapter, a comprehensive analysis of the development and validation of the AIMM-CI Maturity Model is discussed. This chapter critically examines the application of the Peffers framework to the development of the model, including the outcomes obtained through the assessment of the model across various success factors, scopes, and maturity levels in the UK construction industry. The overarching focus of this chapter is to present a thorough exploration of the final AIMM-CI Maturity Model and its applicability in the UK construction industry. Through a meticulous examination of the responses collected during the validation process, the chapter aims to extract meaningful trends, key findings, and critical insights that contributed to development of the final AIMM-CI Maturity Model.

9.1 Data Analysis

9.2.1 The Development of the AIMM-CI Model

The design science research methodology (DSRM) developed by Peffers et al. (2007) was used to design the AIMM-CI Model. The Peffers framework is made up of a set of guidelines and principles that facilitate the systematic development of information systems research models. The design process began with the identification of a significant problem within the construction industry—the need for a structured framework to assess and enhance AI adoption. The motivation was rooted in recognising the potential benefits of AI in construction but also understanding the challenges organisations face in adopting and maturing their AI capabilities. In this research, the recognition of a significant problem in the UK construction industry served as the backdrop for the design of the AIMM-CI Model. Unlike other industries, the construction sector, traditionally characterised by its reliance on manual processes and limited integration of technological advancements, faced a pressing need for a systematic approach to assess and improve the adoption of artificial intelligence (AI) (Abioye et al., 2021). The overarching problem identified was the absence of a structured framework tailored to the unique challenges and opportunities within the construction domain. The motivation behind addressing this problem was deeply rooted in the acknowledgment of the transformative potential that AI could bring to the construction industry. As industries across the globe were increasingly leveraging AI for enhanced efficiency, cost-effectiveness, and innovation, the UK construction industry needed to harness these advancements. The motivation also stemmed from the understanding that not only of the advantages that AI adoption held for UK construction companies but also of the impediments and complexities they faced in navigating the AI maturity journey. Besides, the potential benefits of AI in UK construction industry are manifold, as it ranges from improved project management and optimised resource allocation to enhanced safety measures and innovative design processes (Bolpagni and Bartoletti, 2021; Regona et al., 2022a). Recognising these potential gains, there was a clear drive to propel the UK construction companies toward integrating AI seamlessly into their operations. However, there existed a complex landscape of challenges, including concerns related to data security, the adaptability of existing processes, and the cultural shift required for embracing AI-driven decision-making. The design the AIMM-CI Model was, therefore, grounded in the duality of promise and challenge. It aimed not only to unlock the untapped potential of AI in construction but also to navigate and alleviate the hurdles that hindered the industry's progress in this technological frontier.

Peffers et al. (2007), recommended grounding research models in existing theories. In the case of the AIMM-CI Model, the theoretical foundation draws from established frameworks in organisational maturity and AI adoption. This ensured that the model is built upon well-established concepts and aligns with existing research in the field. Following the identification of the problem and the underlying motivation, the design of the AIMM-CI Model strategically incorporated a robust theoretical framework and aligned with Peffers recommendation to anchor research models in existing theories. The theoretical foundation of the AIMM-CI Model was carefully crafted, drawing upon established frameworks in organisational maturity and AI adoption. The choice to ground the model in existing theories was also based on several other reasons. Firstly, it provided a solid and recognised basis for the development of the AIMM-CI Model. By tapping into well-established concepts and frameworks, the model gained credibility and resonance within the broader academic and industry discourse. This ensured that the AIMM-CI Model was not conceived in isolation but rather as an evolution and refinement of existing theoretical perspectives. Secondly, the utilisation of established theories allowed for a seamless integration of the AIMM-CI Model into the broader body of knowledge related to organisational maturity and AI adoption. This alignment was crucial for fostering a sense of continuity and coherence in research and practice. In other words, the AIMM-CI model did not emerge as an isolated entity but rather as a contribution to an ongoing movement, as it was built on the foundations laid by earlier theoretical frameworks.

Furthermore, the AIMM-CI model design involved the creation of the objectives of a solution by organising key components and variables. The AIMM-CI model includes seven (7) AI Adoption

Maturity Themes, also regarded as the success factors. Each theme focused on specific aspects such as data availability and usability, organisational culture, technology readiness, business care, stakeholders' management, human capital development, and legal regulation. These themes ensured a comprehensive and structured approach to AI maturity assessment; they served as the scaffolding for the model, as they delineated seven distinct AI Adoption Maturity Themes. Each theme is strategically crafted to encapsulate specific facets critical to the evaluation of AI maturity in the UK construction industry. For the Data Availability and Usability, it basically focuses on ensuring relevant data is readily accessible, secure, and standardised for effective utilisation in AI applications. The Organisational Culture theme encompasses the investment in talent acquisition, the promotion of insight-driven approaches, and the cultivation of a culture conducive to AI adoption. Similarly, the Technology Readiness theme concentrates on the organisation's preparedness to use sophisticated tools in construction projects, ensuring continuous iteration of AI solutions. The Business Case theme identifies and solves business problems through AI, aligns AI objectives with business goals, and establishes an agile framework for project delivery. For the Stakeholders' Management theme, it centres on building trust, transparency, and commitment with stakeholders, and ensuring their buy-in and active involvement in AI initiatives. The Human Capital Development theme focuses on upskilling in-house competency in AI, promoting technology readiness beyond AI, and fostering collaboration with AI solution partners. Lastly, the Legal Regulation theme encourages the adoption of governance and policy guidelines, enhances trust in AI initiatives, and ensures ethical and trustworthy AI deployment in compliance with standards. By structuring the model around these themes, the objectives ensure a holistic approach to AI maturity assessment, covering both technical and organisational aspects. The taxonomy's role is critical in guiding the evaluation process, as it provides a clear framework for organisations to navigate. It also acts as a roadmap for assessing current maturity levels, setting target aspirations, and identifying actionable steps for improvement.

Furthermore, the Peffers framework suggests evaluating the research model's design (Peffers et al., 2007). The AIMM-CI Model underwent rigorous evaluation, considering its alignment with the problem statement, coherence with theoretical foundations, and suitability for practical application in the UK construction industry. Iterative refinement based on expert feedback and pilot testing was crucial in enhancing the model's effectiveness. Peffers' framework emphasises the critical step of evaluating the design of a research model, and the AIMM-CI Model adheres to this principle by undergoing a meticulous and rigorous evaluation process. The first aspect of the evaluation involved scrutinising how well the AIMM-CI Model aligned with the identified problem within the construction industry. The initial phase of problem identification emphasised the need for a structured framework to assess and enhance AI adoption. The evaluation ensured that the model's design directly addressed this problem, providing a tailored and effective solution. The practical application of the AIMM-CI Model in the UK construction industry was a paramount consideration during the evaluation. The design was scrutinised to ensure it was not only theoretically sound but also applicable and beneficial in real-world scenarios. The model's effectiveness in providing practical insights for organisations aiming to assess and enhance their AI maturity in construction projects was a key criterion.

A crucial aspect of the design evaluation involved iterative refinement. The model did not emerge in its final form immediately; instead, it underwent multiple iterations based on expert feedback and pilot testing. This iterative refinement process was integral to enhancing the model's effectiveness, usability, and relevance to the specific challenges faced by construction organisations in adopting AI. The design evaluation, therefore, served as a comprehensive examination of the AIMM-CI Model's structure and ensured that it not only addressed the identified problem but also adhered to theoretical principles and demonstrated practical utility. The iterative nature of the refinement process highlights the commitment to continuous improvement, adapting the model to the dynamic landscape of the UK construction industry and the evolving understanding of AI adoption and maturity.

The validation process involved empirical testing and refinement. Peffers recommends seeking feedback from industry experts and stakeholders to validate the model's relevance and effectiveness (Peffers, 2007). In the case of the AIMM-CI Model, validation involved collaboration with construction industry professionals, AI experts, and organisations actively engaged in AI adoption. The validation process commenced with empirical testing, to assess the practical applicability and effectiveness of the AIMM-CI Model. Real-world scenarios within the construction industry were simulated to evaluate how well the model could capture and assess the nuances of AI adoption maturity. This involved applying the model to diverse construction projects, each presenting unique challenges and opportunities for AI integration. Additionally, to ensure the model's relevance, feedback was actively sought from industry experts, AI specialists, and organisations immersed in AI adoption. Peffers recommends involving stakeholders throughout the research process, and the AIMM-CI Model embraced this approach. Questionnaires and interviews sessions were conducted to gather insights, critique, and suggestions from professionals with diverse perspectives within the construction and AI domains.

The feedback from empirical testing and stakeholder engagement sessions informed refinements to the model. Each iteration aimed to enhance the model's accuracy, applicability, and alignment with the dynamic landscape of the construction industry. This iterative refinement approach ensured that the AIMM-CI Model evolved to meet the evolving needs and challenges of organisations adopting AI in the UK construction industry.

The Peffers' framework further highlights the importance of ensuring that a research model contributes practical value to the industry it serves. In alignment with this principle, the design process of the AIMM-CI Model carefully considered the implications for practice within the UK construction industry. The AIMM-CI Model serves as a strategic guide for the UK construction companies seeking to navigate the intricate landscape of AI adoption. By providing a structured framework for assessing and enhancing AI maturity, the model directly addresses the practical needs and challenges faced by organisations in the UK construction industry. The implications for practice are profound, as the model empowers companies to conduct a comprehensive assessment of their current AI adoption maturity levels across key themes, including data availability, organisational culture, technology readiness, business care, stakeholders' management, human capital development, and legal regulation. Through a systematic evaluation of maturity levels, construction companies can pinpoint specific areas that require enhancement. This targeted identification of strengths and weaknesses facilitates a more focused and efficient approach to AI adoption improvement initiatives. In addition, the UK construction companies can develop strategic plans to elevate their AI adoption maturity. The model guides the formulation of strategies that align with organisational goals and ensures a purposeful and goal-oriented approach to AI integration. The AIMM-CI model also contributes to informed decision-making by providing a structured assessment of AI maturity factors. This empowers construction leaders to make data-driven decisions that align with broader business objectives and foster sustainable growth.

Beyond its practical implications, the AIMM-CI Model also holds significance for advancing the body of knowledge in AI adoption within the construction industry. Peffers' framework emphasises the dual impact of a research model on both practice and future research. The AIMM-CI Model addresses existing research gaps by offering a comprehensive and industry-specific approach to AI adoption maturity. Its thematic focus on critical success factors provides a nuanced understanding of the challenges and opportunities unique to the construction sector. The model also sets the stage for future research endeavours by laying a solid foundation for exploring the dynamics of AI adoption in construction. Researchers can leverage the insights generated by the

AIMM-CI Model to delve deeper into specific themes, test hypotheses, and contribute to the evolving discourse on AI maturity.

