SCHOOL OF COMPUTING, ENGINEERING & DIGITAL TECHNOLOGIES

ENGINEERING RESEARCH PROJECT (ENG4011)

INVESTIGATING THE COST BARRIER TO AI ADOPTION IN CONSTRUCTION PROJECT PLANNING AND EXECUTION

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I DECLARE THAT THIS SUBMISSION IS WHOLLY MY WORK

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Abstract

Artificial Intelligence (AI) presents significant opportunities to enhance efficiency, accuracy, and decision-making in construction project planning and execution. However, despite its potential, AI adoption within the industry remains limited, often hindered by substantial implementation costs. This research investigates the cost barrier to AI adoption in the UK construction sector, focusing on how perceptions and adoption levels differ across varying company sizes.

The study aimed to assess current AI adoption levels, quantify the prevalence of cost as a barrier across small, medium, and large firms, identify key contributing cost factors, evaluate broader professional perceptions of AI's benefits and risks, and propose strategies to mitigate adoption challenges. A quantitative survey methodology was employed, gathering data from 55 construction professionals (Project Managers, Engineers, Architects, Contractors) in the UK.

Findings reveal a moderate overall AI adoption rate (average 1.31 tools/respondent), strongly correlated with pre-survey awareness and company size. Adoption is significantly lower in small firms (0.78 tools/person, 62.5% non-use) compared to universal and higher adoption in medium (3.05 tools/person) and large firms (3.8 tools/person). High initial implementation cost is perceived as a major barrier by a significant majority (72.7%), with software licensing and hardware/infrastructure costs identified as the most critical factors. This cost perception is acutely pronounced in small firms (93.7% agreement) but significantly less so in large firms (80% disagreement). While professionals recognize AI's benefits, substantial concerns persist regarding reliability, integration complexity, and the need for specialized expertise.

The research concludes that perceived high cost, particularly the initial investment, is a primary barrier limiting AI adoption in UK construction, disproportionately affecting Small and Medium-sized Enterprises (SMEs). Addressing this requires multifaceted strategies involving flexible pricing models from technology providers, targeted training and awareness initiatives, potential financial incentives, and efforts to improve tool usability and integration. Implementing such strategies is crucial for enabling wider AI adoption and unlocking its transformative potential across the construction industry.

Keywords: Artificial Intelligence, AI Adoption, Construction Industry, Project Management, Cost Barrier, Technology Adoption, SMEs, Implementation Costs.

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Chapter One: Introduction

This dissertation's opening chapter lays the groundwork for the study, presenting a detailed perspective on the research area, its relevance, and the central questions the investigation intends to tackle. It starts with foundational information, introducing the idea of Artificial Intelligence (AI) uptake in the construction field and its capacity to revolutionize how projects are planned and carried out. The chapter continues by identifying the core research issue, focusing on the disconnect between AI's potential advantages and its relatively scarce implementation in real-world scenarios. The specific research questions that guide this inquiry are then laid out. Following this, the research's aims and objectives are clearly stated, setting a definite course for the study. The significance of the research is also emphasized, highlighting its prospective impact on both scholarly understanding and practical use in construction project management. Lastly, the chapter wraps up by summarizing the dissertation's layout, describing the organisation and sequence of the chapters to come.

1.1 Background of the Study

In today's rapidly evolving construction industry, emerging technologies like Artificial Intelligence (AI) are transforming project planning and execution. AI offers the potential to optimise scheduling, improve cost estimation, enhance risk management, and streamline execution. However, despite its potential benefits, the adoption of AI in construction remains limited due to several barriers. These barriers include high implementation costs, lack of AI knowledge, data security concerns, and resistance to change.

1.2 Research Problem Statement

While the potential benefits of AI in construction are widely acknowledged, its adoption remains hindered by significant cost barriers, particularly concerning implementation. Existing research has explored the overall issue of limited AI adoption in construction, citing various barriers. However, there is a lack of focused studies specifically investigating the cost barrier and its impact on different sizes of construction firms. This gap is crucial to address, as understanding the key cost challenges and their prevalence is essential for developing effective strategies to enhance AI adoption in construction project management.

1.3 Research Questions

To address the identified research problem, this study aims to answer the following research questions:

1. What is the current level of AI adoption in project planning and execution within the construction industry and how this adoption level differs for various industry size?
2. How does high associated cost of AI implementation affect its integration in the construction industry?
3. How do professionals in the construction industry perceive AI in terms of its usefulness, risks, and limitations?
4. What strategies can be implemented to overcome these barriers and improve AI adoption in construction projects?

These research questions will guide the investigation and provide a framework for data collection and analysis.

1.4 Aims and Objectives of the Research

This research aims to investigate the barriers preventing AI adoption in project planning and execution within the construction industry and propose recommendations to overcome them.

To achieve this overarching aim, the research has set the following objectives:

1. To assess the current level of AI adoption in construction project planning and execution.
2. Quantify how widespread this barrier is across different construction firms (small, medium, large-scale).
3. To discuss the key barrier of cost limiting AI integration in project planning and execution.
4. To evaluate industry professionals' perceptions of AI in construction.
5. To propose strategies to address and mitigate AI adoption challenges.

1.5 Importance of this Research Study

This study is crucial from both academic and practical standpoints. From an academic perspective, it contributes to the growing body of knowledge on AI adoption in the construction industry. It provides empirical evidence on the key barriers hindering AI implementation and their prevalence across different types of construction firms. The findings can help refine existing theories and models related to technology adoption in the construction sector. From a practical standpoint, this research offers valuable insights for various stakeholders:

- Industry Practitioners: By understanding the key barriers and adoption trends, construction firms can make informed decisions regarding AI implementation and develop strategies to overcome challenges.
- Policy Makers and Regulators: The research provides insights into legal and policy concerns affecting AI adoption, enabling the development of supportive regulatory frameworks.
- Technology Providers and Developers: By understanding industry needs and constraints, AI solution designers can develop more effective and relevant tools for the construction sector.

1.6 Research Structure

The remainder of this dissertation is structured as follows:

Chapter 2: Literature Review

Chapter 3: Research Methodology

Chapter 4: Data Analysis, Results and Discussion of Findings

Chapter 5: Conclusion and Recommendation

Chapter 6: Evaluation of Objectives

1.7 Summary

This introductory chapter has provided an overview of the research topic, its significance, and the key questions it aims to address. It has highlighted the gap between the potential of AI and its limited adoption in construction practice due to cost barriers. The chapter has also outlined the aims and objectives of the research, emphasising its potential contribution to both academic knowledge and practical applications. The subsequent chapters will explore deeper, the literature, methodology, findings, and discussions, providing a comprehensive and insightful exploration of AI adoption in the construction industry.

Chapter 2 – Literature Review

2.1 Introduction

This chapter presents a comprehensive review of the existing literature relating to the research topic, "Investigating the Cost Barrier to AI Adoption in Construction Project Planning and Execution." The primary goal of this review is to establish a theoretical foundation for understanding the key concepts, trends, and challenges associated with AI adoption in the construction industry, with a particular focus on the cost-related barriers. The literature review will evaluate various aspects, including:

- **Theoretical Foundations:** Examining established technology adoption models, cost-benefit analysis frameworks, and innovation adoption theories relevant to the construction sector.
- **AI in Construction; Applications and Benefits:** Exploring the diverse applications of AI in construction project planning and execution, including its impact on sustainability, highlighting the potential benefits and challenges reported in the literature.
- **Cost Barriers to AI Adoption:** Identifying and categorising the various cost-related factors that impede the wider adoption of AI technologies in construction.
- **Case Studies of AI Adoption and Cost Management:** Analysing real-world examples of AI implementation in construction projects, focusing on how companies have addressed cost challenges and achieved successful outcomes.

By critically evaluating the existing body of knowledge, this literature review aims to identify research gaps and provide a contextual framework for the empirical research conducted in this study. The insights gained from this review will inform the development of the research methodology, data analysis, and the formulation of practical recommendations to address the cost barrier to AI adoption in construction.

2.2 Theoretical Foundations

The investigation of cost barriers to AI adoption in construction project planning and execution is grounded in several theoretical frameworks that addresses the factors influencing technology adoption decisions. This section synthesises key models and concepts that provide conceptualisation for understanding these dynamics.

2.2.1 Technology Adoption Models

The Diffusion of Innovation Theory, by Everett Rogers, serves as a foundational framework for understanding how new technologies, such as AI, are adopted within the construction industry. This theory categorises adopters into five groups: innovators, early adopters, early majority, late majority, and laggards, based on their willingness to embrace new technologies (Rogers, 1983). Each category exhibits distinct characteristics and motivations, which can illuminate the challenges and opportunities associated with AI adoption in construction. For instance, innovators may be more willing to invest in AI despite high initial costs, while laggards may resist due to perceived risks and costs associated with new technology (Ghansah et al., 2020). However, the specific factors that drive the transition between adopter categories in the context of AI in construction remain an area for further investigation.

Complementing this is the Technology Acceptance Model (TAM), proposed by Fred Davis, which posits that perceived usefulness and perceived ease of use are critical determinants of technology adoption (Davis, 1989). In the context of AI in construction, demonstrating the practical value and usability of AI tools is essential for gaining acceptance among construction professionals. Research indicates that when users perceive a technology as beneficial and easy to use, they are more likely to adopt it (Sepasgosar and Davis, 2018; Sorce and Issa, 2021). This model underscores the importance of addressing user concerns regarding the complexity and utility of AI applications in construction settings.

2.2.2 Cost-Benefit Analysis in Technology Adoption

Cost-benefit analysis is a vital tool for evaluating the economic feasibility of technology investments, particularly in the construction sector where financial constraints are prevalent. This analytical approach involves comparing the costs of implementing and maintaining AI technologies against the anticipated benefits, such as increased efficiency and reduced project delays (Wang et al., 2021). Studies have shown that construction firms often face significant barriers related to upfront costs and ongoing maintenance expenses, which can deter investment in innovative technologies like AI (Onososen et al., 2023). A thorough cost-benefit analysis enables firms to make informed decisions by quantifying the potential return on investment associated with AI adoption (Wang et al., 2021, Chan et al., 2018). However, the complexity of construction projects and the long-term nature of AI benefits can make it challenging to accurately assess all costs and benefits, potentially leading to uncertainty in the decision-making process (Wyk et al., 2021).

Moreover, the construction industry's risk-averse nature often leads to a preference for traditional methods over innovative solutions, further complicating the cost-benefit evaluation process (Hwang and Tan, 2012). The identification of specific cost-related barriers, such as lack of government incentives and financing options, is crucial for understanding the broader economic landscape influencing AI adoption (Wang et al., 2021). However, the influence of non-cost factors, such as organisational culture and regulatory uncertainty, on the perceived value of AI investments requires further exploration (Nguyen and Nguyen, 2021).

2.2.3 Innovation Adoption in the Construction Industry

The construction industry is characterised by unique challenges that impact the adoption of innovative technologies. Factors such as risk aversion, fragmented project delivery methods, and a culture resistant to change create substantial barriers to the adoption of AI (Ghansah et al., 2020; Hwang and Tan, 2012). The industry's historical reliance on conventional practices often results in a reluctance to embrace new technologies, which can be perceived as disruptive or risky (Elshafey et al., 2020). While these challenges are widely acknowledged, research on effective strategies to overcome them in the context of AI adoption is still developing.

Furthermore, studies indicate that economic factors, including high initial costs and the absence of supportive regulatory frameworks, significantly impede the adoption of AI and other advanced technologies in construction (Onososen et al., 2023; Nnaji and Karakhan, 2020). Understanding these industry-specific dynamics is essential for analysing the cost barriers to AI adoption, as they highlight the need for tailored strategies that address the unique characteristics of the construction sector (Sepasgosar and Davis, 2018; Nnaji et al., 2023). However, the interplay between these economic factors and other barriers, such as skills gaps and data limitations, requires further investigation to develop comprehensive solutions for promoting AI adoption (Yap et al., 2022)

By integrating these theoretical perspectives, this study aims to develop a comprehensive understanding of the factors influencing AI adoption decisions in construction, particularly emphasising cost considerations. This theoretical foundation will guide the analysis of empirical data and the formulation of practical recommendations to promote AI adoption in the construction industry.

2.3 AI in Construction: Applications and Benefits

Artificial intelligence (AI) is increasingly being integrated into the construction industry, revolutionising various aspects of project planning, execution, and management. The applications of AI span the entire construction project lifecycle, offering significant benefits that enhance efficiency, accuracy, and safety.

