MASTER THESIS

FROM BARRIERS TO BUSINESS

Analysing AI Adoption in Construction via TOE and DOI, and Building a Consultancy Business Opportunity with Discovery-Driven Planning framework

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ABSTRACT

The construction industry has been slow in adopting artificial intelligence, despite its potential to improve productivity, safety, and decision-making. This thesis investigates the key challenges hindering AI adoption in construction firms and explores how consultancy services could serve as a solution to accelerate digital transformation. A qualitative research design was employed, combining a comprehensive literature review with expert interviews to identify current AI use cases, barriers to adoption, and propose a market opportunity for technology-neutral consultancy. The findings reveal that AI adoption remains in the early innovation lifecycle phase and is constrained by fragmented stakeholder ecosystems, low digital maturity, especially among SMEs, and the high cost of proprietary technologies. These barriers indicate that AI adoption is not solely a technological challenge, but also an organizational and strategic one. A tailored consultancy model is proposed to bridge the gap between awareness and implementation, particularly for underserved SMEs. While the model presents a promising business opportunity, it remains untested in real-world settings. This study contributes to both academic and practical understanding by combining technology related innovation management and entrepreneurial theories to analyse a pressing industry problem. Future research should incorporate real-world use cases or practical experimentation to validate the proposed consultancy model, particularly in relation to geographic and construction-specific characteristics. This approach would strengthen the development of the concept beyond the limitations of relying solely on external sources. The study suggests that overcoming adoption barriers through accessible consultancy services can promote more inclusive and sustainable digital transformation in the construction sector.

TABLE OF CONTENTS

TABLE OF FIGURES

I. CHAPTER

1 INTRODUCTION

The construction industry is under increasing pressure to modernize in response to global demands for greater efficiency, sustainability, and productivity. Among the technologies with the potential to support this transformation, artificial intelligence stands out as a powerful tool for automating processes, enhancing decision-making, and optimizing resource use. To establish a foundation and better understand this landscape, the first research question investigates ***how artificial intelligence defined within the construction industry and what types of AI applications are currently used in the sector.*** The findings were categorized and introduced into five groups namely, automation, robotics, and digital integration; cost estimation and contract management; data-driven project management; safety and risk management; and sustainability.

Despite the growing availability and application of such tools, the construction industry faces several persistent barriers that hinder widespread AI integration. To explore this issue further, the thesis examines ***the key technological, organisational, and environmental barriers influencing AI adoption in construction firms.*** Using the combination of Diffusion of Innovation theory and Technology-Organization-Environment framework, the study aims to clarify why certain firms struggle to adopt AI and what systemic conditions are holding back broader transformation. The findings include high implementation costs, lack of digital skills, unclear return on investment, and fragmented collaboration among stakeholders. While some large firms have begun integrating AI into their operations, the majority of SMEs remain digitally underdeveloped.

In response to these findings, the study explores a potential entrepreneurial opportunity: the development of a consultancy service specifically aimed at supporting AI adoption among SMEs. Traditional consultancies often cater to large, well-resourced clients, offering solutions that are either too costly or overly complex for smaller firms. This gap signals a significant market opportunity for a technology-neutral, implementation-focused consultancy that can raise awareness about AI technologies, offer tailored products, and help SMEs transition from interest to execution. The third research question investigates ***how an ai consultancy business opportunity can be developed, using the discovery-driven planning framework.*** This process included the creation of four key planning tools: a reverse income statement, pro forma operations specifications, a key assumptions checklist, and a milestone planning table, detailing when and how key assumptions should be tested. Together, these tools helped structure the business model around real market needs, but the assumptions made still require validation through practical experimentation to refine the real-world viability and scalability of the proposed consultancy.

II. CHAPTER

2 PROBLEM STATEMENT AND RESEARCH QUESTIONS

2.1 Problem Statement

The construction industry is an important contributor of the global economy, accounting for approximately 13% of global GDP and employing around 7% of the world's workforce (Korke, R, Shewale, & Khartode, 2023; Pan & Zhang, 2021; Ivanova, Kuznetsov, Zverev, & Rada, 2023; Mischke, Stokvis, & Vermeltfoort, 2024). Its significance is projected to grow even further, with global construction spending forecasted to rise from $13 trillion in 2023 to $22 trillion by 2040, reflecting a compound annual growth rate of 3.2% (Mischke, Stokvis, & Vermeltfoort, 2024). At the same time, the industry is expected to expand by 85%, reaching $15.5 trillion by 2030, driven by surging demand from leading markets such as China, the United States, the United Kingdom, Germany, and Nigeria (Korke, R, Shewale, & Khartode, 2023; Regona, Yigitcanlar, Xia, & Li, 2022). These projections highlight the growing importance of the construction sector for infrastructure development and global economic employment.