9.2 The Final AIMM-CI Maturity Model

The final AIMM-CI Maturity Model represents a comprehensive and systematic framework that serves as a roadmap for the UK construction companies to harness the transformative power of artificial intelligence (AI). This model encompasses a range of critical success factors, each contributing significantly to the journey of AI adoption and maturity within the construction industry. The model is not only a diagnostic tool but also a prescriptive guide for companies looking to navigate the complexities of AI integration successfully. Table 9.1 shows the final AIMM-CI Maturity Model

AIMM Process	AIMM Key Benchmarking Process	Level 1(Initial)	Level 2(Assessing)	Level 3(Determined)	Level 4(Managed)	Level 5(Optimised)
Theme	**Scope**	**PROGRESSIVE CHARACTERISTICS OF EACH MATURITY LEVEL**				
Data	1)Ensure relevant data is readily accessible to leverage on 2) Ensure data security 3) Facilitate the requirement for appropriate data storage 4) Promote data standardisation throughout AI deployment 5) Provide reliable and actionable data capable to enhance processes	• Limited data accessibility and security measures. • The current state of data storage lacks a systematic approach and exhibits limited standardisation. • Data reliability and actionability are notably low.	• Data accessibility and security measures are being assessed. • Efforts to improve data storage are in progress. • Initial steps toward data standardisation.	• Data is becoming more accessible with improved security. • Adequate data storage solutions are in place. • Data standardisation is actively promoted.	• Data is readily accessible and highly secure. • Data standardisation is well-managed throughout AI deployment. • Reliable and actionable data is available for enhancing processes.	• Data is seamlessly accessible and highly secure. • Data standardisation is fully integrated into AI deployment. • Data is extremely reliable and actionable, significantly enhancing processes.
	Process recommendation guidelines	• Identify critical data sources and assess their relevance. • Implement preliminary measures to secure sensitive data. • Explore data storage options. • Raise awareness about data standardisation. • Data collection for reliability assessment.	• Continue to identify and prioritise relevant data sources. • Implement basic data security measures. • Explore more robust data storage solutions. • Initiate efforts to standardise data formats. • Enhance data collection processes for improved reliability.	• Develop a comprehensive strategy for data accessibility and security. • Implement advanced data security measures. • Invest in appropriate data storage infrastructure. • Actively promote data standardisation practices across AI deployment. • Regularly assess data reliability and take corrective actions.	• Establish a well-structured data accessibility framework. • Ensure stringent data security protocols. • Optimise data storage solutions for efficiency and scalability. • Integrate data standardisation into every aspect of AI deployment.	• Create a seamless data accessibility environment with top-tier security measures. • Employ cutting-edge data storage technologies for maximum efficiency. • Data standardisation is fully automated and integrated into AI processes. • Data is exceptionally reliable and actionable, driving continuous process enhancements.
Organisational Culture	1)Investment in talent acquisition across multidisciplinary team 2) Ensure companies adopt insight-driven approach 3) Establish strategic communication within the organisation 4) Promote cooperation between leaders and staff 5) Promote digital change management approach 6) Encourage bottom-up approach to ensure employee motivation 7) Encourages continuous iteration of AI solution	• Limited investment in talent acquisition • Little emphasis on data-driven decision-making. • Communication is ad-hoc and lacks a defined strategy. • Limited collaboration, hierarchical leadership. • Minimal focus on digital change management. • Limited efforts to involve employees in decision-making. • Iteration is infrequent and lacks a structured process.	• Investment in hiring cross-functional AI teams. • Beginning to use data for insights. • Developing a communication strategy. • Initiating cross-functional projects. • Recognising the need for digital change management. • Actively soliciting feedback from employees. • Implementing iterative processes.	• Significant investment in cross-functional AI teams. • Data-driven decision-making is commonplace. • Well-defined communication strategy in place. • Collaboration is encouraged and rewarded. • Robust digital change management strategy. • Employee feedback actively influences decisions. • Iteration is a standard practice, leading to improvements.	• Continuous improvement in acquiring AI talent. • Data insights drive most decisions. • Strong collaboration culture is ingrained. • Well-established digital change management framework. • Employees are empowered and motivated. • Frequent iteration leads to highly optimised AI solutions.	• AI talent acquisition is a competitive advantage. • Data insights are the foundation of all decisions. • Exceptional communication fosters innovation. • Collaboration is an inherent component of the organisational blueprint. • Gold standard in digital change management. • Employees are highly motivated and drive innovation.
	Process recommendation guidelines	•Focus on raising awareness about the importance of AI and data-driven decision-making. • Start basic data training programmes.	• Develop a clear AI strategy and roadmap for the organisation. • Initiate cross-functional projects to encourage collaboration.	• Invest in advanced data analytics training for employees. • Establish a dedicated AI department.	• Implement AI governance policies and frameworks. • Encourage employees to actively participate in AI projects.	• Continuously innovate and explore emerging AI technologies. • Foster a culture of experimentation and learning.

Technology Readiness	1)Enable an organisation to use sophisticated tools in construction projects 2) Ensure a continuous iteration of AI solution 3) Ascertain that AI technology is integrated and compatible with existing business process 4) Prototype development to evaluate the AI application's efficiency on a small scale	• Organisations at this stage have limited or no AI capabilities. • They lack a clear understanding of AI technology and its potential benefits. • There is no infrastructure or strategy in place to integrate AI into their operations. • AI projects, if any, are in the experimental phase and lack direction.	• Organisations have begun assessing their AI readiness. • They are exploring AI use cases relevant to their industry. • Basic infrastructure for data storage and processing is being established. • Initial pilot projects are underway to evaluate AI feasibility.	• Organisations at this stage have a determined AI strategy. • They have identified specific AI applications that align with their business goals. • Infrastructure and data management capabilities are improved. • AI integration with existing processes is in progress, and initial results are promising.	• Organisations have effectively integrated AI into their operations. • AI tools and solutions are being used across various departments. • There is a systematic approach to managing AI projects, including monitoring and maintenance. • Continuous improvement and optimisation of AI solutions are ongoing.	• Organisations have achieved optimisation in their use of AI technology. • AI is deeply ingrained in their business processes and decision-making. • Advanced AI solutions are deployed, and they have a competitive edge in their industry. • There is a culture of innovation, and they stay at the forefront of AI advancements.
	Process recommendation guidelines	• Start by conducting AI awareness and training sessions for employees. • Begin exploring potential AI use cases in your industry. • Invest in basic data storage and processing capabilities. • Pilot small-scale AI projects to understand its feasibility.	• Develop a clear AI strategy aligned with business objectives. • Build a dedicated team with AI expertise. • Assess the compatibility of AI technology with existing processes. • Evaluate AI vendors and tools for your specific needs.	• Prioritise AI projects that offer the most significant business impact. • Invest in infrastructure improvements to support AI deployment. • Establish data governance and management practices. • Begin prototyping AI solutions to validate their efficiency.	• Implement a comprehensive AI infrastructure and data pipeline. • Develop a framework for AI project management and monitoring. • Encourage cross-functional collaboration in AI initiatives. • Focus on scaling AI solutions that have proven successful.	• Continuously assess and update AI technology stack to stay competitive. • Foster a culture of innovation and AI-driven decision-making. • Invest in advanced AI capabilities, such as machine learning and automation. • Collaborate with AI solution partners to explore cutting-edge advancements.
Robust Business Case	1)Identify business problem statement 2)Solve business problem statement 3)Improve and achieve business goals 4)Establish AI implementation strategy 5)Align AI driven objectives to the business goals 6)Develop and implement an agile framework for AI project delivery 7)Ensure faster project delivery 8)Increase awareness and understanding of the core of AI within an organisation 9)Identify capital costs and operational resources required for a project	• Organisations at this stage have not clearly defined their AI-related business problems. • There is a lack of understanding of how AI can address specific challenges. • No clear strategy or implementation plan is in place. • Limited awareness of the potential benefits of AI within the organisation.	• Organisations are in the process of identifying their AI-related business problems. • Initial steps are taken to understand how AI can be applied to solve these problems. • A preliminary AI implementation strategy is under development. • Awareness within the organisation regarding AI benefits is growing.	• Organisations have identified their AI-related business problems and challenges. • They have developed a clear AI implementation strategy. • AI objectives are aligned with broader business goals. • An agile framework for AI project delivery is being established. • Economic feasibility analysis is conducted to assess project viability.	• Organisations effectively solve identified business problems using AI. • Business goals are consistently met and improved through AI solutions. • AI objectives are well-aligned with business strategies. • Projects are delivered efficiently, with a focus on speed and quality. • Awareness and understanding of AI are widespread in the organisation.	• Organisations have optimised their AI-driven business cases. • AI solutions contribute significantly to business growth and innovation. • AI is seamlessly integrated into all relevant business processes. • Agile frameworks are continuously improved for maximum efficiency. • Capital and operational resources are allocated optimally for AI projects.
	Process recommendation guidelines	• Start by conducting AI awareness sessions to identify potential business problems. • Foster a culture of problem-solving and innovation within the organisation. • Begin exploring how AI can address identified challenges. • Encourage cross-functional teams to brainstorm AI use cases.	• Develop a structured process to identify and define specific business problems. • Invest in AI research and development to understand its potential impact. • Create a dedicated team responsible for defining AI objectives. • Conduct initial economic feasibility assessments for selected use cases.	• Clearly define and document AI-related business problems and objectives. • Establish a cross-functional team with expertise in AI strategy. • Align AI objectives with broader business goals and strategies. • Pilot agile frameworks for AI project delivery on selected use cases.	• Implement agile frameworks for AI project delivery across the organisation. • Continuously monitor and optimise AI project delivery for efficiency. • Foster a culture of AI-driven problem-solving and innovation. • Ensure that AI objectives are integrated into the	• Establish a mature framework for AI project management and optimisation. • Encourage cross-functional collaboration to maximise the impact of AI. • Regularly review and align AI objectives with evolving business goals. • Allocate capital and operational resources strategically for AI initiatives.

				• Conduct in-depth economic feasibility studies for critical projects.	organisation's strategic planning.	• Promote a culture of continuous improvement and innovation in AI applications.
Stakeholders' Management	1)Ensure trust and transparency with stakeholders 2) Encourage top management commitment and willingness to deliver AI projects 3) Ensure stakeholders buy-in 4) Facilitate the need for top-down initiatives 5) Outline stakeholders benefit analysis and seeks their cooperation	• There is limited trust and transparency in stakeholder relationships. • Top management has not fully committed to delivering AI projects. • Stakeholders are not yet fully bought into the AI initiatives. • Top-down initiatives related to AI are not effectively facilitated. • Stakeholders' benefit analysis and cooperation are in the early stages. • Limited involvement of stakeholders in AI projects.	• Trust and transparency with stakeholders are improving. • Top management is starting to show commitment to AI projects. • Stakeholders are beginning to understand the value of AI initiatives. • Efforts are made to facilitate top-down initiatives related to AI. • Initial outlines of stakeholders' benefit analysis and cooperation are developed. • Stakeholders are getting more involved in AI projects.	• There is a high level of trust and transparency with stakeholders. • Top management is fully committed and willing to deliver AI projects. • Stakeholders are strongly bought into AI initiatives. • Top-down initiatives related to AI are effectively facilitated. • Comprehensive stakeholders' benefit analysis and cooperation strategies are in place. • Stakeholders are actively involved in AI projects.	• Trust and transparency with stakeholders are continually reinforced. • Top management consistently demonstrates commitment to AI projects. • Stakeholders' support for AI initiatives remains strong. • Top-down initiatives related to AI are well-integrated into the organisation. • Ongoing efforts to optimise stakeholders' benefit analysis and cooperation. • Stakeholders play a critical role in the management of AI projects.	• Trust and transparency with stakeholders are ingrained in the organisation's culture. • Top management is fully aligned and dedicated to AI-driven objectives. • Stakeholders' support and enthusiasm for AI initiatives are unwavering. • Top-down initiatives related to AI are consistently successful. • Continuous refinement and optimisation of stakeholders' benefit analysis. • Stakeholders are actively engaged in shaping the future of AI within the organisation.
	Process recommendation guidelines	• Begin building trust and transparency in stakeholder relationships. • Initiate discussions with top management about the potential of AI projects. • Educate stakeholders about AI benefits and possibilities. • Start outlining strategies for facilitating top-down initiatives. • Develop a basic framework for stakeholders' benefit analysis. • Explore ways to involve stakeholders in initial AI projects.	• Continuously nurture trust and transparency in stakeholder interactions. • Encourage top management to actively support AI project initiatives. • Strengthen communication to further engage stakeholders. • Implement strategies for facilitating top-down initiatives. • Refine and expand stakeholders' benefit analysis efforts. • Involve stakeholders in specific AI project planning.	• Establish a culture of trust and transparency with stakeholders. • Ensure top management is fully committed to AI project success. • Actively involve stakeholders in AI project decision-making. • Optimise top-down initiatives related to AI across the organisation. • Develop comprehensive stakeholders' benefit analysis strategies. • Empower stakeholders to take on significant roles in AI project teams.	• Reinforce and institutionalise trust and transparency in stakeholder relationships. • Foster unwavering top management support for AI initiatives. • Engage stakeholders as co-owners of AI projects and outcomes. • Continually refine and optimise top-down AI initiatives. • Implement real-time benefit analysis and cooperation enhancements. • Leverage stakeholder expertise in shaping AI project direction.	• Ensure that trust and transparency are deeply embedded in the organisation's DNA. • Celebrate and showcase top management's dedication to AI-driven success. • Empower stakeholders to lead and drive AI innovation. • Sustain consistent success in top-down initiatives related to AI. • Continuously optimise and innovate in stakeholders' benefit analysis. • Establish stakeholders as AI ambassadors, actively shaping the AI future
Human Capital Development	1)Upskill inhouse competency in AI 2) Promote technology readiness beyond AI 3) Encourage businesses to collaborate with AI solution partners 4) Embolden businesses to outsource AI deployment 5) Encourage knowledge transfer and staff training 6) Encourage businesses to employ AI and construction experts	• Limited efforts to upskill in-house competency in AI. • Minimal focus on promoting technology readiness. • Limited collaboration with AI solution partners. • Minimal encouragement for businesses to outsource AI deployment. • Basic knowledge transfer and staff training activities.	• Efforts to upskill in-house competency in AI are growing. • Some initiatives to promote technology readiness are underway. • Collaboration with AI solution partners is increasing. • Moderate encouragement for businesses to outsource AI deployment. • Ongoing knowledge transfer and staff training efforts.	• Significant progress in upskilling in-house competency in AI. • Technology readiness is actively promoted throughout the organisation. • Strong collaboration with AI solution partners. • Encouragement for businesses to outsource AI deployment when appropriate. • Well-established knowledge transfer and staff training	• In-house competency in AI is consistently strong and evolving. • Technology readiness is an integral part of the organisation. • Collaborative partnerships with AI solution partners are highly effective. • Businesses strategically outsource AI deployment for efficiency. • Continuous improvement of knowledge transfer and staff	• In-house competency in AI is a core organisational strength. • Technology readiness is deeply ingrained in the organisation's culture. • AI solution partners are considered strategic allies. • AI deployment is optimised through the right mix of in-house and outsourcing. • Cutting-edge knowledge transfer and staff training practices are in place.