2.3.1 Applications of AI in Construction

AI technologies, including machine learning, deep learning, and computer vision, are being employed across several key areas in construction.

Project Planning and Scheduling: AI algorithms can analyse historical data to optimise project schedules and resource allocation. For instance, predictive analytics can help identify potential delays and suggest adjustments to keep projects on track (Rane et al., 2024; Darko et al., 2020).

Cost Estimation and Budgeting: AI-powered tools are transforming cost estimation by analysing various factors such as material prices, labour costs, and equipment rentals. Studies show that machine learning techniques can significantly improve the accuracy of cost predictions, leading to better budgeting and financial planning (Hashemi et al., 2020, Wang et al., 2021).

Risk Assessment and Mitigation: AI can enhance risk management by identifying potential risks and predicting their likelihood based on historical data. This proactive approach allows project managers to implement mitigation strategies before issues arise, thus minimising disruptions (Alhasan, 2024).

Quality Control and Safety: Computer vision systems powered by AI can monitor construction sites in real-time, detecting safety hazards and quality deviations. This capability not only enhances safety but also ensures that construction standards are met (Victor, 2023).

Predictive Maintenance: AI can predict equipment failures by analysing usage patterns and historical maintenance data, allowing for timely interventions that reduce downtime and maintenance costs (Rane et al., 2024).

Design Optimisation: AI assists in optimising building designs for various factors, including energy efficiency and structural integrity. This optimisation can lead to more sustainable and cost-effective construction practices (Akinola et al., 2024).

2.3.2 Benefits of AI Adoption in Construction

The integration of AI into construction processes yields numerous benefits that can significantly enhance project outcomes.

Improved Efficiency and Productivity: AI automates repetitive tasks and streamlines workflows, leading to increased productivity. Automation of routine activities allows human resources to focus on more complex tasks, thereby enhancing overall efficiency (Victor, 2023).

Enhanced Accuracy and Reduced Errors: AI's ability to process large datasets enables it to identify patterns and insights that may be overlooked by human analysts. This capability reduces errors in tasks such as cost estimation and scheduling, leading to more accurate project outcomes (Hashemi et al., 2020; Wang et al., 2021).

Cost Reduction: By optimising resource allocation and predicting potential issues, AI can lead to substantial cost savings. Studies indicate that AI technologies can significantly reduce waste and improve project efficiency, resulting in lower overall costs (Rane et al., 2024; Wang et al., 2021).

Enhanced Safety: AI-driven safety systems can proactively identify hazards and alert workers, thereby reducing the risk of accidents and injuries on construction sites (Victor, 2023).

Improved Decision-Making: AI provides data-driven insights that enhance decision-making throughout the project lifecycle. Predictive analytics can inform strategic choices, enabling project managers to make more informed decisions based on real-time data (Rane et al., 2024; Darko et al., 2020).

2.3.3 AI's Impact on Sustainability in Construction Projects

The intersection of artificial intelligence (AI) and sustainability in construction is increasingly recognised as a paradigm shift that addresses various inefficiencies and enhances resource management throughout the construction lifecycle. By integrating AI-driven solutions, construction firms can optimise building designs, ensuring energy efficiency and sustainability are prioritised from the outset. For instance, AI algorithms analyse large datasets to inform the design process, leading to outcomes that reduce material wastage and enhance structural integrity (Lei et al., 2023;). These algorithms can predict energy consumption patterns, allowing architects and engineers to make design choices that maximise efficiency and minimise environmental impact (Zhang et al., 2024).

Moreover, the role of AI extends into project management and execution. AI applications help predict potential delays, suggesting adjustments that can streamline workflows and reduce waste. This is particularly crucial in the construction sector, where delays and cost overruns are prevalent. For instance, AI can assist in cost estimation by analysing current material prices along with labour and environmental factors, thereby enabling better budgeting practices that reduce excess material orders. Predictive maintenance, enabled by AI, further enhances sustainability efforts by optimising the lifespan of machinery and reducing unnecessary resource consumption during operation (Laissy et al., 2024).

AI also influences safety protocols on construction sites, presenting significant ramifications for sustainability. By utilising AI to forecast potential hazards and streamline safety measures, companies can reduce the incidence of accidents, thereby conserving resources and minimising waste associated with injury-related delays (Schia et al., 2019). With AI supporting human behaviours in construction, sites are becoming more autonomous and integrated, resulting in improved project outcomes and promoting a more sustainable workflow (Sætra, 2021).

Nonetheless, the path to effectively harnessing AI for sustainability in construction is fraught with challenges, particularly regarding data availability and the requisite skillset for implementation. Many construction firms are still grappling with integrating new technological solutions into their existing frameworks, which can impede potential advancements in sustainability (Torgautov et al., 2021). However, as the sector evolves to embrace these technologies, the potential benefits become increasingly apparent. AI's ability to optimise resource use, enhance safety measures, and promote accurate decision-making is critical to creating a construction environment that prioritises sustainability while remaining economically viable (Khakurel et al., 2018).

In summary, AI offers transformative opportunities for the construction industry to enhance sustainable practices through improved resource management, energy efficiency, and safety. The continuous development and integration of AI technologies into construction processes are essential for navigating the complex challenges of modern sustainable practices within the built environment.

2.3.3 Challenges and Considerations

Despite the promising benefits, the adoption of AI in construction faces several challenges that must be addressed.

Data Availability and Quality: Effective AI algorithms require large volumes of high-quality data for training. The construction industry often struggles with data silos and inconsistent data quality, which can hinder AI implementation (Sammari and Ayob, 2023).

Integration with Existing Systems: Integrating AI tools into existing workflows can be complex and resource intensive. Construction firms must navigate the challenges of aligning new technologies with established practices (Rane et al., 2024).

Skills Gap: There is a notable shortage of professionals with the necessary skills to implement and manage AI solutions in construction. This skills gap can impede the effective adoption of AI technologies (Tunji-Olayeni et al., 2022).

Ethical and Legal Considerations: The deployment of AI raises ethical and legal issues, including concerns about data privacy, algorithmic bias, and liability in case of failures. Addressing these concerns is crucial for the responsible use of AI in construction (Tunji-Olayeni et al., 2022).

In conclusion, while the integration of AI in construction presents significant opportunities for enhancing project efficiency and safety, it also requires careful consideration of the associated challenges. By addressing these challenges, the construction industry can fully leverage the transformative potential of AI technologies.

2.4 Cost Barriers to AI Adoption in Construction

The adoption of Artificial Intelligence (AI) in the construction industry has been significantly impeded by various cost-related barriers. These barriers can be categorised into initial investment costs, training and development costs, ongoing maintenance and support costs, and the perceived return on investment (ROI). Understanding these factors is crucial for stakeholders aiming to leverage AI technologies effectively.

2.4.1 Initial Investment Costs

The initial investment required for AI adoption in construction can be substantial, particularly for small and medium-sized enterprises (SMEs). This investment encompasses several components, including software, hardware, data acquisition, and integration costs. The cost of acquiring AI software licenses or subscriptions can be prohibitive, especially for advanced tools that promise significant improvements in efficiency and productivity (Regona et al., 2022). Furthermore, the implementation of AI often necessitates significant upgrades to existing IT infrastructure, including powerful computers and servers, which adds to the financial burden (Tunji-Olayeni et al., 2022). Additionally, the acquisition and preparation of high-quality data, essential for training AI algorithms, can incur considerable costs (Maldonado-Canca et al., 2025). Integration of AI tools into existing workflows can also be complex and time-consuming, leading to further financial implications (Patil et al., 2024).

2.4.2 Training and Development Costs

Training employees to utilise AI tools effectively is another significant cost barrier. Developing or acquiring training programs and materials can be expensive, particularly for companies with limited resources. Moreover, the time required for training can detract from employees' productivity, potentially impacting project timelines and overall efficiency. This dual impact of financial and productivity costs can deter companies from pursuing AI adoption, particularly in a sector where margins are often tight (Akinola et al., 2024).

2.4.3 Ongoing Maintenance and Support Costs

Once AI systems are implemented, ongoing maintenance and support costs become a critical concern. AI software typically requires regular updates and maintenance to remain effective and secure, which can add to the overall cost of ownership (Victor, 2023). Additionally, companies may need to invest in technical support services to troubleshoot issues and ensure the smooth operation of AI systems, further straining financial resources (El Hajj and Hammoud, 2023). These ongoing costs can create a perception that AI adoption is a long-term financial commitment that may not yield immediate benefits.

2.4.4 Perceived Return on Investment (ROI)

A significant challenge for construction companies is quantifying the ROI associated with AI adoption. While AI has the potential to improve efficiency, reduce errors, and enhance safety, these benefits can be difficult to measure in concrete financial terms (Darko and Chan, 2016). This uncertainty surrounding ROI can make it challenging for companies, especially those with limited budgets, to justify the initial and ongoing investments required for AI technologies. The difficulty in demonstrating clear financial benefits can lead to hesitation in adopting AI, as stakeholders may prefer to invest in more traditional methods with more predictable outcomes (Osuizugbo et al., 2020).

2.4.5 Addressing the Cost Barrier

To overcome these cost-related barriers, a multi-faceted approach is necessary. Technology providers should focus on developing cost-effective AI solutions that are accessible to a broader range of construction companies, including SMEs (Baabdullah et al., 2021). Demonstrating the potential ROI of AI through case studies and quantifiable metrics can help alleviate concerns and encourage investment (Liu, 2024). Additionally, providing accessible training programs and support services can empower companies to develop the necessary skills to implement AI effectively. Finally, government incentives and funding can play a crucial role in promoting AI adoption by alleviating some of the financial burdens associated with initial investments (Hassan et al., 2024).

In conclusion, while the potential benefits of AI in the construction industry are substantial, cost-related barriers remain a significant hurdle. Addressing these barriers through strategic initiatives can facilitate the wider adoption of AI technologies, ultimately enhancing project planning and execution processes.

2.5 Case Studies of AI Adoption and Cost Management in Construction Projects

The adoption of Artificial Intelligence (AI) in the construction industry is increasingly recognised as a transformative force that enhances project planning, execution, and cost management. Several case studies exemplify how construction firms are leveraging AI technologies to mitigate risks, optimise schedules, and ultimately achieve significant cost savings.

Case Study 1: Suffolk Construction - Hospital Extension Project in Boston, United States

nPlan is a company that uses AI and machine learning to analyse construction project plans and predict potential risks and delays with the aim of improving the accuracy of project forecasting and help construction projects finish on time and within budget. Suffolk Construction's collaboration with nPlan to implement AI-powered risk management in a hospital extension project illustrates the practical benefits of AI in construction. Suffolk had to overcome the challenge of gathering and preparing a vast amount of data, sharing over 11,000 schedules from past projects with nPlan for the AI model training, which reflects the initial investment costs discussed earlier. Additionally, ensuring close collaboration among project personnel was crucial for effective integration into existing workflows, addressing the integration challenges mentioned previously. By utilising this historical data, the AI platform forecasted potential risks and delays, increasing activity-level forecasting accuracy from 48% to 74%. This proactive approach allowed Suffolk to address critical risks, particularly in testing and balancing activities, which led to the avoidance of 20 days of delay and a cost saving of $1.25 million (nPlan, 2021). Such outcomes underscore the potential of AI to enhance decision-making and resource allocation in construction project risk management, directly addressing the challenge of quantifying ROI discussed earlier.

Case Study 2: SKANSA-COSTAIN-STRABAG Joint Venture (SCS JV) – High Speed 2 (HS2) London United Kingdom

The three construction companies: SKANSA, COSTAIN and STRABAG are currently working collaboratively to complete the High Speed 2 rail project. The venture is working collaboratively with nPlan in identifying, classifying and mitigating risks before they become an issue.

The SCS JV's application of nPlan's AI platform in the construction of the HS2 high-speed railway further exemplifies the effectiveness of AI in managing complex projects. Effective utilisation required using visualisation tools like 'driving paths' (driving paths is a proprietary algorithm developed by nPlan that allows for summarising and visualising the project paths most likely to affect the project completion date) to understand complex data and make informed decisions through close collaboration between SCS JV and nPlan, highlighting the ongoing support and collaboration needs discussed earlier.

The AI system has identified approximately 140 risk insights that could have resulted in around 250 days of delay, costing an estimated £120 million so far (nPlan 2024). By addressing these risks proactively, SCS JV has been able to maintain both project schedule and budget, showcasing how AI can replace traditional Quantitative Schedule Risk Analysis (QSRA) processes with more efficient AI-led analyses. This shift not only reduced overheads but also improved overall project efficiency, aligning with findings that AI adoption can significantly enhance productivity and reduce human error in construction. The substantial ROI from mitigating these risks directly addresses the concerns about quantifying AI benefits discussed earlier.