This upward trajectory is closely tied to demographic shifts. As the global population is projected to increase from 8.5 billion in 2030 to 9.7 billion by 2050 and then may reach around 10.4 billion by 2100 (Datta, Islam, Sobuz, Ahmed, & Kar, 2024). The need for urban infrastructure, housing, and transport systems will grow accordingly. However, while the demand for construction services rises, the sector's ability to provide it is limited due to a series of structural problems.

One of the most critical issues is persistently low productivity. Over the past two decades, construction productivity has improved by just 10%, equivalent to an average annual rate of 0.4%, far behind the broader economy's 2% and manufacturing's 3% annual improvements (Mischke, Stokvis, & Vermeltfoort, 2024; Regona, Yigitcanlar, Xia, & Li, 2022). From 2020 to 2022, the situation worsened with an 8% decline in global construction productivity (Mischke, Stokvis, & Vermeltfoort, 2024). This persistent stagnation in productivity has directly contributed to escalating construction costs, which have risen 1–3% annually above the general inflation rate (Mischke, Stokvis, & Vermeltfoort, 2024). Between 2015 and 2023, costs increased by 36% in Europe and 52% in the United States, placing additional financial strain on projects and stakeholders (Mischke, Stokvis, & Vermeltfoort, 2024).

Closely linked to these productivity challenges is the growing labour shortage. In advanced economies, the workforce is aging rapidly: 41% of the pre-2020 construction labour force in the United States is expected to retire by 2031, while the United Kingdom anticipates losing 25% of its workforce over the next 15 years (Mischke, Stokvis, & Vermeltfoort, 2024). Meanwhile, near-zero or negative workforce growth in countries like China further reduces the availability of skilled labour. These shortages are already having tangible consequences. For example, the construction of a $40 billion chip factory in Arizona was delayed due to an insufficient number of qualified workers (Mischke, Stokvis, & Vermeltfoort, 2024).

Safety also remains a major concern. Construction is one of the most hazardous industries, responsible for 30–40% of global workplace fatalities (Pan & Zhang, 2021; Ivanova, Kuznetsov, Zverev, & Rada, 2023). Non-fatal injuries are also significantly higher compared to other industries, with the rate of serious non-fatal injuries, such as fractures, dislocations, and other physical traumas, being 71.51% higher in construction than the average across economic sectors (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Despite increased awareness, these figures reveal a persistent gap in the industry's ability to ensure worker safety.

At the core of many of these issues lies a broader challenge: the construction sector's limited digital transformation. It remains one of the least digitized industries worldwide (Blanco, Rockhill, Sanghvi, & Torres, 2023; Ivanova, Kuznetsov, Zverev, & Rada, 2023). AEC firms typically invest just 1% of their revenue in IT, far below the 3–5% average of other industries (Blanco, Rockhill, Sanghvi, & Torres, 2023). This digital underinvestment not only limits the potential for innovation but also perpetuates inefficiencies across planning, execution, and operational processes.

Among these challenges, Artificial Intelligence emerges as a powerful enabler of transformation. The global AI market is projected to grow from $93.53 billion in 2020 to $997.77 billion by 2028, representing an annual growth rate of 40.2% (Rafsanjani & Nabizadeh, 2023). Specifically in construction, AI's market value is forecasted to rise from $429.20 million in 2018 to $4.51 billion by 2026, with a projected industry-wide value gain of $520 billion by 2035, accounting for up to 19% of the sector's worth (Rafsanjani & Nabizadeh, 2023).

Artificial Intelligence offers transformative potential for the construction industry by addressing many of its long-standing challenges. Through the automation of repetitive and time-consuming tasks, AI improves operational efficiency while freeing up human resources for more complex activities. It also supports better decision-making through data-driven insights and improves on-site safety via real-time monitoring systems. These advancements could boost labour efficiency by up to 40% and potentially double annual economic growth rates by 2035 (Pan & Zhang, 2021), while also reducing costs, mitigating risks, and reshaping the construction sector into a more productive and resilient industry (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024).