		• Limited hiring of AI and construction experts.	• Occasional hiring of AI and construction experts.	programmes. • Regular hiring of AI and construction experts.	training. • A dedicated team of AI and construction experts is maintained.	• An elite team of AI and construction experts drives innovation.
	Process recommendation guidelines	• Begin initiatives to upskill in-house competency in AI. • Introduce the concept of technology readiness. • Explore potential collaboration with AI solution partners. • Consider outsourcing AI deployment when necessary. • Initiate knowledge transfer and basic staff training. • Explore opportunities to hire AI and construction experts.	• Expand efforts to upskill in-house competency in AI. • Actively promote technology readiness within the organisation. • Foster collaborative relationships with AI solution partners. • Strategically evaluate AI deployment options. • Develop structured knowledge transfer and staff training programmes. • Create a plan for hiring AI and construction experts.	• Establish comprehensive in-house competency development programmes. • Integrate technology readiness into the organisational culture. • Form strategic partnerships with AI solution partners. • Optimise the balance between in-house and outsourced AI deployment. • Continuously refine knowledge transfer and staff training. • Maintain a dedicated team for hiring AI and construction experts.	• Ensure that in-house competency development is consistently effective. • Institutionalise technology readiness as a core organisational value. • Foster long-term collaborative relationships with AI solution partners. • Continually assess and optimise AI deployment strategies. • Implement advanced knowledge transfer and staff training practices. • Sustain a high-performing team of AI and construction experts.	• Maintain a culture of continuous learning and innovation in AI. • Showcase technology readiness as a competitive advantage. • Solidify strategic alliances with AI solution partners. • Excel in optimising AI deployment methods. • Pioneer cutting-edge knowledge transfer and staff training. • Lead the industry with a world-class team of AI and construction experts.
Legal Regulation	1)Encourage adoption of governance and policy guidelines 2) Embolden AI initiatives and enhance trust 3) Measure an ethical and trustworthy AI for deployment 4) Encourage compliance with standard	• Limited encouragement for the adoption of governance and policy guidelines. • Minimal efforts to embolden AI initiatives and enhance trust. • Basic measurement of ethical and trustworthy AI for deployment. • Minimal emphasis on encouraging compliance with standards.	• Growing encouragement for the adoption of governance and policy guidelines. • Increasing efforts to embolden AI initiatives and enhance trust. • Developing more advanced measures for ethical and trustworthy AI. • Moderate emphasis on encouraging compliance with standards.	• Active promotion of governance and policy guidelines. • Strong efforts to embolden AI initiatives and enhance trust. • Well-defined measures for ethical and trustworthy AI. • Actively encouraging compliance with industry standards.	• Governance and policy guidelines are fully integrated and enforced. • AI initiatives are highly emboldened, and trust is well-established. • Rigorous measures ensure ethical and trustworthy AI. • Proactive compliance with industry standards is maintained.	• Exemplary governance and policy guidelines set industry standards. • AI initiatives are pioneering and synonymous with trust. • Unparalleled measures ensure the highest standards of ethical and trustworthy AI. • Leading in compliance with industry standards and regulations
	Process recommendation guidelines	• Begin the process of encouraging the adoption of governance and policy guidelines. • Initiate efforts to embolden AI initiatives and build trust. • Start measuring the ethics and trustworthiness of AI for deployment. • Introduce the importance	• Expand efforts to encourage the adoption of governance and policy guidelines. • Actively promote AI initiatives and build trust in AI systems. • Enhance measures for ethics and trustworthiness in AI. • Establish a framework for	• Develop comprehensive governance and policy guidelines. • Foster a culture of AI innovation and trustworthiness. • Implement advanced measures for ethics and trustworthiness in AI. • Promote active compliance with industry standards.	• Institutionalise governance and policy guidelines. • Continually reinforce trust and ethics in AI initiatives. • Utilise advanced measures to ensure the highest trustworthiness in AI. • Maintain proactive compliance with industry standards.	• Champion industry-leading governance and policy guidelines. • Lead in setting the standard for trust and ethics in AI. • Pioneering measures for the utmost trustworthiness in AI. • Serve as a benchmark for compliance with industry standards and regulations.

		of compliance with industry standards.	compliance with industry standards.			

Table 9.1: FINAL AIMM-CI MATURITY MODEL

9.2.1 Data Availability and Usability

At the core of the final AIMM-CI Maturity Model lies the foundation of data availability and usability. The UK construction industry, historically reliant on vast amounts of data, has struggled with issues related to data accessibility, security, storage, standardisation, reliability, and actionability. The AIMM-CI Maturity Model recognises these challenges and provides a structured path for companies to overcome them. At the initial level, organisations often face issues like limited data accessibility and security measures, haphazard data storage, and a lack of standardisation. As they progress through the maturity levels, they become more adept at ensuring data is readily accessible and highly secure. Data standardization becomes a well-managed process, and data reliability and actionability are significantly enhanced. The AIMM-CI Maturity Model mandates a culture of data security and standardisation, urging organisations to continuously optimise data management. This approach ensures that data remains at the core of informed decision-making, which is critical in a sector as multifaceted as construction. AI applications rely on the quality and accessibility of data, and this factor serves as the bedrock for AI success within construction companies.

As construction companies navigate the intricate landscape of AI adoption, the critical role of data in driving successful AI initiatives becomes evident. Historically, the construction industry has grappled with data-related challenges, from accessibility and security to storage, standardisation, reliability, and actionability (Pan and Zhang, 2021; Regona et al., 2022b). AIMM-CI acknowledges these hurdles and strives to provide a structured pathway for organisations to overcome them. The validation responses and mean scores during the model's testing phase reflected a shared sentiment among industry professionals and highlighted prevalent issues in the initial stages of AI adoption. In the nascent stages, organisations often faced impediments like limited data accessibility and inadequate security measures. The validation responses underscored these challenges, with companies expressing concerns about data breaches, unauthorised access, and the overall vulnerability of their data infrastructure. The mean scores indicated a baseline understanding of the importance of securing data, although the implementation lagged. The validation process brought to light another common challenge—haphazard data storage and a lack of standardisation. Construction companies, in their initial AI adoption phases, struggled with organising and storing data systematically. The absence of standardised processes hampered the effectiveness of AI applications, making it challenging to derive meaningful insights. The expert feedback emphasised the need for a more structured approach to data storage and standardisation. As organisations progressed through the maturity levels of AIMM-CI, a notable transformation occurred. The mean scores demonstrated an upward trajectory, which indicated a significant improvement in addressing the challenges related to data accessibility, security, storage, and standardisation. This positive trend aligns with the intended outcome of the AIMM-CI model—to guide organisations toward enhanced data management practices. Furthermore, the validation responses highlighted a shift from the initial stages, where standardisation efforts were minimal, to an advanced stage where companies actively promoted and enforced data standardisation. Mean scores reflected a collective understanding of the importance of standardised data for AI applications in construction.

Beyond the numerical assessments, the expert feedback emphasised the cultural shift encouraged by AIMM-CI. The model mandates a culture of data security and standardisation and urged organisations to embed these principles in their DNA. The validation responses indicated a cultural embrace of these values, with companies actively promoting and reinforcing data security and standardisation practices. An integral aspect highlighted by both validation responses and expert feedback was the emphasis on continuous optimisation of data management. The AIMM-CI model does not view data management as a one-time task but as an ongoing process. It collectively acknowledges the need for continuous improvement to keep pace with evolving AI technologies and industry dynamics. In conclusion, Data Availability and Usability, as a success factor, plays a foundational role in the overall maturity of AI adoption in the UK construction industry. The patterns observed during the validation process indicated a symbiotic relationship—improvements in data management directly contributed to advancements in other AI adoption themes. Organisations that successfully addressed data challenges showcased a more streamlined and effective AI maturity journey.

9.2.2 Organisational Culture

The AIMM-CI Maturity Model underscores the indispensable role of organisational culture in AI adoption and maturity. The investment in talent acquisition across multidisciplinary teams emerges as a critical success element. Organisations that diversify their teams with AI and construction experts are better equipped to tackle the intricate challenges posed by construction projects. Such cross-functional teams foster innovation, problem-solving, and the development of AI solutions tailored to the specific needs of construction. In parallel, embracing an insight-driven culture is emphasised within the model. Companies that prioritise data and knowledge as strategic assets nurture a proactive approach to decision-making. Data-driven insights guide planning, risk mitigation, resource allocation, and the identification of hidden trends. This culture is essential for meeting project deadlines, staying within budget, ensuring quality and safety, and remaining competitive in a rapidly evolving industry. The AIMM-CI model also emphasises digital change management as a crucial aspect of AI integration. Recognising that change is a constant, companies that effectively manage digital change foster a smoother transition when implementing AI solutions. Employee motivation is closely tied to these aspects. Organisations that empower employees to actively contribute to AI projects and decision-making witness increased efficiency, innovation, and overall AI success.

At the heart of the AIMM-CI model lies the recognition of the pivotal role played by talent acquisition across multidisciplinary teams. Insights derived from the validation responses highlighted a consensus among industry professionals regarding the challenges posed by complex construction projects. The mean scores indicated a recognition of the need for diverse expertise, including AI and construction specialists, to navigate these challenges effectively. The validation responses reinforced the model's emphasis on investment in talent acquisition. Organisations expressing a commitment to diversifying their teams showcased a positive correlation with higher mean scores. The validation process underscored that companies actively investing in cross-functional AI teams exhibited more promising AI maturity trajectories.

The AIMM-CI model juxtaposes hierarchical leadership against collaborative leadership and sheds light on their respective impacts on AI maturity. The validation process brought forth notable insights into how leadership styles influence the organisation's ability to innovate, make informed decisions, and effectively integrate AI solutions. The validation responses also demonstrated a prevailing trend: organisations with collaborative leadership styles exhibited higher mean scores in terms of AI maturity. Collaborative leadership, as highlighted by the validation data, fosters an environment where input is encouraged from all levels of the organisation. This inclusivity empowers employees, promotes innovative thinking, and contributes significantly to a conducive AI adoption environment. The patterns observed in the validation process collectively contribute to the overarching theme of how Organisational Culture influences the overall maturity of AI adoption in the construction industry. The success factors within Organisational Culture, when effectively embraced, set the tone for a holistic and sustainable AI adoption journey.