Case Study 3: STRABAG - Risk Assessment and Generative Design

STRABAG's implementation of the AI-driven risk analysis platform DARIA highlights another dimension of AI's impact on construction. DARIA, an in-house AI platform developed by STRABAG to help minimise financial risk by implementing a data-driven risk analysis powered by AI. STRABAG had to navigate a cultural shift within the organisation and invest in training to ensure employees could effectively leverage these new technologies, which reflects the training and development costs, and the challenges related to cultural change discussed previously.

The platform achieved an 80% accuracy rate in risk assessments, which is critical for minimising costly setbacks. Additionally, the integration of generative design into STRABAG's workflows allowed for the rapid generation and evaluation of numerous design options, thereby saving time and resources during the planning phase. Furthermore, the incorporation of AI-enhanced 3D concrete printing facilitated faster, more customisable, and cost-effective construction processes, demonstrating the multifaceted benefits of AI in enhancing project efficiency and cost-effectiveness.

These case studies collectively illustrate that AI is not merely a technological advancement but a strategic asset that can transform construction project management. By facilitating better risk management, optimising schedules, and improving decision-making processes, AI contributes to significant cost savings and enhanced project outcomes. The ongoing integration of AI technologies in construction is essential for addressing the increasing complexity of projects and achieving higher efficiency levels.

2.6 Summary of Key Learning and Research Gap

This literature review has examined the transformative potential of AI in construction, highlighting its capacity to optimise project planning and execution while addressing cost barriers. The key findings can be summarised as follows:

AI offers significant potential benefits for construction project planning and execution, including improved efficiency, reduced costs, enhanced safety, and better decision-making. Cost is a major barrier to AI adoption, especially for SMEs, due to initial investment costs, training and development costs, ongoing maintenance costs, and uncertainty about ROI. Several real-world case studies demonstrate the potential of AI to address cost barriers and improve project outcomes.

Despite the growing body of literature on AI in construction, there is still a research gap in understanding the specific cost components that contribute to the cost barrier and how these perceptions vary across different types of construction firms. This research aims to fill this gap by conducting a survey of construction professionals to gather data on their perceptions of cost barriers and their strategies for overcoming them. The findings of this research will contribute to a better understanding of the cost barrier to AI adoption and provide practical recommendations for construction companies to effectively implement AI solutions.

Specifically, this research will focus on the following questions:

- What are the most significant cost components that deter construction companies from adopting AI?
- How do perceptions of cost barriers to AI adoption differ between small, medium, and large construction firms?

By addressing these questions, this research will provide valuable insights for construction companies, technology providers, and policymakers seeking to promote the wider adoption of AI in the construction industry.

Chapter 3: Methodology

3.1 Introduction

This chapter meticulously details the methodological framework employed in this research to investigate the cost barriers hindering the adoption of Artificial Intelligence (AI) in construction project planning and execution. It provides a comprehensive description of the research design, data collection method, sampling technique, data analysis procedures, and ethical considerations. The chapter aims to provide a clear and transparent account of the research process, ensuring the validity and reliability of the findings and enabling others to scrutinise and replicate the study.

3.2 Research Design and Approach

This research adopts a quantitative research approach to gather empirical data on the cost barriers to AI adoption in construction. A quantitative approach allows for the collection of numerical data from a significant sample size, enabling statistical analysis and the identification of trends and patterns. This approach aligns with the research objectives, which seek to quantify the prevalence of cost barriers and assess their impact on AI adoption across different types of construction firms.

3.3 Population and Sampling

The target population for this research comprises construction professionals involved in project planning and execution, including project managers, engineers, architects, and quantity surveyors. A random sampling technique was employed to ensure representation from different construction industry sectors, including residential, commercial, and infrastructure. This sampling method ensures the sample reflects the diverse population, and findings can be generalised to the broader construction industry. The sample size was 120 participants.

3.4 Data Collection Instrument

A structured questionnaire was used as the primary data collection instrument. The questionnaire was designed to gather quantitative data on the perceived cost barriers to AI adoption, including:

- **Initial investment costs:** This includes the cost of software, hardware, data acquisition, and integration.

- **Training and development costs:** This encompasses the cost of training employees to use AI tools effectively.

- **Ongoing maintenance and support costs:** This covers the cost of software updates, maintenance, and technical support.

The questionnaire also included demographic questions to gather information on company size, sector, and AI adoption levels. This enables analysis of how cost barriers vary across different firm characteristics and adoption stages. The questionnaire underwent pilot testing with a small group of construction professionals to ensure clarity and validity before being distributed to the wider sample.

3.5 Data Collection Procedure

The questionnaire was distributed electronically to the target population via email and professional networking platforms. This method allows for efficient and cost-effective data collection from a geographically dispersed population. Participants received clear instructions on completing the questionnaire and were informed that their responses will be kept confidential and anonymous. The data collection period was two weeks, with reminders sent to potential participants to encourage a high response rate.

3.6 Data Analysis Methods

Descriptive statistics, including mean and median were used to summarise the quantitative data on the perceived cost barriers to AI adoption. This provided an overview of the distribution and central tendency of the data, highlighting the most perceived cost barriers. Inferential statistics using various plots and graphs was employed to compare the perceptions of cost barriers across different types of construction firms.

This allowed for the identification of any significant differences in perceptions based on firm characteristics. The relationship between the perceived cost barriers and the level of AI adoption was examined to identify any correlations. This helped in determining whether the perceived significance of cost barriers influences the likelihood of AI adoption. The data analysis and visualisation were conducted using Excel Spreadsheet Package.

3.7 Ethical Considerations

In line with Edery et al., (2023) this research adhered to research ethical guidelines, including obtaining informed consent from participants, ensuring anonymity and confidentiality of data, and protecting the privacy of individuals. Ethical approval was sought from the University's ethics review board before data collection. The data source to be used for this study is free of manipulation, falsification or fabrication with proper referencing to prevent plagiarism. Responses recorded from the participants regarding their work-related information was handled with confidentiality and anonymity. As recommended by Saunder et al., (2019), the study avoids any form of discrimination based on protected characteristics when selecting participants.

3.8 Data Reliability and Validity

To ensure the validity of the research findings, the questionnaire was designed to measure the constructs of interest accurately. A pilot test was conducted where the draft questionnaire was distributed to a project management professional and the supervisor for feedback on question structure and relevance to the research question. This allowed for identification of potential issues, and these were corrected for the final questionnaire.

3.9 Summary

This chapter has outlined the methodological framework for this research, providing a detailed description of the research design, data collection method, sampling technique, data analysis procedures, and ethical considerations. The quantitative approach provides a comprehensive understanding of the cost barriers to AI adoption in construction project planning and execution. The next chapter will present the findings of the data analysis.

Chapter 4: Data Analysis, Results and Discussion of Findings

This section provides an in-depth discussion of the analysis and interpretation of the primary data collected through the survey. First, the response rates will be discussed, followed by demographic characteristics of the participants analysing response rate for various research variables including AI awareness of participants, perception of AI implementation cost and the associated cost types, followed by perception of AI in construction project planning and execution. After this, each demographic categorisation will be used to analyse each of the research objectives.

4.1 Examination of Response Statistics for Research Participants

4.1.1 Response Rate

Table 4.1 shows that out of 120 targeted respondents, 55 (45.8%) completed the online questionnaire (see **Appendix 1: Survey Questions**). Despite the response rate, the analysis proceeded with these 55 valid responses, deemed sufficient for reliable results. It is worth noting that responses to certain questions were not included in the analysis, for example the question 5, this is due to the non-relevance of the question to the research objective (reflected upon in **Appendix 2: Reflective Account of the Research Journey**)

Table 4.1: Survey Response

	Frequency	Percentage (%)
Number of Surveys Distributed	120	100
Survey Response Collected	55	45.8

4.1.2 Participant Job Roles

Figure 4.1 illustrates the diverse job roles of respondents. Project managers comprised the largest group at 38%, followed by engineers (30%) and architects (21%). Contractors represented 9% of responses, and no respondents identified as IT specialists

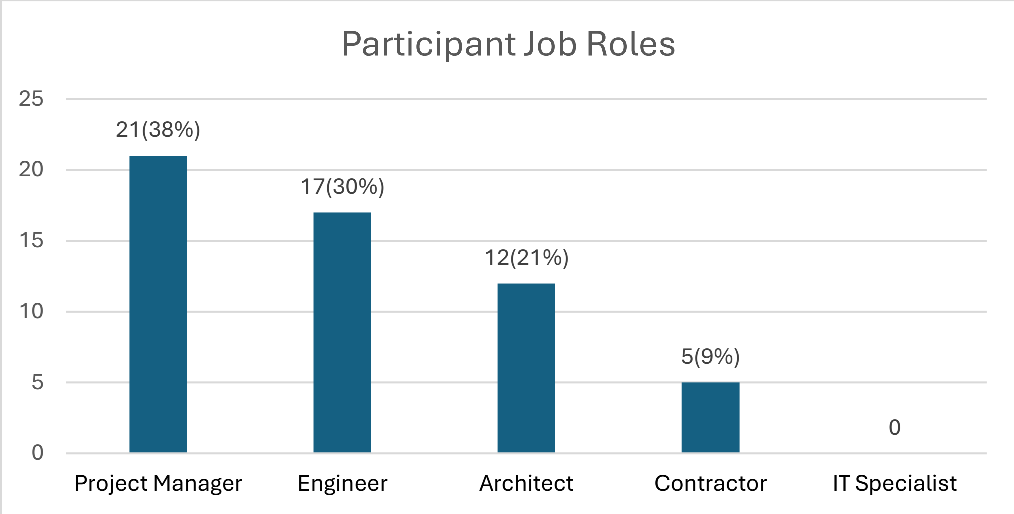

Figure 4.1: Participant Job Roles

4.1.3 Company Size

Figure 4.2 details the company size of the 55 respondents, categorised by yearly revenue: Small (£1-9.99 million), Medium (£10-99.99 million), and Large (£100+ million). The majority (58.2%) worked for small companies (32 participants), followed by medium-sized companies (32.7%, 18 participants), and large companies represented 9.1% (5 participants)

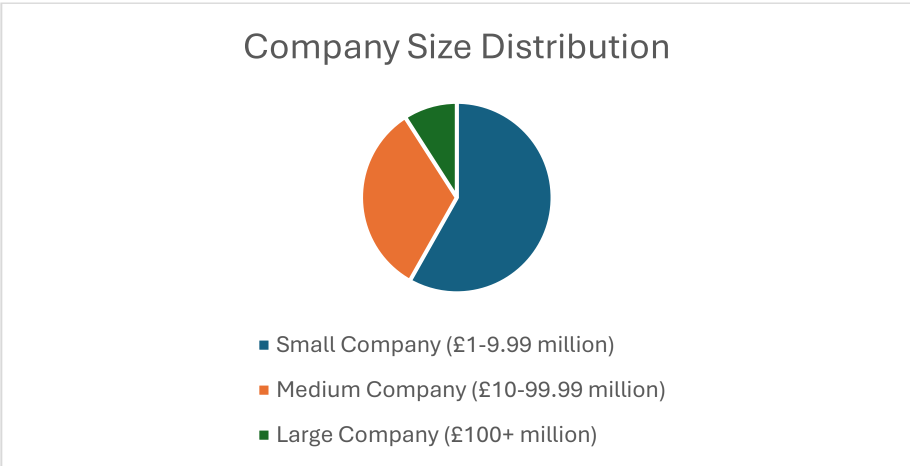

Figure 4.2: Company Size

4.1.4 Company Type

Figure 4.3 illustrates the distribution of respondents across different construction industry types. Recognising that companies often undertake multiple project types; respondents could select more than one category. The survey results indicate that 35 respondents worked in residential construction, 19 in commercial, 14 in industrial, and 8 in infrastructure.