However, despite its potential, AI adoption within the construction sector remains limited (Abioye, et al., 2021; Pan & Zhang, 2021). This thesis therefore aims to investigate the current environment of AI within the construction industry and explore the key challenges hindering its adoption. The knowledge gained through this research is intended to identify indicators for potential entrepreneurial contributions that can help address these deeply rooted industry problems.

2.2 Research Questions

To navigate the complex intersection between entrepreneurial opportunity and implementation challenges in the construction industry, this thesis is guided by three research questions. These questions were formulated to provide a structured pathway.

The starting point for was to gain sufficient knowledge and establish a conceptual clarity around what constitutes AI in the context of construction. By identifying current use cases and implementation trends, this question aims to provide a comprehensive overview of how AI is being applied across various construction functions and workflows.

HOW IS ARTIFICIAL INTELLIGENCE DEFINED, AND WHAT TYPES OF AI APPLICATIONS ARE CURRENTLY USED IN THE CONSTRUCTION INDUSTRY?

Once a clear picture of the industry's technological state is formed, it becomes possible to investigate the underlying reasons for the gap between potential and practice. The next part applies the TOE framework to categorize and analyse the key challenges that construction firms face when adopting AI. It considers technological, internal, and external conditions.

WHAT ARE THE TECHNOLOGICAL, ORGANISATIONAL, AND ENVIRONMENTAL BARRIERS INFLUENCING AI ADOPTION IN THE CONSTRUCTION INDUSTRY?

By revealing the root causes of resistance and identifying where firms typically struggle, the groundwork is laid for proposing actionable solutions. The final question moves from diagnosis to design. It leverages the findings from the first two questions to conceptualize a viable business opportunity.

Based on the previous findings:
HOW CAN AN AI CONSULTANCY BUSINESS OPPORTUNITY BE DEVELOPED, USING THE DISCOVERY-DRIVEN PLANNING FRAMEWORK?

III. CHAPTER

3 METHODOLOGY

3.1 Research Design

This study adopts an exploratory research design, which is particularly suitable for addressing undefined or emerging problems, as it aims to develop a better understanding of complex issues that are not yet clearly articulated (Saka, 2023). A key strength of this approach is its flexibility and adaptability to change, allowing for an initially broad focus that becomes more refined as new data and insights emerge (Saka, 2023). It encourages the researcher to remain open to shifting directions based on findings, without compromising the overall direction of inquiry.

Exploratory research may incorporate both quantitative and qualitative techniques, including literature review, online desk research, and semi-structured interviews (Saka, 2023).

Given the multifaceted nature of AI and construction, the research is framed within an interpretive approach. This paradigm emphasizes the importance of understanding reality from multiple, subjective perspectives (Adil, et al., 2022). Rather than seeking a single objective truth, the interpretive approach focuses on how individuals and organizations interpret and give meaning to technological change. It is particularly useful for understanding social phenomena that are context-dependent, such as innovation adoption in traditional industries.

The study employs a narrative, concept-centric style to structure its findings (Webster & Watson, 2002). This involves organizing themes based on conceptual relationships found in the literature and empirical data, rather than chronologically or author-by-author. By drawing on multiple data sources, including academic publications, digital content, and practitioner insights, the study ensures a form of triangulation, which improves the credibility and robustness of the results (Bans-Akutey & Tiimub, 2021).

Problem Framing
Identified a relevant problem in construction and explored AI as a potential solution
Defined the knowledge needed to understand the issue

Research Design
Applied an exploratory, interpretive qualitative approach

1st Research Question – Inductive Analysis
Mapped current AI landscape in construction
12 articles + 49 software providers

2nd Research Question – Deductive Analysis
Identified adoption barriers
21 articles + 6 Interviews

3rd Research Question – Deductive Analysis
Explored business opportunity from the challenges
4 articles + 8 Interviews

Figure 1, Research roadmap

3.2 Data Collection

This thesis employed a twofold data collection strategy combining a structured literature review and semi-structured expert interviews.