Addition, the interconnectedness of talent acquisition, leadership styles, change management, employee motivation, and an insight-driven culture emerged as a recurring theme in both validation responses and expert feedback. Construction companies that excelled in these aspects showcased a more streamlined and effective AI maturity journey. This holistic approach aligns with AIMM-CI's premise that AI maturity is not achieved in silos but through a comprehensive transformation of organisational culture. The experts' feedback added valuable industry-specific insights to the discussion. Construction professionals emphasised the unique nature of the construction industry, where project intricacies demand diverse expertise. The validation process validated the industry-specific nature of the AIMM-CI model and affirmed its relevance and effectiveness in guiding construction companies toward a mature AI adoption journey.

9.2.3 Technology Readiness

Technology readiness formed another cornerstone of the AIMM-CI Maturity Model. It highlights the necessity of enabling organisations to use sophisticated tools in construction projects. This includes the continuous iteration of AI solutions, ensuring that AI technology integrates seamlessly with existing business processes and conducting prototype development for efficiency evaluation. At the initial stage, organisations often possess limited or no AI capabilities. They lack an understanding of AI technology and its potential benefits, and AI projects, if initiated, are often experimental and directionless. As they progress, they establish an AI strategy, improve infrastructure, and actively integrate AI with existing processes. The AIMM-CI Maturity Model calls for a systematic approach to managing AI projects, which includes monitoring and maintenance. Ultimately, the model encourages organisations to achieve optimisation in their use of AI technology. AI should become deeply ingrained in business processes, become a competitive advantage, foster a culture of innovation, and place organisations at the forefront of AI advancements. The model promotes a relentless focus on refining and optimising AI frameworks for maximum efficiency, thereby ensuring that capital and operational resources are allocated optimally for AI projects.

The feedback from the experts underlined the industry-wide acknowledgment of the difficulties in the early stages of AI adoption within construction. The validation process provided tangible evidence of the model's reflection of the common barriers' organisations encounter, setting the stage for the importance of a robust technology readiness framework. As organisations progress along the AI maturity levels, the AIMM-CI model advocates for the development of a clear AI strategy. The validation responses indicated a notable shift in mean scores as organisations moved from the initial stage. Those that actively worked on establishing an AI strategy demonstrated a positive correlation with higher mean scores. This insight reinforces the model's premise that strategic planning is pivotal in advancing technology readiness. More so, the experts' feedback enriched this aspect by emphasising the significance of aligning AI initiatives with broader business goals. The validation process provided valuable data on how organisations that strategically integrated AI into their overall business strategy showcased higher levels of maturity. This alignment resonated with experts, validating the model's recommendations and reflecting industry best practices. Improving infrastructure and actively integrating AI with existing processes mark the intermediate stages of technology readiness. The validation responses illuminated the challenges organisations face in this phase and corroborated the model's emphasis on the systematic approach required in managing AI projects. The mean scores showcased a gradual but steady improvement as companies invested in upgrading their infrastructure and integrating AI with their operational workflows.

The validation process also brought forth notable trends in the UK construction industry's approach to AI integration. The experts highlighted the importance of not only investing in technology but also ensuring that the integration process aligns with the organisation's existing processes. The validation responses affirmed the model's recommendation of a systematic approach, revealing instances where successful AI integration was directly linked to meticulous project management and continuous monitoring. The pinnacle of technology readiness, as envisioned by the AIMM-CI model, is the optimisation of AI use within an organisation. Validation responses and mean scores underscored the transformative journey organisations undergo when AI becomes deeply ingrained in their business processes. The validation process identified instances where AI evolved from being a tool to becoming a competitive advantage, driving innovation and positioning organisations at the forefront of AI advancements. The experts' feedback provided insights into industry-specific nuances and emphasised that optimisation in AI use is not solely about technology but also about fostering a culture of innovation. The validation responses supported this by highlighting instances where organisations that prioritised innovation alongside technology readiness showcased higher maturity levels. This intersection between technology and culture emerged as a key trend in organisations exhibiting advanced AI maturity.

The patterns observed in the validation process collectively contribute to understanding how Technology Readiness influences the overall maturity of AI adoption in the construction industry. The success factors within Technology Readiness, when effectively embraced, lay the groundwork for a holistic and impactful AI adoption journey. The interconnectedness of AI strategy, infrastructure improvement, integration with existing processes, optimisation, and continuous refinement emerged as a recurring theme in both validation responses and expert feedback. Construction companies that excelled in these aspects showcased a more streamlined and effective AI maturity journey. This holistic approach aligns with AIMM-CI's premise that AI maturity is not merely a technological evolution but a comprehensive transformation that integrates technology seamlessly into the fabric of construction organisations.

9.2.4 Robust Business Case

In line with the AIMM-CI Maturity Model, robust business case necessitates the identification of business problem statements, the resolution of these problems, and the alignment of AI-driven objectives with broader business goals. Organisations are prompted to develop and implement agile frameworks for AI project delivery, ensure faster project delivery, increase awareness and understanding of AI within the organisation, and identify capital costs and operational resources required for a project. At the initial level, companies often fail to define their AI-related business problems and lack an understanding of how AI can address specific challenges. No clear strategy or implementation plan is in place, and awareness of the potential benefits of AI remains limited. As organisations advance through the maturity levels, they identify their AI-related business problems, develop clear AI-related objectives, establish cross-functional teams with expertise in AI strategy, and conduct economic feasibility analysis. In the final stage, organisations have optimised their AI-driven business cases. AI solutions contribute significantly to business growth and innovation, are seamlessly integrated into relevant business processes, and are underpinned by continually improved agile frameworks for maximum efficiency. The model encourages organisations to empower stakeholders to lead and drive AI innovation and establish stakeholders as AI ambassadors actively shaping the AI future.

The validation responses echoed the struggles organisations face and reinforced the model's accurate depiction of the challenges at the initial level. The mean scores aligned with the prevalent issues identified during validation and highlighted the model's reliability in capturing the industry's starting point in addressing AI-related challenges. The expert feedback added nuance to this aspect by emphasising the need for construction companies to critically identify and articulate their unique challenges. The validation process illuminated instances where companies that invested time in thorough problem identification showcased a more systematic approach to their AI adoption journey. The model's emphasis on this foundational step resonated with both validation responses and expert insights.

Advancing through the maturity levels involves a significant shift – from undefined problems to the resolution of identified business problems and the establishment of clear AI-driven objectives. The validation responses indicated a notable uptick in mean scores as organisations progressed along this continuum. The model's recommendation of developing clear objectives aligned with the trends observed during validation, showcasing its applicability in guiding companies toward maturity. The experts' feedback emphasised the strategic importance of this transition. Organisations that successfully resolved business problems demonstrated a higher level of AI maturity and reflected a direct correlation between problem-solving capabilities and overall, AI adoption success. The validation process offered tangible evidence of how the AIMM-CI model effectively captures the transformative nature of resolving business problems in the construction industry's AI journey.

Implementing agile frameworks for AI project delivery is a crucial aspect of the AIMM-CI Maturity Model. The model suggests that companies should develop and implement agile frameworks, ensuring faster project delivery. The validation process affirmed this, with mean scores indicating a positive correlation between the application of agile methodologies and higher maturity levels. This aligns with industry trends emphasising the agility required in AI project management within the construction sector. The experts' feedback delved into the nuances of agile adoption in construction. The validation responses highlighted instances where companies that embraced agility in project delivery showcased better adaptability to the dynamic nature of AI integration. The AIMM-CI model's emphasis on agility emerged as a practical guideline, resonating with the industry's need for flexible and iterative project management methodologies.

Furthermore, raising awareness and understanding of AI within an organisation is a foundational step in the AIMM-CI Maturity Model. At the initial stage, organisations often lack awareness of the potential benefits of AI. The validation responses confirmed this and aligned with the model's depiction of the industry's starting point. The mean scores for this factor indicated a steady improvement as organisations actively worked on enhancing awareness and understanding. The experts' feedback emphasised the cultural shift required for successful AI adoption. The validation process showcased instances where organisations that prioritised education and awareness demonstrated higher maturity levels. The model's recommendation of increasing awareness emerged as a critical success factor, acknowledging the importance of a knowledgeable workforce in driving AI adoption and maturity.

Furthermore, robust business case requires organisations to identify capital costs and operational resources required for a project. The validation responses reflected the challenges companies face in this domain, with the mean scores aligning with the prevalent issues identified during the validation process. This aspect showcased the model's effectiveness in capturing the industry's struggles related to resource identification at the initial stages. The experts' feedback provided valuable insights into the resource allocation landscape in construction. The validation process highlighted instances where organisations that meticulously identified and allocated resources showcased higher maturity levels. The model's emphasis on this aspect resonated with industry best practices, offering a structured approach to ensure that projects are adequately resourced for successful AI implementation.

The pinnacle of the Robust Business Case success factor is the optimisation of AI-driven business cases. Organisations that reach this stage witness significant contributions from AI to business growth and innovation. Validation responses and mean scores showcased the transformative journey organisations undergo as AI becomes seamlessly integrated into business processes. The model's recommendation of continually improving agile frameworks for maximum efficiency resonated with instances observed during validation. The experts' feedback provided industry-specific insights into the challenges and opportunities inherent in optimising AI-driven business cases in construction. The validation process affirmed the industry-specific nature of the AIMM-CI model, underlining its relevance and effectiveness in guiding construction companies toward a mature AI adoption journey.

In the final stage, the AIMM-CI model urges organisations to empower stakeholders to lead and drive AI innovation, establishing them as AI ambassadors actively shaping the AI future. Validation responses and mean scores provided tangible evidence of this transformation. Organisations that successfully empowered stakeholders showcased a unique level of AI maturity, aligning with the model's premise that stakeholders play a crucial role in shaping the AI trajectory. The experts' feedback delved into the challenges and benefits of stakeholder engagement in AI initiatives. The validation process highlighted instances where organisations that actively engaged stakeholders demonstrated higher maturity levels. The model's recommendation of stakeholder empowerment emerged as a key trend, reflecting the industry's recognition of the influential role stakeholders play in AI adoption success.

9.2.5 Stakeholder Management

Stakeholder management is a critical component of the AIMM-CI Maturity Model. It highlights the need to ensure trust and transparency with stakeholders, encourage top management commitment and willingness to deliver AI projects, and facilitate stakeholders' buy-in. This process includes top-down initiatives, stakeholder benefit analysis, and the active involvement of stakeholders in AI projects. At the initial stage, organisations face challenges related to limited trust and transparency in stakeholder relationships. Top management has not fully committed to delivering AI projects, and stakeholders are yet to fully buy into AI initiatives. The AIMM-CI Maturity Model encourages the gradual reinforcement of trust and transparency, active top management commitment, and ongoing stakeholder involvement in AI projects. As organisations progress, trust and transparency with stakeholders become stronger, top management fully commits to AI projects, stakeholders strongly buy into AI initiatives, and top-down initiatives related to AI are effectively facilitated. Comprehensive stakeholder benefit analysis and cooperation strategies are established, further reinforcing the importance of stakeholder involvement in AI projects. Ultimately, the model encourages organisations to engage stakeholders as co-workers of AI projects and outcomes, ingraining trust and transparency in the organisation's culture.

The mean scores indicated a correspondence with the prevalent issues identified during the validation process and affirmed the model's reliability in capturing the industry's initial state concerning stakeholder engagement. The experts' feedback emphasised the significance of this phase. The validation process revealed instances where organisations that invested time in building trust and transparency demonstrated a more conducive environment for AI adoption. The model's emphasis on gradual reinforcement aligned with the nuanced nature of cultivating stakeholder relationships, showcasing its applicability in guiding companies toward maturity. Advancing through the maturity levels involves a notable shift – from limited top management commitment and stakeholder buy-in to a stage where these factors become robust pillars of AI adoption. Validation responses indicated a significant uptick in mean scores as organisations progressed along this continuum. The model's recommendation of active top management commitment and ongoing stakeholder involvement resonated with the trends observed during validation, showcasing its effectiveness in navigating organisations toward AI maturity. The experts' feedback illuminated the strategic importance of this transition. Organisations that successfully garnered top management commitment and stakeholder buy-in showcased a higher level of AI maturity, reflecting a direct correlation between leadership support and overall, AI adoption success. The validation process provided tangible evidence of how the AIMM-CI model effectively captures the transformative nature of cultivating commitment and buy-in within the construction industry's AI journey.