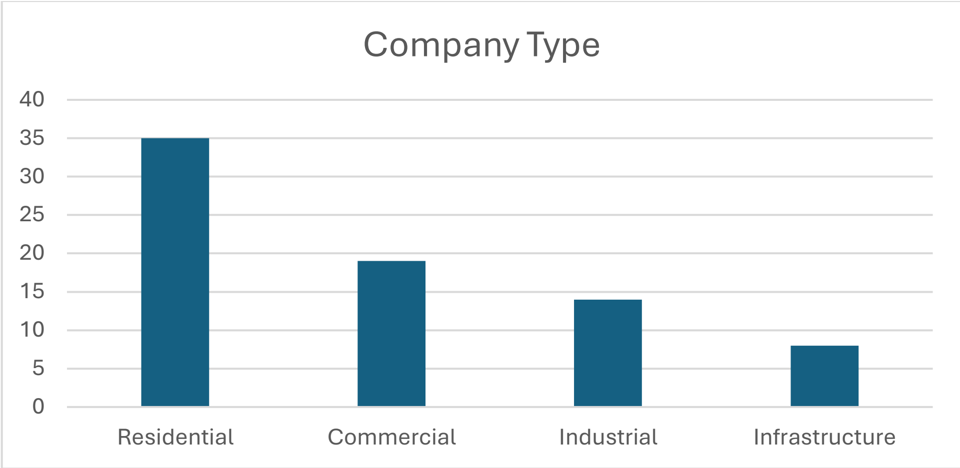

Figure 4.3: Company Type

4.2 AI Usage and Cost Perception

4.2.1 AI Usage Awareness

This section examines participants' awareness of AI usage. As depicted in Figure 4.4, the survey revealed that 69% (38 respondents) were aware of using AI tools in their workflow before taking the survey, while 31% (17 respondents) were unaware.

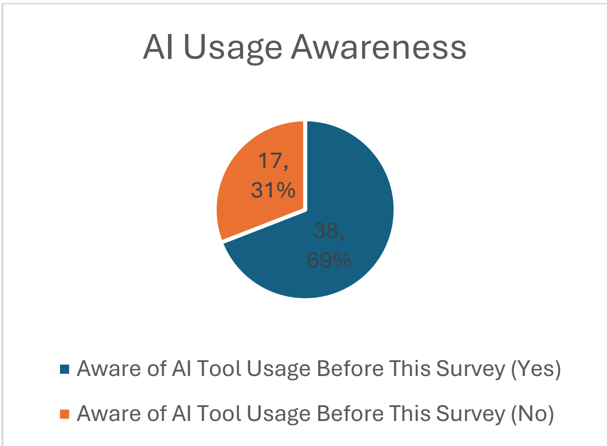

Figure 4.4: AI Usage Awareness

4.2.2 AI Tools Usage

Figure 4.5 details the AI tools currently used by respondents in their job roles. Generative AI Tools (Large Language Models) were the most common (28 users), followed by no AI tool usage (20 users). Building Information Modelling and Microsoft Copilot in Microsoft365/Project were each used by 12 respondents. AI-Powered Project Management Tools and Computer Vision systems had 6 users each, while Machine Learning algorithms and Predictive analysis tools were used by 5 and 3 respondents, respectively. The average number of AI tools used per respondent was 1.31

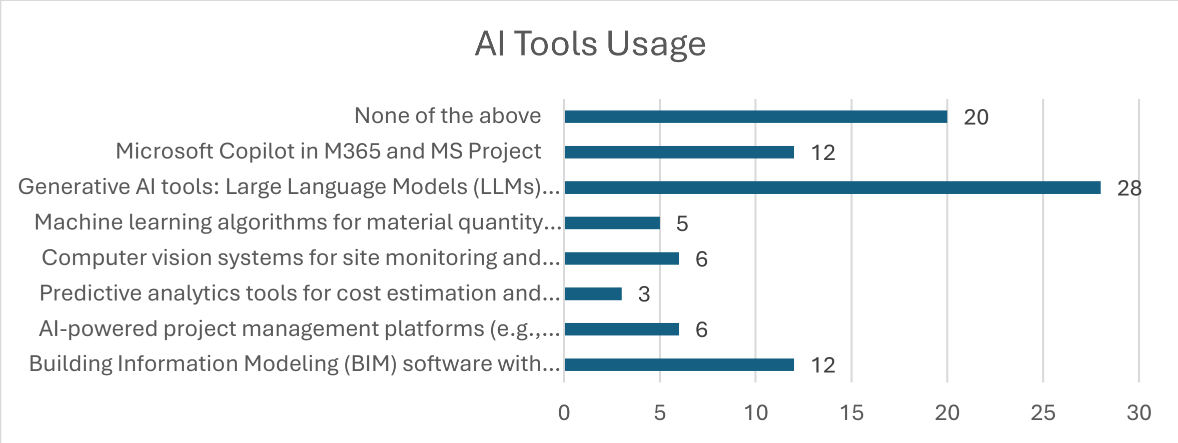

Figure 4.5: AI Tools Usage

4.2.3 Cost Factors in Implementation of Artificial Intelligence

Table 4.2 reveals that a significant majority of respondents (72.3%, 40 participants) perceived the initial cost of AI implementation as too high (47.3% strongly agreed, 25.4% agreed). Only 9.1% (5 participants) were neutral, while 18.2% (10 participants) disagreed. This indicates a prevalent view among construction professionals that the upfront investment in AI is substantial.

Table 4.2: AI Initial Investment cost

	SA		A		N		D		SD	
	F	%	F	%	F	%	F	%	F	%
The Initial Investment Cost of AI is too high	26	47.3	14	25.4	5	9.1	9	16.4	1	1.8

Respondents ranked five cost components associated with AI implementation, with the first rank indicating the most significant cost. Table 4.3 details these rankings. By weighting these rankings (5 points for 1st choice to 1 point for 5th), Figure 4.6 identifies software licensing costs as the most significant perceived cost factor, while ongoing maintenance and support costs were considered the least significant.

Table 4.3: Cost Perception

	1st Choice Selection (Freq %)	2nd Choice Selection (Freq %)	3rd Choice Selection (Freq %)	4th Choice Selection (Freq %)	5th Choice Selection (Freq %)
Software Licensing Cost	24(43.6)	23(41.8)	5(9.1)	1(1.8)	2(3.6)
Hardware and Infrastructure Cost	20(36.4)	18(32.7)	10(18.2)	5(9.1)	2(3.6)
Training and development costs	7(12.7)	7(12.7)	10(18.2)	22(40)	9(16.4)

Integration and implementation cost	3(5.5)	6(10.9)	14(25.5)	20(36.4)	12(21.8)
Ongoing maintenance and support cost	1(1.8)	1(1.8)	16(29.1)	7(12.7)	30(54.5)

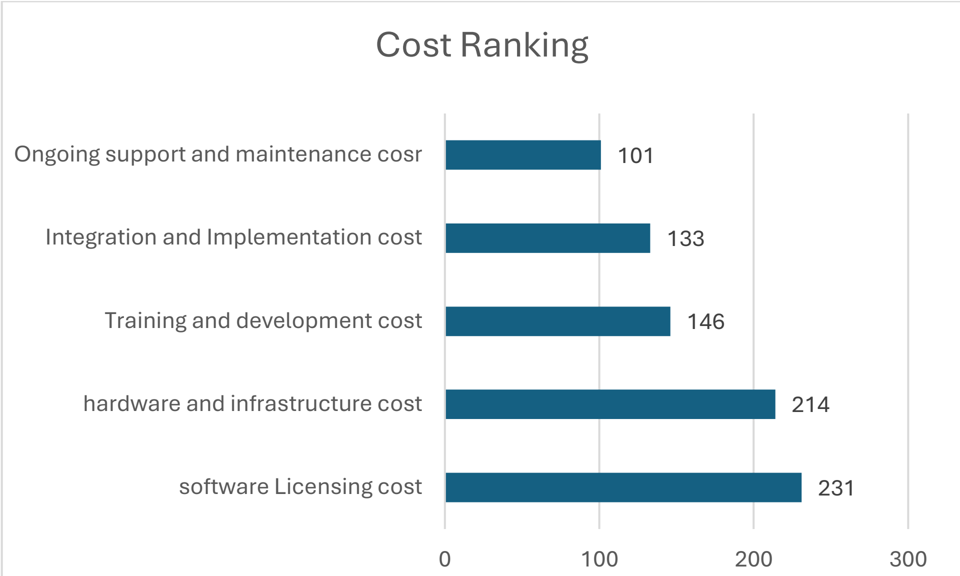

Figure 4.6: Ranking of Cost Factors

4.3 Perception of AI in construction Project Planning and Execution

This section presents the perception of AI in construction Project Planning and Execution, outlining both its perceived benefits (Table 4.7) and associated risks (Table 4.8), based on respondent agreement levels.

Table 4.4: AI Benefits in Construction

	SA		A		N		D		SD	
	F	%	F	%	F	%	F	%	F	%
AI tools can significantly improve efficiency and productivity in construction projects.	29	53	13	24	8	15	5	9	-	-
AI can enhance the accuracy of cost estimation and scheduling	24	44	22	40	6	11	2	4	1	2
AI can help mitigate risks and improve safety on construction sites	20	36	24	44	7	13	1	2	3	5
AI can enable better decision-making in construction projects	25	45	18	33	10	18	2	4	-	-

75% of respondents believed AI tools can significantly help increase efficiency and productivity in construction projects, 15% were neutral in their responses, while 10% disagreed showing that most professionals saw AI as helpful in increasing efficiency. 84% of respondents also believed that AI could enhance cost estimation and scheduling, 11% were neutral while 6% disagreed, this also aligns with AI being helpful in enhancing cost and schedule estimation. 80% of respondents believe AI can help mitigate risks and improve safety on construction sites, 13% were neutral, while 7% disagreed, this shows positive correlation between AI usage and risk mitigation and site safety. Regarding decision making, 78% of respondents believe AI helps in this regard, 18% were neutral while 4% disagreed, this points at professionals seeing AI as helpful in enhancing the decision-making process.

Table 4.5: AI Risks in Construction

	SA		A		N		D		SD	
	F	%	F	%	F	%	F	%	F	%
There are significant risks associated with using AI tools in construction	33	60	17	31	2	4	3	5	-	-
AI tools may be unreliable or produce inaccurate results.	28	51	16	29	4	7	7	13	1	2
AI tools may be difficult to integrate with existing workflows	27	49	10	18	7	13	10	18	1	2
AI tools may require specialised expertise to operate and maintain.	23	43	17	31	5	9	8	15	1	2

A significant majority of respondents, 91% (60% strongly agreed and 31% agreed), believed that there are significant risks associated with using AI tools in construction projects, while a small minority were neutral (4%) or disagreed (5%), indicating a strong perception of potential risks. Regarding the reliability of AI tools, 80% of respondents (51% strongly agreed and 29% agreed) felt that AI tools may be unreliable or produce inaccurate results, with 7% being neutral and 15% disagreeing, suggesting a considerable concern about the dependability of AI outputs.

Furthermore, 67% of respondents (49% strongly agreed and 18% agreed) believed that AI tools may be difficult to integrate with existing workflows, while 13% were neutral and 20% disagreed, highlighting potential challenges in adopting AI within current construction practices. Finally, a substantial 74% of respondents (43% strongly agreed and 31% agreed) agreed that AI tools may require specialised expertise to operate and maintain, with 9% being neutral and 17% disagreeing, indicating an understanding that specific skills might be necessary for the effective implementation and upkeep of AI in construction.

4.4 Discussion and Evaluation of Research Objectives

This section will provide a professional analysis and discussion of the survey findings, structured around the research objectives and leveraging respondent demographics for detailed insights. Initially, AI awareness will be used to examine the current utilisation of AI tools within participants' roles. Subsequently, AI adoption patterns will be assessed across varying construction company sizes (small, medium, and large) and organisational types. The perceived cost of AI implementation will then be discussed in relation to company size, identifying the most significant cost factors for each category. Furthermore, the perceived benefits and risks of AI will be evaluated across different construction industry professions. Finally, potential strategies for mitigating identified challenges will be explored

4.4.1 AI Adoption Level

Figure 4.4 reveals that prior to the survey, 69% of respondents were aware of using AI tools, while 31% were not. The overall average number of AI tools used was 1.3. Notably, respondents aware of their AI usage reported an average of 2.5 tools, significantly higher than the 0.24 tools used by those initially unaware. Among those aware, only 13% did not use any AI tools, compared to 88% of the initially unaware group. This strong correlation between awareness and usage suggests that a lack of awareness often equates to non-use. However, the 12% of initially unaware respondents who identified AI usage during the survey indicates a potential underestimation of AI adoption across the construction industry, with individuals unknowingly utilising AI within their workflows.