3.2.1 Literature Review

This section describes the methodology used to conduct the literature review for the entire thesis. The aim was to establish a structured and sufficient understanding of the academic and industry-based knowledge related to Artificial Intelligence and its deployment to the construction industry.

The role of a literature review is to classify and map existing knowledge about a specific area (Rowe, 2014). The review used the first dimension of literature review typologies, which focuses on building an understanding of a new and emerging phenomenon by connecting it to established theories and frameworks. In this case, the phenomenon is AI applications and their integration into the construction industry, a field still considered emerging and fragmented in academic literature.

A comprehensive search was conducted across major academic databases, including the AAU Library, ScienceDirect, and ResearchGate. The searching process used the combinations of the following key words: “AI”, “Artificial Intelligence”, “Construction”, “Digitalisation”, “Application”, “Adoption”, “Challenges”, and “Transformation”.

The inclusion criteria for selecting sources were: (1) publications from 2020 onwards to ensure relevance to recent developments, (2) peer-reviewed scientific journal articles, academic books, or reputable industry reports, (3) direct or indirect relevance to AI technologies, their applications, or adoption challenges in the construction industry, and (4) English-language publications only.

A total of 42 scientific articles were selected: 10 for the Problem Statement section, 32 (including the 10 from the Problem Statement) for the Analysis sections, and an additional 10 for the Methodology section. These are listed in the Appendix II. Chapter, categorized based on where they were used within the thesis. The review process continued until theoretical saturation was reached, meaning no new concepts or themes emerged from the literature (Webster & Watson, 2002).

In addition to academic literature, online desk research was conducted to explore real-world AI services providers, resulting in the identification of 49 examples, which are also presented in the Appendix III. Chapter with a brief introduction about their services. This involved systematically reviewing company websites, news articles, industry portals, and public reports to gather data on current AI adoption and market trends.

3.2.2 Interviews

Semi-structured interviews were conducted to gather in-depth insights from professionals with diverse backgrounds, roles, and perspectives related to construction, AI and digital transformation. Participants were selected through purposive sampling to ensure relevance to the research objectives. Invitations were sent via LinkedIn, where participants were asked to schedule a short online call. The final sample included professionals from different geographic locations, area of operation, and levels of expertise.

Most interviews were conducted online, with one held in person. Each session lasted approximately 30–45 minutes. A semi-structured interview guide was followed to maintain consistency while allowing flexibility to elaborate on their experiences and views. Interviews began with 2–3 warm-up questions tailored to the participant's background, followed by five main questions aligned with the research questions. When questions were unclear or required further elaboration, follow-up questions were asked to clarify or expand on their responses. All participants gave verbal consent prior to the interviews. With permission, the sessions were recorded and later transcribed for analysis.

The core questions focused on:

1. Readiness or motivation of construction firms to adopt AI-based technologies.
2. General problems or inefficiencies observed in the industry, and the most valuable contribution AI currently offers.
3. Major obstacles to AI implementation, whether technical, cultural, or organizational.
4. How they support construction firms in adopting new technologies through their services.
5. Future predictions about AI and digital technology over the next 5–10 years.

A total of 8 people were interviewed for this study. Further details about each interview can be found in Appendix I. Chapter. This includes the name of each interviewee, their location, LinkedIn profile, the date and type of interview whether in-person or online, a short professional introduction as presented at the beginning of each session, a summary of the interview, and the full transcription.

3.3 Data Analysis

This section outlines the analytical approaches used to answer the three research questions of the thesis. Two different strategies were applied based on the nature of the questions and the type of data collected: a literature-based inductive analysis for the first research question, and a theory-guided deductive analysis for the second and third research questions.

3.3.1 Inductive Analysis

The first research question aimed to develop a foundational understanding of how AI technologies are used in the construction industry, including their current applications and future potential. Since this question was exploratory in nature and addressed through a review of existing academic literature, an inductive qualitative analysis was employed.

Inductive analysis is a method of identifying patterns, categories, and themes that emerge directly from the data, without being constrained by pre-existing theories or models (Thomas, 2006; Sauce & Matzel, 2017). This approach is especially useful when the goal is to build a general understanding based on observed evidence.

The analysis followed a systematic and transparent process. First, the selected literature was thoroughly reviewed to gain familiarity with the content and identify relevant segments. These insights were then grouped into thematic categories, including AI technologies and their application areas. Overlapping or redundant categories were merged or refined to enhance clarity. Finally, a visual overview was developed to organize the findings and illustrate the connections between the categories.