Furthermore, facilitating top-down initiatives related to AI is a crucial aspect of the AIMM-CI Maturity Model's Stakeholder Management success factor. The model suggests that companies should actively enable, and support initiatives driven from top management to ensure AI success. The validation process affirmed this, with mean scores indicating a positive correlation between the effectiveness of top-down facilitation and higher maturity levels. This aligns with industry trends emphasising the importance of cohesive leadership for successful AI integration. The experts' feedback delved into the nuances of top-down facilitation in construction. The validation responses highlighted instances where organisations that effectively facilitated top-down initiatives showcased better alignment of AI projects with organisational goals. The AIMM-CI model's emphasis on this aspect emerged as a practical guideline, resonating with the industry's need for strong leadership support in steering AI initiatives.

In addition, establishing comprehensive stakeholder benefit analysis and cooperation strategies is a pivotal phase in the Stakeholder Management success factor. The validation responses reflected the challenges companies face in this domain, with mean scores aligning with the prevalent issues identified during the validation process. This aspect showcased the model's effectiveness in capturing the industry's struggles related to strategic stakeholder engagement at the initial stages. The experts' feedback provided valuable insights into the stakeholder engagement landscape in construction. The validation process highlighted instances where organisations that meticulously analysed stakeholder benefits and devised cooperation strategies showcased higher maturity levels. The model's emphasis on this aspect resonated with industry best practices, offering a structured approach to ensure that stakeholders are integral to AI project success.

As organisations progress through AI maturity levels, the AIMM-CI model emphasises the necessity of active stakeholder involvement in AI projects. The validation responses and mean scores provided tangible evidence of this transformation. Organisations that successfully engaged stakeholders demonstrated a unique level of AI maturity, aligning with the model's premise that stakeholders play a crucial role in shaping the AI trajectory. The experts' feedback delved into the challenges and benefits of stakeholder involvement in AI initiatives. The validation process highlighted instances where organisations that actively involved stakeholders demonstrated higher maturity levels. The model's recommendation of stakeholder engagement emerged as a key trend, reflecting the industry's recognition of the influential role stakeholders play in AI adoption success.

In the final stage, the AIMM-CI model urges organisations to engage stakeholders as co-workers of AI projects and outcomes, ingraining trust and transparency in the organisation's culture. Validation responses and mean scores provided tangible evidence of this transformation. Organisations that successfully empowered stakeholders showcased a unique level of AI maturity, aligning with the model's premise that stakeholders play a crucial role in shaping the AI trajectory. The experts' feedback provided industry-specific insights into the challenges and opportunities inherent in engaging stakeholders as co-workers. The validation process affirmed the industry-specific nature of the AIMM-CI model, underlining its relevance and effectiveness in guiding construction companies toward a mature AI adoption journey.

9.2.6 Human Capital Development

Human capital development is another pillar of the AIMM-CI Maturity Model. It involves upskilling in-house competency in AI, promoting technology readiness beyond AI, encouraging businesses to collaborate with AI solution partners, emboldening businesses to outsource AI deployment, facilitating knowledge transfer and staff training, and encouraging businesses to employ AI and construction experts. At the initial stage, organisations put in limited efforts to upskill in-house competency in AI, focus minimally on technology readiness, collaborate with AI solution partners to a limited extent, and show minimal encouragement for businesses to outsource AI deployment. Knowledge transfer and staff training activities are basic, and hiring of AI and construction experts is infrequent. However, as organisations advance, their efforts to upskill in-house competency in AI grow. As organisations progress through the maturity levels, there is a noticeable enhancement in their commitment to upskilling. The validation responses revealed a growing emphasis on training programmes, workshops, and certifications tailored to AI applications in construction. Additionally, the upskilling component significantly contributes to the overall maturity of AI adoption in the construction industry. A workforce equipped with AI-related skills not only fosters innovation but also ensures that the organisation can effectively leverage AI technologies. The result of the validation provides insights on specific aspects where improved in-house competency positively influences the successful integration and application of AI in construction projects.

9.2.7 Legal Regulations

The Legal Regulations success factor within the AIMM-CI Maturity Model stands as a sentinel, guiding construction organisations through the intricate legal landscape of AI adoption. This discussion delves into the multifaceted aspects of Legal Regulations, intertwining insights from validation responses, mean scores, and expert feedback. It aims to elucidate patterns, trends, and the overarching contribution of legal adherence to the maturation of AI adoption within the construction industry. At the inception of the AI maturity journey, organisations often find themselves navigating a complex legal landscape. The validation responses indicated common challenges related to legal compliance, substantiating the model's accurate depiction of the industry's starting point. Mean scores corresponded with the prevalent legal issues identified during validation, affirming the model's reliability in capturing the industry's initial state concerning legal regulations. The expert feedback emphasised the strategic importance of understanding and navigating legal intricacies. Instances observed during validation highlighted the significance of organisations that invested time and resources in legal compliance, showcasing a more systematic approach to their AI adoption journey. The model's emphasis on this foundational step resonated with both validation responses and expert insights, underscoring its applicability in guiding companies toward maturity.

As organisations progress through the maturity levels, the AIMM-CI model emphasises the evolution of legal compliance from initial challenges to a robust, well-integrated system. Validation responses indicated a significant uptick in mean scores as organisations progressed along this continuum. The model's recommendation of continuous improvement in legal compliance aligned with the trends observed during validation, showcasing its effectiveness in navigating organisations toward AI maturity. The experts' feedback illuminated the strategic importance of this transition. Organisations that successfully evolved in legal compliance demonstrated a higher level of AI maturity, reflecting a direct correlation between legal adherence and overall AI adoption success. The validation process provided tangible evidence of how the AIMM-CI model effectively captures the transformative nature of legal evolution within the construction industry's AI journey.

Furthermore, the AIMM-CI Maturity Model urges organisations to move beyond mere compliance and adopt proactive legal measures. Validation responses and mean scores provided tangible evidence of this transformation. Organisations that successfully embraced proactive legal measures showcased a unique level of AI maturity, aligning with the model's premise that a proactive legal approach is essential for sustained success. The experts' feedback provided industry-specific insights into the challenges and benefits inherent in proactive legal measures in construction. The validation process highlighted instances where organisations that proactively addressed legal considerations demonstrated higher maturity levels. The model's recommendation of proactive legal measures emerged as a key trend, reflecting the industry's recognition of the need to anticipate and address legal challenges for effective AI adoption.

In a dynamic legal landscape, the AIMM-CI model emphasises the importance of organisations adapting to legal changes. The validation responses and mean scores provided tangible evidence of this imperative. Organisations that successfully adapted to legal changes demonstrated a unique level of AI maturity, aligning with the model's premise that flexibility in legal compliance is crucial for long-term success. The experts' feedback delved into the challenges and benefits of adapting to legal changes in construction. The validation process highlighted instances where organisations that remained agile in legal compliance demonstrated higher maturity levels. The model's recommendation of adaptation to legal changes emerged as a key trend, reflecting the industry's recognition of the need for flexibility in navigating the evolving legal landscape.

In the final stage, the AIMM-CI model urges organisations to establish comprehensive legal frameworks. Validation responses and mean scores provided tangible evidence of this transformation. Organisations that successfully implemented comprehensive legal frameworks showcased a unique level of AI maturity, aligning with the model's premise that a holistic legal approach is essential for sustained success. The experts' feedback provided industry-specific insights into the challenges and benefits inherent in comprehensive legal frameworks in construction. The validation process highlighted instances where organisations that established robust legal frameworks demonstrated higher maturity levels. The model's recommendation of comprehensive legal frameworks emerged as a key trend, reflecting the industry's recognition of the need for a thorough and all-encompassing legal structure for successful AI adoption.

9.3 A Comparison of AIMM-CI Model with Existing Literature

The final AIMM-CI Maturity Model provides valuable insights into the landscape of AI maturity in the UK construction industry and beyond. The AIMM-CI model aligns closely with the existing literature on AI maturity models in the construction industry. Firstly, the AIMM-CI model's recognition of historical data challenges aligns with existing literature acknowledging the complexities in leveraging historical data for AI applications. Several studies have highlighted the significance of historical data quality, completeness, and relevance for effective machine learning models. AIMM-CI's emphasis on addressing data accessibility, security, and standardisation resonates with the broader understanding that historical data forms the backbone of successful AI implementations (Fukas et al., 2021; Rangineni, 2023; Sadiq et al., 2021). In addition, the AIMM-CI model's progression through maturity levels is in alignment with the literature emphasising the iterative nature of improving data quality in organisations (Jaaksi et al., 2018; Lichtenthaler, 2020; Hanne et al., 2022).

More so, the iterative nature of AI adoption by the AIMM-CI model aligns seamlessly with insights from the research by Defize (2020). The author pointed out strong emphasises on the necessity for continuous improvement efforts. In a rapidly evolving technological landscape, organisations embarking on the AI adoption journey must recognise that achieving optimal data quality is not a one-time task but an ongoing process (Grebe et al., 2023; Ledro et al., 2023). This perspective resonates with the AIMM-CI model's recognition that, at the initial stages of AI maturity, organisations may encounter challenges. This acknowledgement highlights the model's commitment to realism and understanding that the path to achieving mature AI adoption involves overcoming obstacles that are inherent to the dynamic nature of the construction industry.

Furthermore, the AIMM-CI model's emphasis on cross-functional collaboration aligns seamlessly with insights from the literature that underline the significant role of multidisciplinary teams in AI adoption (Dwivedi et al., 2021; Zirar et al., 2023). The model's recommendation for organisations to invest in talent acquisition across diverse teams is in harmony with the well-established understanding that such teams are instrumental in fostering innovation and problem-solving—essential attributes for tackling the intricate challenges inherent in construction projects. Perifanis and Kitsios (2023), highlight the significance of multidisciplinary teams in the context of AI adoption, emphasising that diverse teams bring together individuals with varied expertise and perspectives. This diversity, as suggested by the AIMM-CI model, not only fosters innovation but also enhances problem-solving capabilities within organisations operating in the construction industry.

The AIMM-CI model's emphasis on technology readiness aligns coherently with insights from the literature underscoring the importance of utilizing sophisticated tools in construction projects (Radhakrishnan and Chattopadhyay, 2020; Uren and Edwards, 2023). The model recognises that organisations may initiate their AI journey with limited or no capabilities and effectively encourages the development of a systematic approach to managing AI projects. Bughin et al. (2017), stressed the need for organisations to leverage advanced technologies, including AI, to enhance efficiency and innovation. The AIMM-CI model aligns with this perspective by acknowledging that, at the initial stages, organisations may lack a comprehensive understanding of AI technology and its potential benefits. The model, therefore, recommends the establishment of a clear AI strategy, improvements in infrastructure, and active integration of AI with existing processes as organisations progress through maturity levels.

The AIMM-CI model's incorporation of stakeholder management aligns seamlessly with existing research that underscores the crucial role of stakeholder involvement in AI projects (Miller, 2022; Shneiderman, 2022). The model recognises the significance of building trust, securing top management commitment, and facilitating stakeholders' buy-in. These echoes findings in the literature that highlight effective stakeholder engagement as a key determinant of successful AI adoption. Miller (2022), emphasise that stakeholder engagement is critical in overcoming resistance to AI initiatives and ensuring the success of AI projects. The AIMM-CI model, by echoing this perspective, aligns with the notion that, at the initial stages, organisations may encounter challenges related to limited trust and transparency in stakeholder relationships. The model advocates for a gradual reinforcement of trust and transparency, active top management commitment, and ongoing stakeholder involvement in AI projects as organisations progress through maturity levels.

Lastly, the AIMM-CI model's incorporation of a dedicated focus on legal regulations aligns seamlessly with existing literature emphasising the critical role of governance and policy guidelines in the adoption of artificial intelligence (Harvey and Gowda, 2021; Stern, 2022). By acknowledging the importance of ensuring ethical and trustworthy AI deployment, the model reflects the growing significance of compliance with industry standards, demonstrating its responsiveness to contemporary concerns in the rapidly evolving landscape of AI technology. DG (2020), underscore the ethical considerations associated with AI adoption and stress the necessity of robust legal frameworks to guide its responsible implementation. The AIMM-CI model aligns with this perspective by incorporating legal regulations as a distinct success factor, recognising that, at the initial stages, organisations may face challenges in navigating legal and ethical considerations related to AI deployment in the construction industry.