AI adoption levels correlate strongly with company size. Respondents from small companies (58.2% of total) reported low average usage at 0.78 AI tools per person, with only 12 out of 32 using any AI, while 20 used none. In contrast, medium-sized companies (32.7% of respondents) averaged 3.05 tools per person, and all respondents used at least one AI tool. Large companies (9.1% of respondents) showed the highest adoption, averaging 3.8 tools per person, also with universal usage (all used at least one tool). This trend indicates AI adoption increases with company size, suggesting firms with more resources and complex projects integrate AI more readily. Next, we will examine the relationship between perceived AI implementation costs, company size, and average tool usage

In conclusion, this assessment determined the current AI adoption level in construction project planning and execution averages 1.3 tools per respondent, signifying a moderate level of overall integration at this stage. Addressing the research question regarding adoption patterns, the data reveals a stark dichotomy heavily influenced by company size, which also strongly correlates with pre-survey awareness. Adoption is demonstrably low within small firms, averaging only 0.78 tools per person and marked by significant non-use (62.5% reported using zero tools). This low adoption likely intertwines with lower awareness (as seen in the general awareness data, though not explicitly broken down by size *and* awareness in this summary). Several postulates arise from this: smaller firms may lack not only the financial resources but also the dedicated personnel or strategic focus to actively explore, implement, and crucially, *recognise* AI tools, leading to both lower usage and lower awareness.

This contrasts sharply with the findings for respondents from medium-sized (3.05 tools/person) and large organisations (3.8 tools/person), where adoption is significantly higher and universal among respondents. This higher adoption rate is likely coupled with greater awareness, driven by several factors inherent to larger organisations:

- Resource Allocation: Greater capacity to invest in specific AI platforms and training.
- Strategic Implementation: More formal processes for technology adoption, often including communication and training that ensures users are aware they are using AI.
- Complexity Demand: Larger, more complex projects may necessitate advanced AI tools for scheduling, risk management, or analytics, pushing deliberate adoption.
- Specialised Roles: Presence of IT, innovation, or data analysis teams actively promoting and managing AI usage.

The initial finding that 12% of respondents *unaware* of using AI prior to the survey identified usage *during* it adds a layer of complexity, suggesting some AI penetration occurs "under the radar," possibly through embedded features in widely used software. This phenomenon might disproportionately affect the perception of adoption in smaller firms where usage could be less deliberate and awareness less cultivated.

Thus, AI penetration is currently concentrated heavily in larger firms, a trend substantially explained by the availability of resources and the demands of more complex projects. However, awareness emerges as a critical, intertwined factor. Higher adoption in larger firms is paralleled by, and likely reinforced by, greater awareness, while the low adoption in smaller firms is compounded by a corresponding lack of awareness, potentially even undercounting existing, albeit limited, usage.

4.4.2 AI Cost Evaluation

Perception of AI implementation cost varies significantly by company size, as detailed in Section 4.2.3 and Figure 4.7. Respondents from small companies overwhelmingly perceived costs as too high (n=32: 71.8% strongly agreed, 21.9% agreed), with only 6.3% neutral and no disagreement. Medium-sized companies showed more mixed views: while 16.7% strongly agreed and 38.9% agreed costs were high, 5 respondents disagreed and 1 strongly disagreed. Conversely, large companies predominantly disagreed that costs were prohibitive (n=5: 80% disagreed, 20% neutral).

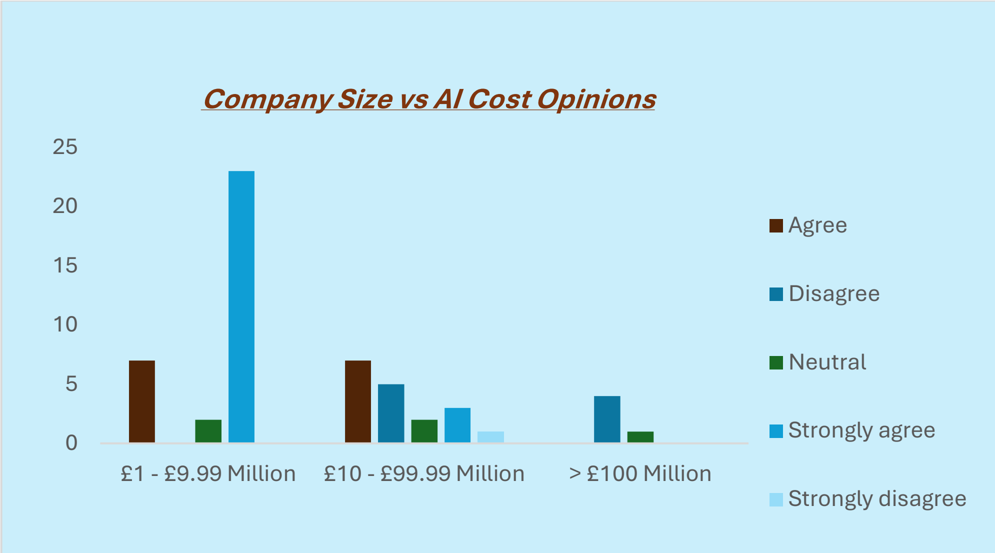

Figure 4.7: Cost Perception Across Size

Analysing perceptions across different construction types reveals further nuances:

- Residential (n=35): Showed the strongest agreement that costs are too high (65.7% strongly agreed, 14.3% agreed), with only 2 disagreeing and 5 neutral.
- Commercial (n=19): Also tended to agree (26.3% strongly agreed, 47.4% agreed), while 4 disagreed and 1 was neutral.
- Industrial (n=14): Presented mixed views, with slightly more agreeing (14.3% strongly agreed, 35.7% agreed) than disagreeing (6 respondents), alongside 1 neutral.
- Infrastructure (n=8): Respondents were evenly divided, with 4 agreeing (12.5% strongly, 37.5% agree) and 4 disagreeing.

This breakdown highlights a fundamental dynamic: the perception of AI implementation cost as a major barrier is inversely correlated with company size within the construction industry. Smaller firms, as evidenced by the overwhelming agreement (93.7% combined agreement) that costs are too high, likely view AI as prohibitively expensive due to several potential factors:

- Limited Capital: They operate with tighter budgets and less access to discretionary funds for significant technology investments that may not offer immediate, guaranteed returns.

- Higher Relative Cost: The upfront cost of AI solutions (software, hardware, training, potential consultants) represents a much larger proportion of their overall turnover or project budgets compared to larger enterprises.
- Risk Aversion: With smaller margins for error, the financial risk associated with adopting new, potentially complex technology like AI is perceived as significantly higher.
- Uncertainty of ROI: They may struggle to identify clear, quantifiable benefits or possess the internal expertise to accurately forecast the return on investment for AI within their specific operational context.

Conversely, the strong disagreement among large companies (80% disagreeing costs are prohibitive) suggests they possess the necessary financial resources, dedicated IT/innovation departments, and potentially clearer strategic roadmaps for AI integration. They might perceive the cost not as insignificant, but as a manageable investment relative to their scale and the potential for substantial efficiency gains, risk mitigation, or competitive advantages on larger projects.

While the trend based on company size is dominant, the variations across construction sectors add nuance. The extreme cost sensitivity in the residential sector (80% agreement), often characterised by numerous smaller firms and potentially lower margins per project, reinforces the small-company perspective. The mixed views in industrial and the split in infrastructure suggest that even within these sectors (which might include larger firms), the *specific application*, project complexity, or maturity of available AI solutions influences cost perception. However, the overarching conclusion remains strongly tied to organisational scale: the financial capacity and strategic positioning inherent in larger companies significantly lessen the perception of AI cost as a prohibitive barrier compared to their smaller counterparts.

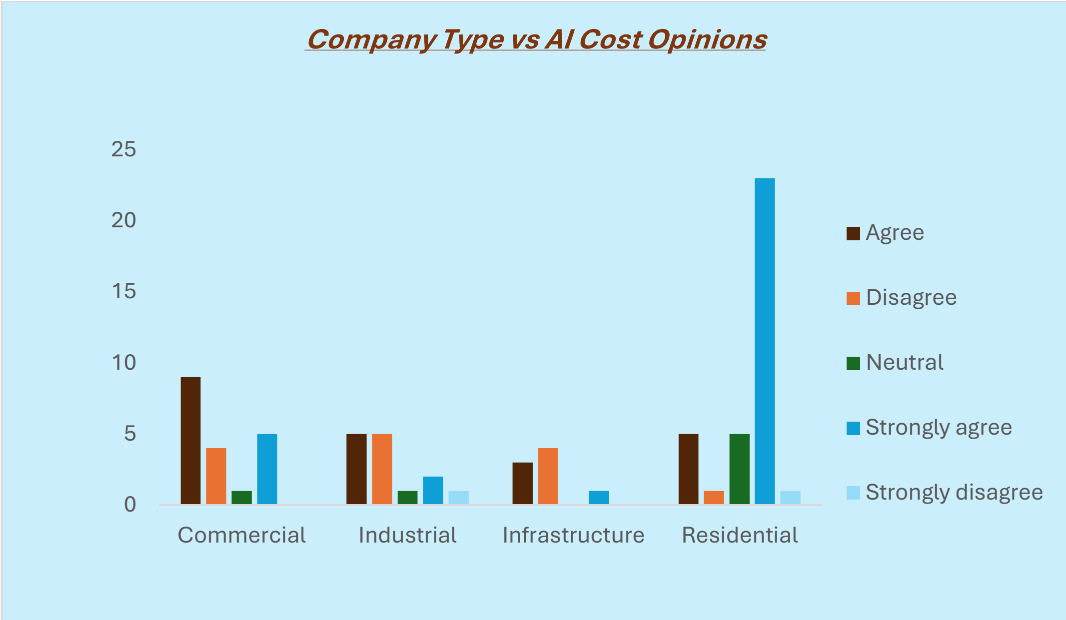

Figure 4.8: Cost Perception Across Company Type

4.4.3: Evaluating Cost Factors

Zooming in on section 4.2.3, cost factors are analysed across various industry. For small companies, software implementation cost ranked highest (137 points), followed closely by hardware and infrastructure cost (125 points). Training and development cost (84 points) and integration and implementation costs (73 points) were next, with ongoing maintenance and support cost considered least significant (61 points).

Medium-sized companies identified software licensing cost as most significant (73 points), again followed by hardware and infrastructure cost (71 points). For this group, ongoing support and maintenance cost ranked third (61 points), ahead of training and development cost (51 points) and integration and implementation cost (47 points).

In large companies, while the overall points were lower, software licensing cost (21 points) and hardware and infrastructure cost (18 points) remained the top two concerns. Integration and implementation cost ranked third (13 points). Notably, ongoing support and maintenance cost and training and development cost were jointly considered the least significant factors (12 points each). Across all sizes, software and hardware consistently emerge as the primary cost factors.

In conclusion, the data presented here demonstrates that high perceived costs, especially those associated with software and hardware, significantly impede AI integration in the construction industry, directly answering the research question regarding cost's impact. This finding fulfils the objective of discussing cost as a key barrier limiting AI adoption in project planning and execution. The consistent prominence of these upfront expenses across all company sizes suggests they represent major financial hurdles. It's plausible that these initial capital-intensive expenditures (software licenses, hardware) are perceived as particularly burdensome because they often require significant budget allocation and approval, unlike potentially smaller, incremental ongoing costs.

Although small companies show a relatively higher concern for initial software *implementation* costs, while medium companies place more emphasis on ongoing support and maintenance, these variations likely reflect different operational realities and stages of adoption. Smaller firms, potentially operating with tighter budgets and fewer dedicated IT resources, might view the initial setup and integration effort as the most daunting financial obstacle. Medium-sized companies, perhaps having overcome some initial implementation hurdles, may then become more acutely aware of the accumulating operational expenses associated with licenses, support, and maintaining the tools for a growing user base. Conversely, the lower relative significance attributed to ongoing support and training by large companies could stem from economies of scale, established in-house training programs, dedicated IT support, and potentially more favourable licensing agreements, making these costs less prohibitive within their larger budgets.

Ultimately, the analysis underscores that the perception of high cost, particularly the initial investment required for software and hardware, acts as a primary gatekeeper for AI integration across the construction sector. This financial barrier likely deters not only full-scale adoption but potentially even the exploration and piloting of AI tools, especially for small and medium-sized enterprises (SMEs), thereby hindering potential gains in efficiency, innovation, and competitiveness driven by AI in project planning and execution.

4.4.4 AI Benefit and Risk Perception across Professions

This section evaluates industry professionals' perceptions of AI in construction, addressing the research question: "How do professionals in the construction industry perceive AI in terms of its usefulness, risks, and limitations?". It analyses the perceived benefits and risks across different roles—Architects, Engineers, Contractors, and Project Managers—based on the survey data presented (see Appendix). While overall sentiment shows strong belief in AI's benefits (e.g., 75% agreement on efficiency gains, 84% on enhanced estimation/scheduling) alongside a high awareness of risks (91% agreement on significant risks), examining perceptions by role reveals important nuances.