A concept-centric structure was used to present the results. This approach grouped insights around core themes instead of summarizing sources one-by-one, enabling a more focused and analytical synthesis of the literature (Webster & Watson, 2002). The outcome was a set of well-defined thematic categories that helped structure the answer to the first research question. These findings also formed the basis for the conceptual framework used later in the thesis to reflect on how AI contributes to the construction industry.

3.3.2 Theory-Driven Deductive Analysis

The second and third research questions required a more structured analytical approach, using deductive analysis to guide the coding and interpretation process based on established conceptual frameworks.

Deductive analysis involves applying existing theoretical models to data to test or illustrate their relevance in a specific context (Varpio, Paradis, Uijtdehaage, & Young, 2020). It follows a top-down logic: rather than allowing themes to emerge freely, it starts from predefined categories derived from theory (Fife & Gossner, 2024).

For RQ2, which focused on identifying AI adoption challenges, the analysis was guided by two well-established models: the Technology-Organization-Environment (TOE) Framework and the Diffusion of Innovation (DOI) Theory. These models were integrated into a unified structure which was necessary to avoid redundancy and ensure conceptual clarity, as they address overlapping but distinct areas of innovation adoption.

The integration was carried out as follows:

- The Technological context was aligned with DOI technology attributes such as relative advantage, observability, compatibility, trialability, and complexity.
- The Organizational context incorporated DOI's concept of the social system, addressing organisational structure, culture and leadership, communication, and firms size.
- The Environmental context includes industry characteristics and external technology, regulatory environments, social and stakeholder dynamics, and DOI's time element.

The RQ3 analysis was a continuation of the previous findings. The opportunities were derived directly from the insights gained through the development of the thesis, including the literature review, interviews, and the first and second analysis. First, promising areas for potential business were identified using entrepreneurial opportunity theory. This opportunity was then further developed using the Discovery-Driven Planning (DDP) framework, which provided a systematic approach for transforming preliminary idea into well-defined business concept.

3.4 Validation

To enhance the validity and reliability of the findings, triangulation was used by integrating data from academic literature, online desk research, and semi-structured interviews. Triangulation is classically defined as "looking at one research object from different perspectives" (S. Caillaud, 2021; Bans-Akutey & Tiimub, 2021). This approach enabled a more comprehensive understanding of the topic by comparing and verifying insights across multiple sources.

During the literature review, only concepts supported by multiple authors were considered. Interview questions were asked consistently across different professionals to detect patterns, and desk research helped validate findings in practice. All interpretations were documented transparently to refine and validate the emerging insights. This combination of perspectives ensured the robustness of results while reducing the risk of bias or misinterpretation.

3.5 Limitations

This study acknowledges several limitations. First, the number of expert interviews was limited due to time and resource constraints, potentially narrowing the range of perspectives and depth of insights obtained. Second, the use of publicly available online data restricted access to internal company strategies and processes, which may have limited the completeness of the findings. Third, while qualitative methods enabled an in-depth understanding of the topic, the results are context-specific and cannot be generalized to the entire construction industry. Lastly, as the researcher conducted all data analysis independently, there is a risk of subjective interpretation and bias, despite efforts to ensure transparency and validation through triangulation.

IV. CHAPTER

4 ANALYSIS OF THE FIRST RESEARCH QUESTION

HOW IS ARTIFICIAL INTELLIGENCE DEFINED, AND WHAT TYPES OF AI APPLICATIONS ARE CURRENTLY USED IN THE CONSTRUCTION INDUSTRY?

Artificial Intelligence (AI) refers to the study and development of intelligent systems that replicate human-like reasoning, problem-solving, and decision-making capabilities (Datta, Islam, Sobuz, Ahmed, & Kar, 2024). The philosophical foundations of AI include philosophy, literature, computer science, electronics, and engineering (Abioye, et al., 2021; Datta, Islam, Sobuz, Ahmed, & Kar, 2024).