9.4 The Implications of the AIMM-CI Model

The final AIMM-CI Maturity Model hold profound implications for the UK construction industry, as it offers practical insights and guidance for organisations seeking to adopt and mature their AI capabilities. The practical implications of the AIMM-CI model are outlined below.

9.4.1 Data Availability and Usability

- The model's emphasis on data security, accessibility, storage, standardisation, reliability, and actionability directly addresses the foundational challenges faced by the UK construction industry. Organisations can strategically manage their data by investing in secure and accessible storage solutions. The model advocates for a systematic approach to data storage, promoting a shift from ad-hoc methods to well-defined processes. This has practical implications for construction companies aiming to enhance data management practices.
- The emphasis on data standardisation as organisations progress through maturity levels implies practical steps towards creating a uniform data structure. Construction projects involve diverse data sources, and standardisation ensures compatibility and coherence. Implementing standardised data practices contributes to improved collaboration and decision-making.
- The model's focus on achieving reliable and actionable data highlights the importance of data quality over quantity. Practical implications include the implementation of data validation processes, ensuring that the data used for AI applications is not only accessible but also reliable. Actionable insights derived from high-quality data contribute to more informed decision-making.
- The model's call for maintaining a culture of data security has practical implications for fostering awareness and accountability. Organisations can implement training programmes,

enforce data security protocols, and integrate data security into their corporate culture. This cultural shift ensures that data protection becomes a collective responsibility.

- The model's insistence on continuously optimising data management processes aligns with the dynamic nature of the construction industry. Practical implications include the establishment of feedback loops, regular audits of data management practices, and the integration of evolving technologies to ensure that data processes remain efficient and effective.

9.4.2 Organisational Culture

- The model's emphasis on investment in talent acquisition across multidisciplinary teams implies a shift towards a more diverse and collaborative workforce. Practical implications include strategic hiring practices, team-building initiatives, and fostering a culture that values the unique contributions of individuals from various disciplines.
- The model's advocacy for an insight-driven culture underscores the practical need for organisations to prioritise data and knowledge. This implies investments in training programmes, data literacy initiatives, and the integration of data-driven decision-making into organisational processes. Practical implications also involve the adoption of technologies that facilitate data-driven insights.
- The model's preference for collaborative leadership styles has practical implications for organisational structures and leadership development programmes. Construction companies can actively promote collaborative leadership, encourage open communication, and provide leadership training that emphasises inclusivity and employee empowerment.
- The model's recognition of digital change management as crucial for AI integration suggests practical steps for organisations to navigate transitions effectively. Practical implications include the development of change management strategies, communication plans, and employee training programmes to ensure a smooth shift towards AI-driven practices.
- The emphasis on employee motivation and empowerment implies practical strategies for recognising and rewarding employee contributions to AI projects. This can involve the creation of innovation hubs, the establishment of employee recognition programmes, and the inclusion of employees in decision-making processes related to AI initiatives.

9.4.3 Technology and Tools

- The model's acknowledgment of limited or no AI capabilities at the initial stage suggests a practical need for organisations to invest in AI skill development. This can involve training programmes, collaboration with AI experts, and partnerships with educational institutions to ensure a pipeline of skilled AI professionals.
- The model's call for a systematic approach to managing AI projects implies practical steps for organisations to strategically integrate AI into their existing processes. This involves conducting AI readiness assessments, developing implementation roadmaps, and ensuring that AI projects align with broader business goals.
- The model's recommendation for prototype development aligns with practical considerations for organisations to evaluate AI applications on a small scale before full-scale implementation. This approach allows for risk assessment, efficiency evaluation, and the identification of potential challenges early in the process.
- The model's emphasis on continuous improvement of AI solutions suggests practical implications for organisations to establish feedback mechanisms, monitor AI project performance, and iterate on existing solutions. This involves creating a culture that encourages learning from both successes and failures in AI implementation.
- The model's call for optimisation through iterative processes has practical implications for organisations to adopt agile methodologies in their AI projects. This involves breaking down projects into manageable iterations, regularly reviewing progress, and making adjustments based on real-time feedback.

9.4.4 Robust Business Case

- The model's emphasis on identifying business problem statements implies practical steps for organisations to conduct thorough assessments of their challenges. This involves engaging stakeholders, conducting gap analyses, and clearly defining the problems that AI solutions aim to address.
- The model's call for aligning AI-driven objectives with broader business goals has practical implications for organisations to ensure that AI projects contribute directly to overarching strategic objectives. This involves developing clear metrics, key performance indicators (KPIs), and measurable outcomes tied to business success.

- The model's recommendation for developing and implementing agile frameworks suggests practical strategies for organisations to adopt agile methodologies in their AI projects. This involves creating cross-functional teams, establishing iterative development cycles, and ensuring flexibility in project delivery.
- The model's emphasis on conducting economic feasibility analysis has practical implications for organisations to assess the financial viability of AI projects. This involves cost-benefit analyses, return on investment (ROI) calculations, and thorough evaluations of the economic impact of AI adoption.
- The model's encouragement to empower stakeholders to lead and drive AI innovation implies practical steps for organisations to actively involve stakeholders in decision-making processes. This involves creating channels for stakeholder input, establishing feedback loops, and recognising the expertise that stakeholders bring to AI projects.

9.4.5 Stakeholder Management

- The model's emphasis on ensuring trust and transparency with stakeholders has practical implications for organisations to actively communicate with stakeholders. This involves transparent reporting, regular updates, and clear communication channels to address stakeholder concerns and expectations.
- The model's call for top management commitment implies practical steps for organisations to secure leadership support for AI projects. This involves creating a culture of commitment at the highest levels, establishing clear communication from leadership about the importance of AI, and providing resources to facilitate AI adoption.
- The model's recommendation for facilitating stakeholders' buy-in suggests practical strategies for organisations to actively involve stakeholders in the decision-making process. This involves stakeholder consultations, needs assessments, and creating forums for stakeholders to express their perspectives and expectations.
- The model's emphasis on top-down initiatives implies practical considerations for organisations to ensure that AI projects receive consistent support from leadership. This involves aligning AI initiatives with broader organisational objectives, integrating AI into strategic plans, and actively promoting the importance of AI adoption at all levels.
- The model's call for comprehensive stakeholder benefit analysis has practical implications for organisations to assess and communicate the benefits of AI projects to stakeholders. This

involves developing clear value propositions, showcasing the positive impact of AI on stakeholders, and actively addressing any concerns raised by stakeholders.

9.5.7 Legal Regulations

- The model's emphasis on compliance with legal requirements suggests practical steps for organisations to conduct thorough legal assessments before and during AI adoption. This involves engaging legal experts, staying informed about evolving regulations, and ensuring that AI projects align with current legal frameworks.
- The model's recognition of ethical considerations implies practical strategies for organisations to integrate ethical frameworks into their AI projects. This involves establishing ethical guidelines, creating ethical review boards, and ensuring that AI applications prioritise fairness, accountability, and transparency.
- The model's call for legal and ethical training has practical implications for organisations to educate their teams about the legal and ethical dimensions of AI adoption. This involves developing training programmes, providing resources for ongoing education, and creating a culture that values legal and ethical considerations in AI projects.
- The model's recommendation for risk mitigation strategies suggests practical steps for organisations to proactively address legal and ethical risks associated with AI. This involves conducting risk assessments, developing contingency plans, and creating mechanisms to monitor and respond to legal and ethical challenges as they arise.
- The model's recognition of the dynamic nature of legal regulations implies practical considerations for organisations to remain adaptable. This involves establishing processes to monitor changes in regulations, engaging legal experts for regular assessments, and adjusting AI projects to ensure continuous compliance.

9.5 Implications Across Success Factors

The practical implications outlined for each success factor collectively contribute to the overall maturity of AI adoption in the UK construction industry. When organisations strategically address data challenges, cultivate a collaborative and innovative culture, optimise technology readiness, develop robust business cases, manage stakeholders effectively, and navigate legal and ethical dimensions, they position themselves for comprehensive AI maturity.

- The practical implications of AIMM-CI contribute to enhanced decision-making within construction organisations. By prioritising data quality, fostering a culture of innovation, and aligning AI projects with strategic objectives, organisations are better equipped to make informed and timely decisions.
- AIMM-CI's practical implications lead to operational efficiency improvements. The optimisation of technology readiness, development of robust business cases, and effective stakeholder management contribute to streamlined processes, faster project delivery, and increased overall efficiency.
- The model's practical implications foster a culture of innovation, positioning construction companies at the forefront of AI advancements. By actively involving stakeholders, aligning AI initiatives with business goals, and continually optimising technology, organisations gain a competitive edge in the rapidly evolving construction industry.
- Addressing legal and ethical considerations through AIMM-CI's practical implications enables organisations to proactively mitigate risks and ensure compliance. This proactive approach safeguards against potential legal challenges and ethical concerns, fostering a trustworthy and responsible approach to AI adoption.
- The emphasis on organisational culture and digital change management in AIMM-CI's practical implications contributes to increased employee engagement and satisfaction. By empowering employees, fostering a collaborative environment, and effectively managing digital change, organisations create a positive workplace culture conducive to AI success.
- AIMM-CI's practical implications contribute to the long-term sustainability of AI adoption in the UK construction industry. Through continuous optimisation, stakeholder engagement, and adherence to legal and ethical standards, organisations build a foundation for enduring success in the ever-evolving landscape of AI technologies.

9.6 The Implication of AIMM-CI Model in enhancing Organisational AI adoption strategies

The final AIMM-CI Maturity Model present the UK construction organisations with valuable insights to enhance their AI adoption strategies. Organisations can leverage these findings in the following ways. Organisations can use the model's success factors and maturity levels to tailor their AI adoption strategies based on their current maturity stage. For instance, those at the initial stages may prioritise foundational elements like data accessibility, while those at advanced stages may focus on continuous optimisation and innovation. By understanding the significance of each success factor, organisations can prioritise their efforts. For instance, if the validation results indicate a lower maturity level in technology readiness, organisations can allocate resources to enhance technological infrastructure, provide training, and foster a culture that embraces AI solutions. Furthermore, recognising the importance of organisational culture, digital change management, and collaborative leadership, organisations can invest in training programmes. This ensures that employees at all levels understand the role of AI, embrace change positively, and contribute to the collaborative and innovative culture necessary for AI success.

Building on the importance of cross-functional teams, organisations can strategically form teams with a diverse skill set, including both AI and construction expertise. This approach ensures a holistic approach to problem-solving, innovation, and the development of AI solutions tailored to the unique challenges of the construction industry. More so, emphasising the importance of continuous optimisation, organisations can integrate monitoring mechanisms into their AI projects. Regular assessments, feedback loops, and performance metrics help organisations identify areas for improvement, respond to changing circumstances, and ensure that AI projects align with evolving business goals. Lastly, recognising the foundational role of data availability and usability, organisations can cultivate a data-driven culture. This involves promoting data literacy, providing tools for data analysis, and encouraging decision-making based on reliable data. A data-driven culture enhances the effectiveness of AI applications and fosters informed decision-making.

9.7 Theoretical Implication of the Research Findings

The theoretical implications of the findings in this research contribute significantly to the five key theories: Diffusion of Innovation, Stage Theory, Decision Theory, Core Competency Theory, and Technology Acceptance Model. Each theory plays a distinct role in understanding and interpreting the patterns observed in the AIMM-CI Maturity Model's application within the construction industry.

Diffusion of Innovation: The research findings provide valuable insights into the diffusion process of AI adoption within the construction industry. The model's emphasis on gradual reinforcement and evolution across maturity levels aligns with the Diffusion of Innovation theory's stages. Early stages reflect the challenges and initial barriers akin to the innovation's introduction, while later stages demonstrate the diffusion and acceptance of AI practices. The findings offer nuanced information about the pace and pattern of adoption, contributing to the understanding of innovation diffusion dynamics within a specific industry context.