Perceived Benefits:

- Efficiency and Productivity: Strong agreement was observed across all roles, particularly Project Managers and Engineers. This widely shared belief likely reflects how professionals in roles focused on project delivery (PMs, Engineers, Contractors) see direct value in tools that automate tasks or optimise processes, leading to high agreement.
- Accuracy of Cost Estimation and Scheduling: Engineers and Project Managers showed particularly strong agreement here. Architects also largely agreed, while Contractors showed general agreement, but perhaps slightly less uniform enthusiasm compared to PMs/Engineers. This difference may arise because Engineers and PMs, often heavily involved in the quantitative aspects of planning and control, perceive the benefits of AI for accuracy more acutely than architects (focused more on design) or contractors (focused more on execution based on plans).
- Risk Mitigation and Safety: High agreement was prevalent across roles, especially among Project Managers and Engineers. Given that safety and risk management are critical concerns for all roles involved in project delivery, PMs and Engineers, often responsible for planning and oversight, likely recognise AI's potential for predictive analytics or monitoring to enhance safety protocols.
- Decision-Making: Project Managers exhibited very strong agreement on AI's ability to enable better decision-making, closely followed by Engineers and Architects. This strong agreement likely stems from the PM's core function involving decision-making based on complex information, making AI's data processing and insight generation capabilities particularly valuable. Engineers and Architects also value data-driven decisions in their respective domains.

Perceived Risks and Limitations:

- Significant Risks Associated with AI: A very high level of agreement (Strongly Agree/Agree) was evident across all roles, indicating a universal awareness of potential downsides, with no distinct difference among the roles in acknowledging general risk.
- Unreliability/Inaccurate Results: Engineers and Project Managers appeared most concerned (showing high levels of Strong Agree/Agree), with Architects also showing

significant concern. This suggests that roles relying heavily on data accuracy for critical decisions (PMs, Engineers) may be more sensitive to potential AI errors. Architects' concerns might also relate to inaccuracies impacting design integrity or interpretation.

- Difficulty Integrating with Existing Workflows: Contractors and Project Managers expressed notable agreement regarding integration challenges. Engineers and Architects also agreed but perhaps showed slightly more variation in responses. This could be because contractors, working directly on-site with established methods, and PMs, overseeing the entire project ecosystem, perceive the practical hurdles of integrating new technologies into complex, existing workflows more strongly.
- Requirement for Specialised Expertise: Strong agreement was consistent across all roles, indicating a shared understanding that using AI effectively requires specific skills. This likely reflects the current state of many construction AI tools, which are not yet fully 'plug-and-play' and necessitate expertise for operation, customisation, data management, and maintenance, regardless of the user's primary profession.

Synthesis and Conclusion:

In evaluating industry professionals' perceptions, it's clear that while AI is broadly seen as beneficial across roles, particularly for efficiency, accuracy, and decision-making, significant concerns about risks, reliability, integration, and the need for expertise persist universally. Answering the research question, different professionals perceive AI's usefulness and limitations through the lens of their specific responsibilities. Engineers and Project Managers appear particularly attuned to benefits related to accuracy and decision-making, while also showing strong concern for reliability. Contractors highlight integration challenges, reflecting their focus on operational realities. Architects share concerns about reliability while valuing decision support. Despite these nuances, the high perceived risks and need for specialised skills act as common limitations across all surveyed professions, suggesting that addressing these factors is crucial for broader and deeper AI integration in the construction industry.

4.5 Proposed Strategies to Mitigate Identified Limitations

This section outlines proposed strategies designed to address the key barriers and limitations to AI adoption identified through the data analysis in Chapter 4. These recommendations aim to facilitate wider and more effective AI integration within construction project planning and execution, fulfilling the research objective to propose mitigation approaches.

Addressing High Perceived Costs

The analysis revealed that high perceived costs, particularly the initial investment in software and hardware, represent a significant barrier, especially for SMEs. To mitigate this, technology providers should develop more flexible pricing models, such as subscription-based (SaaS) or tiered options, to lower the upfront financial commitment. Simultaneously, focusing marketing and development efforts on AI applications with clearly demonstrable and rapid ROI can help overcome the uncertainty noted among smaller firms. Promoting lower-cost entry points, like generative AI tools or features embedded in existing software, can also encourage initial adoption. Furthermore, consideration should be given by policy makers and industry bodies to financial incentives or subsidies targeted at assisting SMEs with AI adoption.

Improving Awareness and Understanding

A strong correlation was observed between lack of awareness and non-use of AI tools, with potential underestimation due to 'hidden' AI within workflows. Targeted educational initiatives, including industry-specific workshops and practical training, are crucial to demystify AI and highlight its potential applications. Disseminating success stories and case studies, particularly from SMEs, can build confidence and demonstrate tangible benefits. Technology providers also have a role in improving awareness by clearly identifying AI capabilities within their software to increase user recognition.

Easing Integration with Existing Workflows

Professionals expressed concerns about the difficulty of integrating AI tools with existing workflows, a challenge particularly noted by contractors and project managers. Promoting interoperability through industry standards (like enhancing BIM) is essential. Technology developers should design AI tools with robust APIs and modular structures to facilitate easier connection with existing systems. Comprehensive integration support, including clear documentation and technical assistance from vendors, is also necessary.

Bridging the Skills Gap

The perception that AI tools require specialised expertise to operate and maintain is widespread across all professional roles surveyed. Developing AI tools with more intuitive, user-friendly interfaces can lower this barrier. Offering role-specific training focused on leveraging AI within existing skill sets can empower current professionals. Additionally, fostering partnerships between construction firms and AI specialists can provide necessary expertise, especially during initial implementation.

Building Trust and Addressing Risk Perceptions

Significant concerns regarding risks, reliability, and accuracy persist universally among respondents. To build trust, AI developers should increase transparency regarding algorithm functionality and limitations. Establishing rigorous, industry-accepted validation processes and benchmarks can help demonstrate the reliability of AI tools in construction contexts. Developing and sharing clear risk management frameworks and best practices is also vital. Encouraging firms to start with pilot projects allows for controlled testing, builds user confidence, and facilitates smoother adoption before widespread deployment.

By implementing these multifaceted strategies, stakeholders—including technology providers, industry practitioners, policy makers, and regulators—can collaboratively address the identified limitations, thereby fostering a more conducive environment for AI adoption and maximising its potential benefits within the construction sector.

Chapter 5: Conclusion And Recommendations

This chapter concludes the dissertation by revisiting the research questions concerning AI adoption barriers in construction, summarising the key findings from Chapter 4, and presenting recommendations derived from the analysis. It also addresses the study's limitations and proposes avenues for future research in this important area.

5.1 Summary of Findings

This section summarises the principal findings derived from the data analysis presented in Chapter 4, providing a concise overview of the research results concerning AI adoption, cost perception, and professional viewpoints within the UK construction industry.

Respondent Demographics and Survey Response:

- Out of 120 targeted respondents, 55 completed the questionnaire, yielding a response rate of 45.8% (Section 4.1.1, Table 4.1).
- The largest group of respondents were Project Managers (38%), followed by Engineers (30%) and Architects (21%) (Section 4.1.2, Figure 4.1).
- Most respondents (58.2%, n=32) worked for small companies (£1-9.99 million revenue), with 32.7% (n=18) from medium-sized companies and 9.1% (n=5) from large companies (Section 4.1.3, Figure 4.2).
- Respondents represented various construction types, with the highest participation from residential (n=35), followed by commercial (n=19), industrial (n=14), and infrastructure (n=8) (Section 4.1.4, Figure 4.3).

AI Usage and Awareness:

- Prior to the survey, 69% (n=38) of respondents were aware they used AI tools, while 31% (n=17) were unaware (Section 4.2.1, Figure 4.4).
- The overall average number of AI tools used per respondent was 1.31 (Section 4.2.2, Figure 4.5). Usage was significantly higher among aware respondents (average 2.5 tools) compared to unaware respondents (average 0.24 tools) (Section 4.4.1).
- Generative AI tools (LLMs) were the most used (n=28), while 20 respondents reported using no AI tools (Section 4.2.2, Figure 4.5).

- AI adoption correlated strongly with company size: small companies averaged 0.78 tools/person (with 62.5% using none), medium companies averaged 3.05 tools/person, and large companies averaged 3.8 tools/person (Section 4.4.1).

Perception of AI Implementation Costs:

- A significant majority (72.7%, n=40) perceived the initial cost of AI implementation as too high (47.3% strongly agreed, 25.4% agreed) (Section 4.2.3, Table 4.2).
- Software licensing costs were ranked as the most significant cost factor overall, followed by hardware and infrastructure costs. Ongoing maintenance and support were ranked least significant (Section 4.2.3, Figure 4.6).
- Cost perception varied dramatically by company size: 93.7% of small company respondents agreed costs were too high, compared to 55.6% of medium-sized company respondents. Conversely, 80% of large company respondents disagreed that costs were prohibitive (Section 4.4.2, Figure 4.7).
- Across construction types, residential sector respondents showed the strongest agreement (80%) that costs are too high, while infrastructure respondents were evenly split (Section 4.4.2).
- While software and hardware costs were top concerns across all sizes, small companies showed relatively higher concern for initial implementation costs, while medium companies placed slightly more emphasis on ongoing support costs compared to large companies (Section 4.4.3).

Perceived Benefits and Risks of AI:

- Respondents broadly perceived AI as beneficial, with strong agreement on its potential to improve efficiency/productivity (77% agreement), enhance cost estimation/scheduling accuracy (84% agreement), mitigate risks/improve safety (80% agreement), and enable better decision-making (78% agreement) (Section 4.3, Table 4.4).
- Simultaneously, a very high majority perceived significant risks associated with AI (91% agreement). Major concerns included potential unreliability/inaccuracy (80% agreement), difficulty integrating with existing workflows (67% agreement), and the requirement for specialised expertise (74% agreement) (Section 4.3, Table 4.5).

- While perceptions of benefits and risks were generally high across professions, some nuances emerged: Engineers and Project Managers showed particularly strong agreement on benefits related to accuracy and decision-making, while also expressing high concern about reliability. Contractors highlighted integration challenges more strongly (Section 4.4.4).

5.2 Recommendations

Based on the findings highlighting cost, awareness, skills, and integration as key barriers particularly for SMEs, the following recommendations are proposed:

For Construction Firms:

- Strategic Adoption: Initiate AI adoption with pilot projects targeting areas with clear ROI potential to justify investment and build internal support.
- Leverage Accessible Tools: Explore AI features within existing software and utilise lower-cost generative AI options as feasible entry points.
- Skill Development: Invest in targeted training relevant to employee roles to enhance AI tool usability and awareness; consider partnerships with specialists for complex implementations.

For AI Technology Providers:

- Accessible Pricing and Transparency: Offer scalable pricing models (SaaS, tiered) suitable for SMEs and be transparent about all associated costs, including maintenance.
- Focus on Usability and Integration: Prioritise user-friendly interfaces and develop tools with robust Application Programming Interfaces (API) to simplify integration with existing construction workflows.
- Demonstrate Value: Provide clear case studies with quantifiable ROI and offer strong technical and integration support to build trust and address reliability concerns.

For Policy Makers and Industry Bodies:

- Support SME Adoption: Consider financial incentives (grants, subsidies) to help SMEs overcome initial cost hurdles.
- Promote Standards and Knowledge Sharing: Encourage data/interoperability standards and facilitate industry-wide training, workshops, and best practice sharing to improve awareness and skills.

- Develop Guidance: Assist in creating risk management frameworks and guidelines tailored to AI use in construction.

5.3 Limitations of the Research

Key limitations of this study include its reliance on a moderate sample size primarily from the UK construction sector, potentially limiting generalisability. The use of self-reported survey data may be subject to respondent bias. Furthermore, the quantitative approach may not capture the full depth of qualitative nuances behind decision-making, and the findings represent a snapshot in a rapidly evolving technological landscape.

5.4 Future Areas of Study

Building on this research, future studies could:

- Employ qualitative methods (interviews/case studies) to explore the reasons behind cost perception differences and integration challenges in more depth.

- Conduct longitudinal research to track AI adoption trends and the impact of specific strategies over time.

- Investigate methods for more robust ROI quantification for AI in construction projects.