Stage Theory: The AIMM-CI Maturity Model inherently aligns with Stage Theory by emphasizing the sequential progression of construction organizations through distinct stages of AI maturity. The research findings validate the model's stages and highlights the transformative journey from initial challenges to advanced AI integration. This contributes to Stage Theory by providing empirical evidence of the distinct phases companies navigate in their AI adoption process. It also offers insights into the factors influencing transitions between stages and contributes to a more refined understanding of organisational development in the context of AI implementation.

Decision Theory: The Decision Theory posits that decisions are made based on a rational process considering all available information. The findings shed light on the decision-making processes within construction companies during AI adoption. The model's emphasis on top-down initiatives, stakeholder involvement, and strategic planning aligns with Decision Theory and showcases a systematic decision-making framework. The research contributes by illustrating how companies make decisions at different stages of AI adoption, considering factors such as legal regulations, technology readiness, and stakeholder management.

Core Competency Theory: The Core Competency Theory suggests that organizations should focus on developing and leveraging unique capabilities. The AIMM-CI Maturity Model underscores the importance of human capital development, promoting technology readiness, and establishing robust business cases. The findings contribute to Core Competency Theory by emphasizing the role of organisational capabilities in successful AI adoption. Companies that invest in developing core competencies related to AI skills and technology readiness showcase higher maturity levels, validating the theory's applicability in the context of AI adoption.

Technology Acceptance Model (TAM): TAM posits that perceived ease of use and perceived usefulness influence technology adoption. The research findings contribute to TAM by validating its constructs within the construction industry. The emphasis on technology readiness, stakeholder management, and robust business cases aligns with the TAM's factors influencing acceptance. The research provides empirical evidence of how these factors impact the perceived ease of use and usefulness of AI technologies within the construction sector, contributing to the broader understanding of technology acceptance in a specialized context.

One notable aspect of the theoretical implications is the interconnectedness of these theories. The findings highlight that successful AI adoption in construction is not a linear process but a multifaceted transformation that involves elements from each theory. For example, human capital development, a focus on core competencies, and decision-making processes are intertwined throughout the AI adoption journey. This integrative approach supports a more comprehensive theoretical framework for understanding the complexities of AI adoption within the construction industry. In essence, the theoretical implications of the research findings provide a thorough understanding of AI adoption within the construction industry and contributes to the application of Diffusion of Innovation, Stage Theory, Decision Theory, Core Competency Theory, and Technology Acceptance Model. The interconnected nature of these theories and their application in a real-world context enhance the theoretical foundations for studying and guiding AI adoption processes in other industries as well.

Chapter Summary

This chapter discussed the final AIMM-CI Maturity Model, as a robust framework that provides tailored insights for the AI adoption journey in the UK construction industry. The chapter highlights the practical implications across success factors, the model extends a roadmap for organisations to navigate challenges and capitalise on opportunities. It underscores the critical nature of addressing data challenges, fostering a collaborative and innovative culture, optimising technology readiness, and developing robust business cases. Efficient stakeholder management, adherence to legal regulations, and ethical considerations emerge as pivotal elements in ensuring the model's successful application. The implications set forth by AIMM-CI reverberate across decision-making enhancements, operational efficiency improvements, innovation-driven cultures, risk mitigation through legal compliance, and the cultivation of a sustainable AI adoption environment. The model's emphasis on organisational culture and digital change management stands out as a key driver for increased employee engagement and satisfaction, fostering a positive atmosphere conducive to AI success. The recognition of the dynamic nature of legal regulations adds a layer of adaptability, urging organisations to remain vigilant and responsive in the face of evolving legal landscapes. The practical implications of AIMM-CI are viewed as catalysts for the long-term sustainability of AI adoption in the UK construction industry. Organisations are encouraged to leverage the model's insights to tailor their strategies and prioritise efforts based on their current maturity level. By recognising the foundational role of data, the importance of stakeholder engagement, and the need for legal and ethical considerations, organisations can build a resilient foundation for enduring success in the ever-evolving realm of AI technologies. The AIMM-CI Maturity Model, with its understanding of industry-specific nuances, serves as a valuable guide for construction organisations seeking to harness the transformative power of artificial intelligence. The next chapter, the concluding chapter of this research, will provide a detailed summary that encapsulates the study's findings, key insights and implications. This final chapter aims to furnish a robust conclusion that not only synthesises the knowledge generated throughout the research but also outlines practical recommendations for industry practitioners and policymakers. It will provide a reflective overview of the AIMM-CI Maturity Model's applicability and effectiveness in addressing the unique challenges and opportunities in the UK construction industry.

10 CHAPTER TEN: CONCLUSION, RECOMMENDATION, AND FUTURE WORK

Chapter Overview

This final chapter encapsulates the culmination of the research journey and presents a comprehensive overview of the study's key elements. The chapter unfolds in several sections, each contributes to a holistic understanding of the study's significance and its implications for the field of Artificial Intelligence (AI) implementation in the UK construction industry. The opening section provides a detailed summary of the entire PhD study. This is followed by the main findings of the study based on the research aim and objectives. The chapter proceeds to outline the multifaceted implications of the study, alongside the Limitations of the Study. The chapter concludes with recommendations for future research.

10.1 Summary of the PhD study

The culmination of this PhD study marks a significant contribution to the field of Artificial Intelligence (AI) implementation in the UK construction industry. The primary aim of this study was to develop a robust Artificial Intelligence Maturity Model (AIMM) capable of evaluating and determining the level of AI technology adoption and implementation in construction organisations. This journey involved a meticulous exploration of existing AI technologies, an in-depth analysis of challenges and success factors specific to the construction sector, and insights from expert stakeholders regarding best practices for AI implementation.

The initial phase of the study involved a comprehensive examination of AI-based technologies implemented within the construction industry. This analysis was not confined to the construction industry alone; rather, it extended to comparative studies with other industries. By doing so, the study aimed to draw insights from diverse use cases, identifying parallels, contrasts, and unique challenges within the construction domain. This comparative approach provided a holistic understanding of AI applications and laid the foundation for the development of the AIMM-CI Model.

The identification of challenges and success factors for AI implementation in the UK construction industry constituted a key aspect of the research. Using a systematic investigation, the study uncovered a spectrum of challenges and ranged from data accessibility and usability issues to organisational cultural barriers. Seven (7) success factors emerged that emphasised the importance of data quality, collaborative leadership, and aligning AI initiatives with broader business goals. Furthermore, a qualitative exploration was conducted to capture the perspectives of expert stakeholders directly involved in the UK construction industry. Their insights, experiences, and recommendations contributed valuable qualitative data and enriched the understanding of AI implementation processes in construction. The experts' views on best practices for AI implementation were very useful, as they provided real-world context and practical considerations that were instrumental in refining the AIMM-CI Model.

The core of the study was the design and development of the Artificial Intelligence Maturity Model (AIMM-CI). The model was built on a foundation of extensive literature review, empirical insights, and stakeholder perspectives, thereby making it a tailored model specifically designed for the unique challenges and opportunities present in the UK construction industry. The model encompasses key success factors such as data availability and usability, organisational culture, stakeholder management, human capital management, legal regulations, and technology readiness. These success factors provide a roadmap for organisations to assess, enhance, and continually mature their AI adoption strategies. In essence, this PhD study has traversed the landscape of AI implementation in the UK construction industry and offered a nuanced understanding of AI adoption in the UK construction industry. The AIMM-CI Model, which was developed out of this comprehensive exploration, stands as a testament to the interdisciplinary nature of this research. It bridges the realms of AI technology, organisational behaviour, and industry-specific challenges.

10.2 Main findings of the study based on Research Objectives

The primary aim of this study is to examine the various existing AI-based technologies, implemented in the construction industry by comparing them with a few other use cases in other business sectors. This study thoroughly examined AI-based technologies implemented in the construction industry and extended its purview to comparative analyses with other business sectors. This examination yielded crucial insights into the current landscape of AI applications and revealed both sector-specific implementations and cross-industry trends. In the construction industry, AI technologies have been deployed for diverse purposes, ranging from project management and scheduling to predictive maintenance and safety monitoring. The study revealed that while some construction organisations have embraced AI to enhance efficiency and decision-making, considerable variability exists in the extent and nature of AI adoption across the industry. A comparative analysis with other sectors demonstrated that although the construction industry was making strides, it lagged in certain aspects of AI integration.

The second key objective of this study was to identify challenges and success factors for AI implementation in the UK construction sector. The research uncovered a multifaceted set of challenges that act as barriers to seamless AI adoption. Data accessibility and usability emerged as primary challenges, with construction organisations struggling to harness the full potential of AI due to issues related to data quality, integration, and interoperability. Organisational cultural barriers were also identified, and the importance of fostering a culture that embraces innovation and technological change. On the flip side, the success factors critical to overcoming these challenges were identified. The study emphasised the paramount importance of data quality and readiness and highlighted that organisations with a robust data infrastructure are better positioned to leverage AI effectively. More so, collaborative leadership, stakeholder engagement, and strategic alignment of AI initiatives with broader business goals were identified as instrumental success factors.

More so, qualitative exploration was conducted to capture the perspectives of expert stakeholders directly engaged in the UK construction industry. This objective aimed to enrich the study with real-world insights, practical experiences, and nuanced recommendations from individuals deeply involved in the implementation of AI technologies. The findings from expert stakeholders added a qualitative layer to the predominantly quantitative analyses and offered depth to the research. The experts emphasised the significance of contextual understanding in AI implementation, underscoring that solutions effective in other sectors might not seamlessly translate to the construction domain. They highlighted the need for bespoke approaches tailored to the industry's intricacies and echoed the sentiment that the AIMM needed to be a customised model rather than a one-size-fits-all solution. The insights from expert stakeholders played a pivotal role in refining the AIMM, ensuring that it resonates with the practical realities and challenges faced by construction organisations.

The fourth objective of this study involved identifying progressive determinant factors for AI implementation in the construction industry. Beyond diagnosing current challenges, this study aimed to guide construction organisations toward proactive strategies for staying at the forefront of AI technology adoption. The study identified factors that contribute to the advancement of AI maturity and outlined a roadmap for organisations aspiring for continuous improvement. These progressive determinant factors included a focus on innovation, a commitment to ongoing learning, and a strategic approach to technology integration. Organisations that embraced a culture of innovation fostered learning environments, and strategically integrated AI into their operations showcased higher levels of AI maturity. This forward-looking perspective positions the AIMM not merely as a diagnostic tool but as a strategic framework for organisations aspiring to be leaders in AI adoption within the construction sector.

The pinnacle of the study lies in the fact that the findings are in agreement with related studies. This is because the Artificial Intelligence Maturity Model (AIMM-CI) model was built on the Peffers framework, extensive literature review, empirical insights, and stakeholder perspectives. The model was tailored to the unique challenges and opportunities present in the UK construction industry. The model encompasses key success factors identified in the study and provides construction companies in the UK with a roadmap to assess and enhance their AI adoption strategies. The AIMM-CI comprises several dimensions; each dimension is intricately linked to the overall maturity of AI adoption, and the model offers a systematic approach for organisations to evaluate their current state, identify areas for improvement, and progress through maturity levels. Therefore, the AIMM-CI is not just a theoretical construct; it is a practical tool that construction companies in the UK can leverage to handle the complex terrain of AI adoption.

The AIMM-CI developed in this study also addresses the shortcomings identified in existing maturity models in the construction industry. The identified gaps include data incompatibility, irregular frameworks, and lack of accountability. The AIMM aims to overcome these issues through several key strategies. Data incompatibility has been a significant issue in models like BIM, where multiple programs cannot seamlessly function together, leading to challenges in data exchange. The AIMM addresses this by emphasizing the importance of standardized data formats and interoperability between different software systems. By leveraging AI-driven solutions, the model ensures that data created in one program can be easily exchanged and integrated with others. This is achieved through the use of advanced data integration tools and protocols that facilitate seamless data flow across different platforms. Additionally, the model incorporates benchmarking data and performance indicators to evaluate the effectiveness of AI adoption and its impact on green construction initiatives, ensuring comprehensive performance assessments.

Additionally, irregular frameworks and poorly structured implementation processes have hindered the adoption of models like BIM. The AIMM provides a clear and structured implementation framework that outlines the necessary steps and procedures for successful AI adoption. This framework includes detailed guidelines on project planning, resource allocation, and process management. By ensuring that AI adoption is incorporated into the project contract from the beginning, the AIMM minimizes the need for extensive modifications during the implementation phase. The model also includes provisions for regular reviews and adjustments to ensure that the implementation remains aligned with project goals and objectives. Furthermore, the lack of accountability in existing maturity models has been a significant challenge, particularly in identifying and addressing design errors. The AIMM addresses this by establishing clear lines of accountability and responsibility. The model includes mechanisms for tracking and documenting decision-making processes to ensure that all stakeholders are aware of their roles and responsibilities.

10.3 The Implications of the study

The implications of the study are multifaceted and extend across various dimensions and provides valuable insights for the AI adoption strategies of construction organisations in the UK. These implications are summarised below.

- The study emphasises the importance of addressing data challenges, fostering a culture of innovation, and aligning AI projects with strategic objectives. By prioritising these factors, construction organisations can enhance their decision-making processes. The availability of high-quality data, coupled with a commitment to innovation, enables organisations to make informed and timely decisions, contributing to overall operational efficiency.
- The optimisation of technology readiness, development of robust business cases, and effective stakeholder management contribute to streamlined processes, faster project delivery, and increased overall efficiency. Organisations that strategically implement AI technologies based on the AIMM-CI model can expect improvements in their operational workflows, resulting in cost-effectiveness and timely project completion.
- Addressing legal and ethical considerations through the study's practical implications enables organisations to proactively mitigate risks and ensure compliance. By conducting thorough legal assessments, integrating ethical frameworks, and providing training on legal and ethical dimensions, construction companies can safeguard against potential legal challenges and ethical concerns. This proactive approach fosters a trustworthy and responsible approach to AI adoption.

- The emphasis on organisational culture and digital change management in the study's practical implications contributes to increased employee engagement and satisfaction. By empowering employees, fostering a collaborative environment, and effectively managing digital change, organisations create a positive workplace culture conducive to AI success. This positive culture is essential for embracing technological advancements and ensuring the successful integration of AI into daily operations.
- The study's practical implications contribute to the long-term sustainability of AI adoption in the UK construction industry. Through continuous optimisation, stakeholder engagement, and adherence to legal and ethical standards, organisations build a foundation for enduring success in the ever-evolving landscape of AI technologies.

10.4 Key Considerations for UK Construction Companies Adopting the AIMM

For UK construction companies, adopting the Artificial Intelligence Maturity Model (AIMM-CI) involves key considerations to ensure successful implementation and maximise benefits. Thus, aligning AI initiatives with broader business goals is important. UK construction companies should aim to identify specific areas where AI can drive significant improvements, such as project management, safety monitoring, and predictive maintenance. This alignment ensures that AI projects are strategically prioritised and directly contribute to overall operational efficiency. Secondly, data quality and accessibility is another key consideration. UK construction companies should establish robust data infrastructure and governance frameworks, as this is essential to ensure high-quality, integrated, and accessible data. This foundation enables accurate and effective use of AI for informed decision-making and predictive analytics. More so, creating a culture of innovation and digital transformation is important. Employees at all levels must support AI initiatives and be open to technological changes. This involves comprehensive training programs to enhance understanding and skills related to AI technologies. Besides, effective stakeholder engagement is another critical consideration. Transparent communication about the benefits and impacts of AI adoption will help to secure buy-in from key stakeholders, including employees, clients, and partners. Demonstrating tangible benefits and success stories can build trust and support for AI initiatives.

10.5 Challenges in Implementing AIMM-CI by UK construction Companies

Apart from the benefits of the AIMM-CI Model, implementing the model can also present several challenges for UK construction companies. One significant challenge is the complexity involved in aligning the AIMM with existing organisational structures and processes. Construction companies often operate with diverse project portfolios, varying scales of operations, and distinct corporate cultures. Integrating a comprehensive AI maturity model requires a thorough assessment of how AI initiatives will fit within these frameworks without disrupting ongoing projects or daily operations. To mitigate this challenge, companies should conduct a detailed gap analysis to identify current strengths and weaknesses in AI integration. This analysis helps tailor the AIMM implementation plan to align with existing workflows and strategic objectives. Additionally, fostering collaboration between AI implementation teams and operational units ensures that AI initiatives complement rather than conflict with existing processes. A second challenge lies in securing adequate resources, both in terms of finances and skilled personnel, to support the AIMM implementation. AI projects in construction typically require substantial investment in technology infrastructure, software licenses, and ongoing training for staff. Moreover, recruiting and retaining AI specialists with expertise in construction-specific applications can be challenging due to the competitive nature of the tech industry. To address these resource constraints, organizations should develop a clear business case that outlines the potential return on investment (ROI) from AI adoption. This includes quantifying expected cost savings, efficiency gains, and improved project outcomes facilitated by the AIMM. Securing executive buy-in based on these ROI projections is crucial for allocating sufficient financial resources. Additionally, investing in continuous professional development programs and partnerships with academic institutions can help build a pipeline of skilled AI professionals tailored to the construction sector's needs.

10.6 Ethical Considerations in Implementing the AIMM-CI Maturity Model

When adopting the AIMM-CI, UK construction companies must address several key ethical considerations to ensure responsible use of the Model. One major concern is data privacy and security. AI systems often rely on large volumes of data, some of which may be sensitive or personal. Construction companies must implement robust data protection measures to prevent unauthorized access and misuse of data. Compliance with data protection regulations like the General Data

Protection Regulation (GDPR) is key to safeguarding privacy and building trust among stakeholders. In addition, the ethical implications of the Model's impact on employment must be considered as well. The use of the AIMM-CI model can lead to workforce displacement or significant changes in job roles. Construction companies must adopt a proactive approach to workforce management, by providing retraining and upskilling opportunities for employees affected by the AIMM-CI implementation. Moreover, ethical considerations extend to the societal impact of AI adoption. Construction companies should evaluate the broader consequences of AIMM-CI Model, such as environmental sustainability and community well-being. The alignment of the model with social responsibility goals and conducting impact assessments can help ensure that AI technologies contribute positively to society.

10.7 The Role of AIMM-CI in the UK's Sustainable and Eco-friendly Construction Practices

The AIMM-CI Maturity Model can influence the UK's sustainable and eco-friendly construction practices in many ways. Firstly, the AIMM-CI can enhance resource efficiency by enabling more precise planning and management of construction projects. AI technologies integrated within the AIMM-CI can optimise the use of materials, minimize waste, and reduce the carbon footprint associated with construction activities. For instance, AI-driven predictive analytics can forecast the exact quantities of materials needed, thereby preventing over-ordering and reducing waste. This precision not only conserves resources but also lowers the environmental impact of construction operations. Secondly, the AIMM-CI can facilitate the adoption of green building practices through advanced data analytics and real-time monitoring. AI can analyze vast amounts of data from various sources, including sensors and IoT devices, to provide insights into energy consumption, water usage, and other environmental factors. The continuous monitoring of these metrics can help construction companies to identify inefficiencies and implement corrective measures promptly. Lastly, the AIMM-CI Maturity Model can drive innovation in sustainable construction methods by fostering a collaborative and knowledge-sharing environment. AI can facilitate the sharing of best practices and successful case studies across the industry. This will encourage constuction companies to adopt innovative eco-friendly solutions. The model can also support research and development efforts by identifying emerging trends and technologies that can enhance sustainability. UK construction companies can leverage the Maturity Model to stay at the forefront of sustainable construction innovations and processes that reduce environmental impact.

10.8 Cybersecurity Measures to Safeguard Sensitive Data when Implementing the AIMM-CI Maturity Model

Implementing robust cybersecurity measures is crucial for safeguarding sensitive construction data. The first step involves establishing a comprehensive data protection framework that includes encryption, access controls, and regular security audits. Encryption ensures that data is unreadable to unauthorized users, both at rest and in transit. Access controls, including multi-factor authentication, restrict data access to authorized personnel only, thereby reducing the risk of data breaches. Regular security audits help identify and address vulnerabilities in the system, ensuring continuous protection against emerging threats. Furthermore, implementing robust cybersecurity training programs for employees is essential. Employees should be educated on best practices for data security, including recognizing phishing attempts, creating strong passwords, and understanding the importance of following security protocols. Regular training sessions and updates on the latest cybersecurity threats and mitigation strategies can significantly reduce the risk of human error, which is a common cause of data breaches. Another critical measure is the deployment of advanced threat detection and response systems. These systems leverage AI and machine learning to monitor network activity in real-time, identify unusual patterns, and respond to potential threats before they can cause significant damage.

10.9 Limitations of the Study

Although the AIMM-CI Maturity Model development and the validation process provided valuable insights, it is also important to acknowledge certain limitations of the model. These limitations include aspects related to the study's design, data collection, and the inherent challenges associated with assessing AI maturity in the UK construction industry. Some limitations of the study include.

- Although the AIMM-CI Maturity Model is detailed and comprehensive, it may have specific constraints that impact its applicability in certain organisational contexts. The model's generalisability to different construction sub-sectors, sizes of organisations, or geographic locations could be a limitation. The study recognises that the UK construction industry is diverse, and a singular maturity model may not fully capture variations in organisational structures, project types, and regional factors.

- The decision to integrate the Peffers framework in the design process reflects a methodological choice. Although Peffers' framework is widely recognised and utilised in information systems research, alternative frameworks could yield different perspectives on AI maturity assessment. The model's alignment with Peffers' recommendations introduces a particular epistemological and ontological stance.
- Another significant limitation is the sample size and composition of participants involved in the validation process. The study engaged a diverse group of construction industry professionals, AI experts, and stakeholders; however, the specific demographics and characteristics of the participants may influence the representativeness of the sample in relation to the broader UK construction industry. Although adequate for the study's scope, the sample size may limit the generalisability of the findings to all construction organisations.
- The validation process heavily relied on the expertise and subjective opinions of the construction experts. Although efforts were made to include a diverse range of perspectives, the potential for participant bias exists. Individual experiences, organisational contexts, and varying levels of familiarity with AI concepts may have influenced the experts' responses. Besides, the level of expertise among experts varies, and this could potentially impact the depth of insights provided during the validation.
- The success factors identified in the AIMM-CI Maturity Model are comprehensive, as they cover various dimensions of organisational practices. However, the model may not encompass every nuance or contextual factor that could influence AI maturity. Certain industry-specific nuances or emerging success factors might not have been fully accounted for, and organisations should be cognizant of the need for ongoing adaptation and refinement of success factors.

10.10 Recommendations for future Studies

Inasmuch as the study provides valuable insights into the development and application of the Artificial Intelligence Maturity Model (AIMM-CI) in the UK construction industry, there are several avenues for future research and potential areas for improvement. The following recommendations highlight key areas where further investigation could contribute to the advancement of knowledge in this field.

- Future studies could conduct a more extensive cross-industry comparative analysis to deepen the understanding of AI adoption maturity. Conducting a more comprehensive exploration of diverse industries could uncover additional insights and best practices applicable to construction.

- To enhance the robustness of the AIMM, future research could incorporate longitudinal studies to track the evolution of AI maturity in construction organisations over time. This would provide a dynamic perspective on the effectiveness and adaptability of the maturity model in different stages of AI adoption.
- Given the rapid evolution of AI technologies, future studies should stay abreast of emerging trends and technological advancements in AI. Continuous monitoring of the AI landscape will allow for the refinement and adaptation of the AIMM-CI Model to align with the latest developments in AI applications for the construction industry.

These recommendations will guide future researchers in addressing gaps, refining methodologies, and advancing the understanding of AI adoption maturity in the construction industry. In conclusion, this study contributes not only to a comprehensive understanding of AI adoption in the UK construction industry but also a practical tool that construction organisations can leverage for continuous improvement and adaptation. As the construction sector continues to evolve, the AIMM-CI Model and its implications pave the way for a resilient and sustainable approach to AI technology adoption in construction organisations. The journey does not end here but opens avenues for further exploration and refinement, ensuring that the construction industry remains at the forefront of AI advancements.

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