- Perform comparative analyses of AI adoption barriers and strategies across different countries or construction sub-sectors.

5.5 Conclusion

This dissertation confirms that while the benefits of AI in construction are acknowledged, significant barriers hinder its widespread adoption, particularly the high perceived initial cost for SMEs. Adoption levels are currently moderate and concentrated in larger firms. Key challenges beyond cost include awareness gaps, integration difficulties, skill requirements, and reliability concerns. This study contributes empirical data quantifying these issues within the UK context and underscores the critical role of company size. The proposed recommendations offer practical pathways for stakeholders to collaboratively mitigate these barriers, fostering broader AI adoption and helping the construction industry realise the transformative potential of these technologies for improved project planning and execution.

Chapter 6: Evaluation Of Objectives

This chapter reflectively evaluates the extent to which the research objectives, outlined in Chapter One, were achieved. The evaluation considers the methodology employed and the findings presented in Chapter 4, providing insights into the research outcomes.

6.1 Evaluation of Research Objectives

Each research objective was addressed as follows:

1. To assess the current level of AI adoption in construction project planning and execution: This objective was successfully met. The survey analysis established a baseline, indicating moderate overall AI tool usage (average 1.3 tools/respondent) but with significant variation linked to company size and pre-survey awareness. The quantitative approach effectively captured adoption levels, though future qualitative work could explore usage nuances.
2. Quantify how widespread this barrier [cost] is across different construction firms (small, medium, large-scale): This objective was effectively achieved. The analysis clearly quantified the strong inverse relationship between company size and the perception of cost as a prohibitive barrier. The data demonstrated that SMEs perceive cost as a significantly greater obstacle than large firms, fulfilling the objective of quantifying this difference. Future research could explore the specific financial thresholds driving these perceptions.
3. To discuss the key barrier of cost limiting AI integration in project planning and execution: This objective was fully addressed. The research identified high initial investment, particularly in software licensing and hardware, as the most significant cost factors hindering adoption, based on direct respondent feedback and ranking. The discussion detailed how these upfront costs act as primary deterrents across the industry. Further investigation into actual cost values versus perception could be beneficial.
4. To evaluate industry professionals' perceptions of AI in construction: This objective was comprehensively met. The study evaluated perceptions beyond cost, capturing strong agreement on AI's potential benefits (e.g., efficiency, accuracy) alongside widespread concerns about risks (e.g., reliability, integration challenges, skill requirements). Analysis by professional role added further nuance. Future work might track how these perceptions evolve with increased exposure or training.

5. To propose strategies to address and mitigate AI adoption challenges: This objective was successfully achieved by developing a set of evidence-based, actionable strategies presented in Section 4.5 and summarised in 5.2. These strategies directly target the key barriers identified through the research analysis, providing practical recommendations for relevant stakeholders. Assessing the real-world effectiveness of these strategies is a logical next step.

6.2 Summary

The research successfully fulfilled all stated objectives through a quantitative survey and detailed analysis. It provided valuable empirical data on AI adoption levels, cost barriers differentiated by firm size, key cost components, professional perceptions, and proposed relevant mitigation strategies within the UK construction context.

6.3 Lessons Learned

This research journey provided substantial learning in research methodology, from survey design and ethical considerations to data analysis using Excel and interpretation of findings. Managing the survey process, including addressing response rates, offered practical project management experience. Synthesising literature and empirical data into a cohesive argument and actionable recommendations enhanced critical thinking and writing skills. The study provided deep insights into the specific challenges of technology adoption in construction, particularly the significant hurdles faced by SMEs regarding cost and resources. This understanding of real-world barriers and potential solutions will be invaluable in future professional practice related to technology implementation and project management. A full reflective account on the project is given in Appendix 2.

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Appendices

Appendix 1: Survey Questions

Respondent Profession

Job Role - Which of the following best describes your job role?

Options – Project Manager, Engineer, Architect, Contractor, IT Specialist (Including AI specialist), Other

AI Awareness

1. Which of the following AI-related tools or technologies are you currently using in your construction projects? (Check all that apply)

   Options:

   - Building Information Modelling (BIM) software with AI features (e.g., Autodesk BIM 360, Revit)
   - AI-powered project management platforms (e.g., Procore, Autodesk Construction Cloud)
   - Predictive analytics tools for cost estimation and scheduling (e.g., Alice Technologies, RIB Software)
   - Computer vision systems for site monitoring and safety (e.g., Smartvid.io, Pillar Technologies)
   - Machine learning algorithms for material quantity estimation
   - Generative AI tools: Large Language Models (LLMs) for content generation and communication (e.g., Gemini, ChatGPT, Claude, DeepSeek, Copilot); Image generation AI for design visualisation (e.g., Midjourney, DALL-E 2)
   - Microsoft Copilot in M365 and MS Project
   - None of the above
2. Before taking this survey, were you aware that you were using these AI tools or technologies in your projects? (Yes/No)
3. If not, did this survey help you recognise their use? (Yes/No)

AI Cost Perception

1. To what extent do you agree or disagree with the following statements about the cost of AI implementation in construction? (Strongly Disagree to Strongly Agree) The initial investment cost of AI software is too high.
2. Please rank the following cost components in order of their significance as barriers to AI adoption in your company (1 = most significant, 5 = least significant):
   Options:
   - Hardware and infrastructure costs
   - Training and development costs
   - Integration and implementation costs
   - Ongoing maintenance and support costs
   - Software licensing costs

AI Benefits

To what extent do you agree with the following statements about the potential benefits of AI in construction? (Strongly Disagree to Strongly Agree)

1. AI tools can significantly improve efficiency and productivity in construction projects.
2. AI can enhance the accuracy of cost estimation and scheduling.
3. AI can help mitigate risks and improve safety on construction sites.
4. AI can enable better decision-making in construction projects.

AI Risks and Limitations

To what extent do you agree with the following statements about the potential benefits of AI in construction? (Strongly Disagree to Strongly Agree)

1. There are significant risks associated with using AI tools in construction
2. AI tools may be unreliable or produce inaccurate results.
3. AI tools may be difficult to integrate with existing workflows
4. AI tools may require specialised expertise to operate and maintain.

Company Size and Type

1. Company Size - What is your company's approximate annual turnover?
   Options: £1 – 9.99 Million; £10 - £99.99 Million; > £100 Million
2. Company Type - What type of construction projects does your company primarily work on?
   Options: Residential; Commercial; Industrial; Infrastructure; Other

Closing Remark (Optional Text Feedback Text)

Thank you for your participation! Your responses will be valuable to this research project. If you have any additional comments or feedback, please feel free to share them below.

Appendix 2: Reflective Account of the Research Journey

This research project, culminating in this dissertation, has been a significant learning experience, marked by careful planning, unexpected challenges, necessary adaptations, and invaluable support. This reflective account details the journey from inception to completion.

Initial Planning and Early Challenges

The project began with the crucial, yet initially challenging, task of topic selection. I found myself somewhat indecisive, exploring several avenues before refining the focus to "Investigating the Cost Barrier to AI Adoption in Construction Project Planning and Execution." This refinement was essential to ensure the scope was manageable within the dissertation timeframe. My initial project plan, visualised in a Gantt chart (see **Appendix 3: Planned Project Timeline**), projected a completion date of 30th April 2025.

As this was my first experience conducting a dissertation based on primary data collection, there was a steep learning curve. Defining precise research objectives and selecting the appropriate analysis method presented early hurdles. Initially, I considered using regression analysis, but through discussions with my supervisor, Dr. Gill, it became clear that my research was more investigative in nature, exploring adoption levels and perceptions rather than testing direct causal relationships between measured variables. Dr. Gill's guidance was instrumental in clarifying the objectives and aligning the methodology correctly, shifting towards descriptive and comparative statistical analysis using Excel.

The Ethics Approval Setback and Adaptation

A significant, unforeseen challenge arose during the ethics approval process. My initial plan allocated only a few days for this, but because the research involved collecting primary data from human participants, it required advanced ethics approval. This process ultimately took approximately one month, creating a substantial bottleneck as I could not begin survey distribution during this period.

This delay threatened to push the project significantly beyond the university deadline. However, a pivotal meeting with my supervisor, Dr. Gill, led to a crucial adaptation in my working strategy. Instead of following a strictly sequential chapter-writing process (1 through

6), she advised me to work on different sections concurrently. I began drafting Chapter 2 (Literature Review) and simultaneously worked on designing the survey instrument for Chapter 3 (Methodology). Once the literature review was well underway, I tackled Chapters 3 and 1. This non-linear approach allowed me to make productive use of the ethics approval waiting period, significantly mitigating the potential delay. This required considerable adaptability but proved highly effective. The final writing sequence became Chapter 2, then Chapters 3 and 1 concurrently, followed by Chapter 4, and finally Chapters 5 and 6.

Survey Design and Data Collection Experience

Designing the questionnaire presented its own set of challenges. In retrospect, I included some questions that did not directly contribute to answering the research questions, such as asking respondents if the survey itself helped them recognise their AI use. A more significant limitation was my approach to collecting qualitative feedback. Instead of asking specific open-ended questions, I included an optional field for general comments. This resulted in limited qualitative data, with only 10 out of 55 respondents providing comments, making it impossible to identify definitive patterns. This experience highlighted the importance of careful question structuring, particularly for gathering rich qualitative insights. Going forward, I will dedicate more time to crafting targeted open-ended questions. Consulting with colleagues during the design phase was helpful in refining other aspects of the survey.

The data collection phase itself was also challenging. My initial optimistic plan was to send out 100 surveys and receive 100 responses. The reality required sending out 120 surveys to achieve 55 completed responses. While this was lower than hoped, my supervisor commended this 45.8% response rate as good for this type of survey, which was reassuring.

Learning Supports and Overall Experience

Throughout the project, the formal learning opportunities provided through taught classes were invaluable. Sessions on conducting literature reviews, research methodologies, data analysis techniques, source selection, and data reporting provided essential foundational knowledge.

Beyond the formal teaching, the regular guidance and support from my supervisor, Dr. Gill, were critical to navigating the complexities of the research process, particularly during the ethics delay and methodology refinement stages. Furthermore, the requirement to attend campus biweekly, while sometimes tasking, enriched the experience. It provided opportunities for informal discussions with fellow project students, including others supervised by Dr. Gill, creating a supportive peer network.

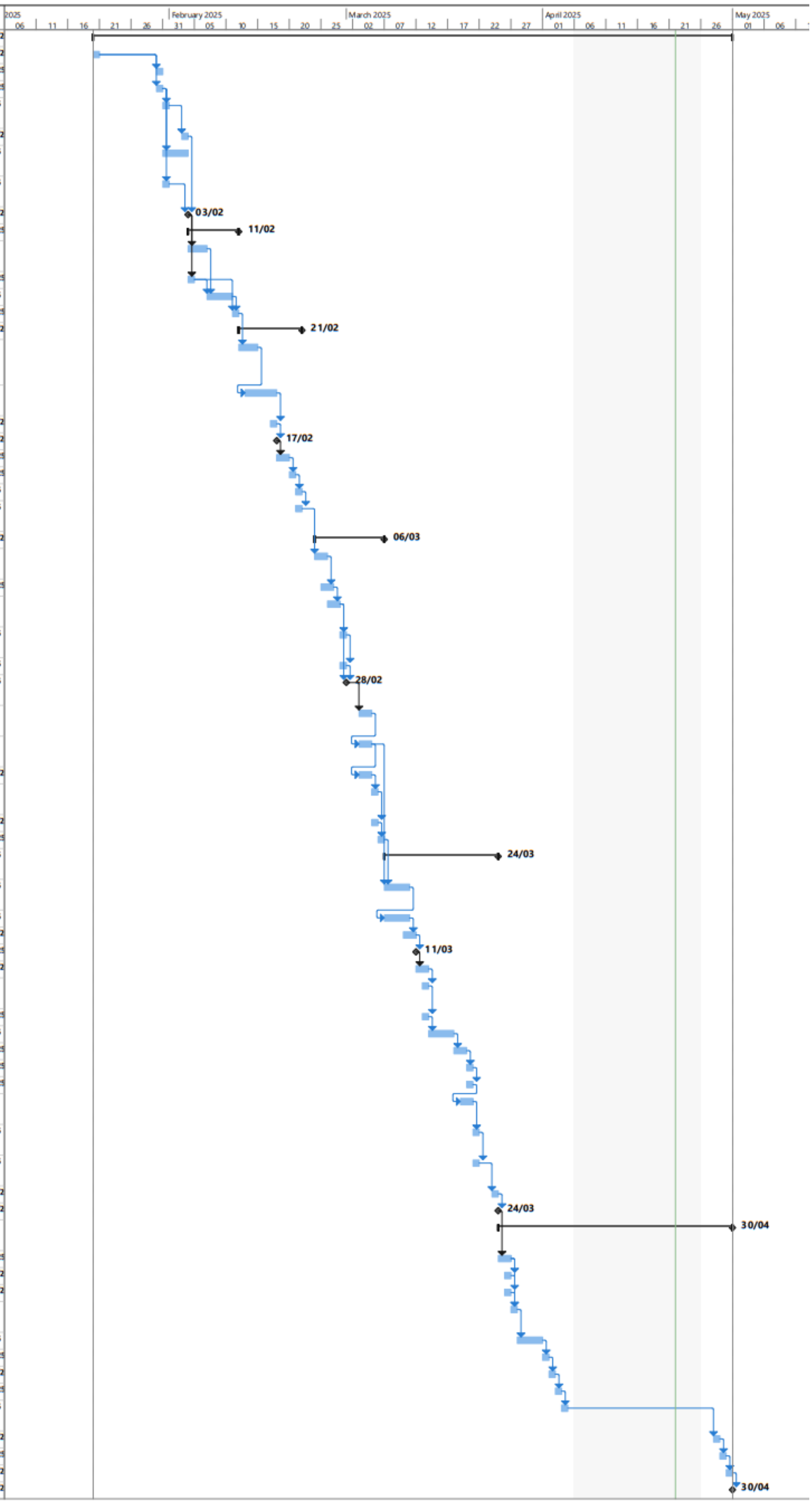
Timeline Outcome and Final Reflections

Despite the significant delay caused by the ethics approval process, the adaptive writing strategy enabled me to largely recover the lost time. The final project completion date is anticipated to be 6th May 2025 (see Appendix 4), only a slight deviation from the original 30th April 2025 target.

Overall, this dissertation journey has been an incredibly valuable and positive experience. It pushed me to develop new skills in primary research, data analysis, and academic writing. It demanded adaptability and resilience in the face of unexpected challenges. The process underscored the importance of meticulous planning, the necessity of seeking and incorporating guidance, and the value of a supportive academic environment. I emerge from this project with greater confidence in my research abilities and a deeper understanding of the complexities of AI adoption in the construction industry.

Appendix 3: Planned Project Timeline

ID		Task Name	Duratio	Start
1		MSc Dissertation Timeline	58 days	Mon 20/01/2
2		Supervisor Assignment	1 day	Mon 20/01/2
3		Supervisor Meeting 1	1 day	Thu 30/01/25
4		Research Proposal	1 day	Thu 30/01/25
5		Research Proposal Feedback and Correction	1 day	Fri 31/01/25
6		Ethics Approval Request	1 day	Mon 03/02/2
7		Preliminary Reading (Literature Review)	2 days	Fri 31/01/25
8		Research Timeline Planning (Gantt Chart)	1 day	Fri 31/01/25
9		Project Kick off	0 days	Mon 03/02/2
10		Chapter 1	6 days	Tue 04/02/25
11		Literature Review Targetted search	3 days	Tue 04/02/25
12		Supervisor Meeting 2	1 day	Tue 04/02/25
13		Structure of Literature R	2 days	Fri 07/02/25
14		correction from feedbac	1 day	Tue 11/02/25
15		Chapter 2 (Literature Revi	8 days	Wed 12/02/2
16		Read through materials gathered for themes and debates	3 days	Wed 12/02/25
17		Literature Review: in-depth Analysis & Theoretical Frame	3 days	Thu 13/02/25
18		Conceptual Framework	1 day	Mon 17/02/2
19		Begin Literature Review	0 days	Mon 17/02/2
20		Literature Review Draft	2 days	Tue 18/02/25
21		Supervisor Meeting 3	1 day	Thu 20/02/25
22		correction from feedbac	1 day	Fri 21/02/25
23		Final draft and submission of Literature Review	1 day	Fri 21/02/25
24		Chapter 3 (Methodology)	9 days	Mon 24/02/2
25		Read for alingnment with theory and practice	2 days	Mon 24/02/25
26		Develop methodology	2 days	Tue 25/02/25
27		Data Collection Preparation -Survey design	2 days	Wed 26/02/25
28		Supervisor Meeting 4 - Methodology Review	1 day	Fri 28/02/25
29		correction from feedbac	1 day	Fri 28/02/25
30		Survey Distribution Commences	0 days	Fri 28/02/25
31		Survey Distribution and Response Collection	2 days	Mon 03/03/25
32		Continue data collection, begin preliminary data	2 days	Mon 03/03/25
33		Write up remaining sect	2 days	Mon 03/03/2
34		Supervisor meeting 5 - Proofread	1 day	Wed 05/03/25
35		correction from feedbac	1 day	Wed 05/03/2
36		Submit Chapter 3	1 day	Thu 06/03/25
37		Chapter 4 - Results and analysis/discussion	12 days	Fri 07/03/25
38		record results from data collection	2 days	Fri 07/03/25
39		data cleaning and orgar	2 days	Fri 07/03/25
40		Review and Validate dat	2 days	Mon 10/03/2
41		Data Analysis Commenc	0 days	Tue 11/03/25
42		Initial result analysis	2 days	Wed 12/03/2
43		supervisor meeting 6 - Initial results	1 day	Thu 13/03/25
44		correction from feedbac	1 day	Thu 13/03/25
45		Data Analysis	2 days	Fri 14/03/25
46		Results Presentation	2 days	Tue 18/03/25
47		supervisor meeting 7	1 day	Thu 20/03/25
48		correction from feedbac	1 day	Thu 20/03/25
49		Findings discussion and write sections	2 days	Wed 19/03/25
50		supervisor meeting 8 - proofread	1 day	Fri 21/03/25
51		chapter correction based on feedback	1 day	Fri 21/03/25
52		submit chapter 4	1 day	Mon 24/03/2
53		Chapter 4 concluded	0 days	Mon 24/03/2
54		chapter 5 and 6 - conclusions and recommendation	12 days	Tue 25/03/25
55		Write chapter 5 and 6	2 days	Tue 25/03/25
56		supervisor meeting 9	1 day	Wed 26/03/2
57		correction from feedbac	1 day	Wed 26/03/2
58		Front page, Table of Content, Abstract and Reference List	1 day	Thu 27/03/25
59		Edit, Review and Improv	2 days	Fri 28/03/25
60		supervisor meeting 10	1 day	Tue 01/04/25
61		Objective Evaluation wr	1 day	Wed 02/04/2
62		Supervisor Meeting 11	1 day	Thu 03/04/25
63		Final Review/rewriting based on corrections	1 day	Fri 04/04/25
64		Reflect on Lesson Learr	1 day	Mon 28/04/2
65		Final Editing and Proofr	1 day	Tue 29/04/25
66		Final Submission	1 day	Wed 30/04/2
67		End of Project	0 days	Wed 30/04/2



Appendix 4: Actual Timeline

ID		Task Name	Duratio	Start	Finish
1		MSc Dissertation Timeline	62 day	Mon 20/01/25	Tue 06/05/25
2			22 day	Mon 20/01/25	Tue 18/02/25
3		Supervisor Assignment	1 day	Mon 20/01/25	Mon 20/01/25
4		Supervisor Meeting 1	1 day	Tue 28/01/25	Tue 28/01/25
5		Research Proposal	2 days	Thu 30/01/25	Fri 31/01/25
6		Research Timeline Planning (Gantt Chart)	1 day	Fri 31/01/25	Fri 31/01/25
7		Supervisor Meeting 2 -Research Proposal Feedback and Correction	1 day	Tue 04/02/25	Tue 04/02/25
8		Survey Question Creation (Needed for	2 days	Tue 04/02/25	Wed 05/02/25
9		Project Topic Amendment	2 days	Wed 05/02/25	Thu 06/02/25
10		Supervisor Meeting 3	1 day	Tue 11/02/25	Tue 11/02/25
11		New Topic Approval	1 day	Tue 11/02/25	Tue 11/02/25
12		Ethics Approval Request and Risk Assessment	1 day	Wed 12/02/25	Wed 12/02/25
13		Preliminary Reading (Literature Review)	2 days	Thu 13/02/25	Fri 14/02/25
14		Project Kick off	0 days	Mon 17/02/25	Mon 17/02/25
15		Supervisor Meeting 4	1 day	Tue 18/02/25	Tue 18/02/25
16		Chapter 2	9 days	Mon 17/02/25	Thu 27/02/25
17		Literature Review: In-depth Analysis & Theoretical Frame	2 days	Mon 17/02/25	Tue 18/02/25
18		Conceptual Framework	1 day	Wed 19/02/25	Wed 19/02/25
19		Begin Literature Review	1 day	Thu 20/02/25	Thu 20/02/25
20		Literature Review Draft (section 1 to 4)	2 days	Fri 21/02/25	Mon 24/02/25
21		Supervisor Meeting 5	1 day	Tue 25/02/25	Tue 25/02/25
22		Correction from the meeting supervisor 3 and complete Literature review	2 days	Wed 26/02/25	Thu 27/02/25
23		Chapter 2 Completed	0 days	Fri 28/02/25	Fri 28/02/25
24		Chapter 3 and 1	14 day	Fri 28/02/25	Thu 20/03/25
25		Read for allingnment with theory and practice	2 days	Fri 28/02/25	Mon 03/03/25
26		Supervisor Meeting 6 - Methodology Discussion	1 day	Tue 04/03/25	Tue 04/03/25
27		Develop methodology section 1 - 6	4 days	Wed 05/03/25	Mon 10/03/25
28		Supervisor Meeting 7	1 day	Tue 11/03/25	Tue 11/03/25
29		Correction from Meeting 7	1 day	Tue 11/03/25	Tue 11/03/25
30		Develop Methodology section 7 to 9	2 days	Wed 12/03/25	Thu 13/03/25
31		Complete Chapter 1	2 days	Fri 14/03/25	Mon 17/03/25
32		Supervisor Meeting 8	1 day	Tue 18/03/25	Tue 18/03/25
33		Correction from Meeting 8	1 day	Tue 18/03/25	Tue 18/03/25
34		Complete Chapter 3 and 1	0 days	Wed 19/03/25	Wed 19/03/25
35		Ethics Correction and Resubmission	1 day	Wed 19/03/25	Wed 19/03/25
36		Ethics Approval	0 days	Thu 20/03/25	Thu 20/03/25
37		Chapter 4	15 day	Thu 20/03/25	Wed 30/04/25
38		Survey Distribution Commences	3 days	Thu 20/03/25	Mon 24/03/25
39		Supervisor Meeting 9	1 day	Tue 25/03/25	Tue 25/03/25
40		Survey Distribution Conti	2 days	Wed 26/03/25	Thu 27/03/25
41		Survey Distribution ends	0 days	Fri 28/03/25	Fri 28/03/25
42		record results from data collection	1 day	Fri 28/03/25	Fri 28/03/25
43		data cleaning and organis	1 day	Mon 31/03/25	Mon 31/03/25
44		Supervisor Meeting 10	1 day	Tue 01/04/25	Tue 01/04/25
45		Review and Validate data	1 day	Tue 01/04/25	Tue 01/04/25
46		Data Analysis Commence	1 day	Wed 02/04/25	Wed 02/04/25
47		Result Collation	1 day	Thu 03/04/25	Thu 03/04/25
48		Writing Chapter Commen	1 day	Mon 28/04/25	Mon 28/04/25
49		Supervisor Meeting 11	1 day	Tue 29/04/25	Tue 29/04/25
50		Corrections on Chapter 4	1 day	Wed 30/04/25	Wed 30/04/25
51		Chapter 4 Completed	0 days	Wed 30/04/25	Wed 30/04/25
52		Chapter 5 and 6	4 days	Thu 01/05/25	Tue 06/05/25
53		Write chapter 5 and 6	2 days	Wed 30/04/25	Thu 01/05/25
54		Front page, Table of Content, Abstract and Reference List	1 day	Fri 02/05/25	Fri 02/05/25
55		Edit, Review and Improve	1 day	Fri 02/05/25	Fri 02/05/25
56		Final Review/rewriting based on corrections	1 day	Mon 05/05/25	Mon 05/05/25
57		Final Editing and Proofrea	1 day	Mon 05/05/25	Mon 05/05/25
58		Final Submission	1 day	Tue 06/05/25	Tue 06/05/25
59		End of Project	0 days	Tue 06/05/25	Tue 06/05/25