Although the study of AI began in the 1950s, its progression from abstract theoretical models to practical, real-world applications has been slow and dramatic (Holzmann & Lechiara, 2022). Over the decades, the definition of AI has evolved alongside technological advancements and shifting research priorities. Earlier proposals mainly focused on symbolic reasoning and rule-based logic, but modern understandings prioritise autonomy, learning, and adaptation. For instance, AI is now widely defined as ***systems that demonstrate intelligent behaviour by perceiving their environment and acting, often with a degree of autonomy, to accomplish defined objectives*** (Holzmann & Lechiara, 2022). Another widely accepted definition defines AI as a ***system capable of accurately processing external input, learning from it, and using that gained knowledge to effectively achieve specific tasks and goals*** (Holzmann & Lechiara, 2022). These modern definitions take a broader and more functional approach, reflecting the present capabilities and expectations of AI technology.

AI is commonly categorized into three hierarchical classifications based on its capabilities: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). ANI, also known as weak AI, is characterized by machine intelligence limited to specific domains and narrowly defined tasks such as playing chess, predicting sales, recommending movies, translating languages, or forecasting weather (Abioye, et al., 2021; Datta, Islam, Sobuz, Ahmed, & Kar, 2024). It focusses on great efficiency within specific contexts rather than trying to replicate every aspect of human intelligence (Datta, Islam, Sobuz, Ahmed, & Kar, 2024). In contrast, AGI or strong AI seeks to develop machines with a general cognitive capability comparable to that of humans. These systems aim to solve a wide range of complex problems across multiple domains while functioning autonomously and showing characteristics such as self-awareness, emotional understanding, and adaptive reasoning (Abioye, et al., 2021). Since the development of machines that can perfectly simulate human intelligence has proven to be both elusive and technically challenging, the concept of AGI is still largely hypothetical (Abioye, et al., 2021). From a technical aspect, AGI's core components are knowledge representation, learning, perception, action, planning, and communication (Datta, Islam, Sobuz, Ahmed, & Kar, 2024). The final classification, Artificial Super Intelligence (ASI), refers to a hypothetical stage in AI development where machines outperform human capabilities in nearly all fields of knowledge and performance (Abioye, et al., 2021). While ASI is still theoretical, it represents the farthest horizon of AI research and serves as a conceptual context for addressing long-term AI possibilities.

In order to establish a comprehensive understanding of artificial intelligence and its conceptual foundations, this study examined a range of relevant AI subfields. This exploration was considered essential to ensure a solid theoretical foundation for the subsequent analysis. Due to limitations in the main body of the thesis, an extended discussion of these subfields is presented in Appendix IV. Chapter.

4.1 AI Applications in the Construction Industry

Artificial intelligence is increasingly being explored and implemented within the construction sector across a variety of functional areas. As the available literature suggests, the use of AI spans a wide range of activities, reflecting the technology's potential to influence multiple stages of the construction lifecycle (Ivanova, Kuznetsov, Zverev, & Rada, 2023; Abioye, et al., 2021). However, due to the diversity of construction processes and the rapid pace of technological development, providing a complete overview of all existing AI applications remains a challenge. Therefore, this section aims to drawn on a thematic literature review to highlight the main categories in which AI is currently applied. The purpose is to offer a structured overview of these application domains, supported by selected examples from academic and industry sources. The categorisation used here includes ***Automation, Robotics, and Digital Integration; Cost Estimation and Contract Management; Data-Driven Project Management; Safety and Risk Management; and Sustainability***. These categories reflect the dominant themes identified in the literature and form the analytical framework for presenting the current state of AI application in the construction industry.

4.1.1 Automation, Robotics, and Digital Integration

Automation and robotics are redefining the construction industry by introducing a new level of efficiency, accuracy, and adaptability. Assisted by AI, these technologies can perform repetitive and labour-intensive tasks with precision and consistency over long period of time without fatigue (Egwim, et al., 2024). AI-driven automation reduces physical strain and the risk of human error as well as improves the industry's ability to tackle complex construction challenges in both routine and hazardous environments. This rising connection between robotics and AI is laying the foundation for a more digital, intelligent, and sustainable construction industry. Consequently, automation technologies have significant effect on workforce evolution. Construction jobs, particularly those requiring low to medium education, face a 38–45% probability of automation by the mid-2030s (Abioye, et al., 2021; Regona, Yigitcanlar, Xia, & Li, 2022). However, new roles are emerging to support AI integration, such as construction AI researchers, trainers, and engineers, each with responsibilities in development, deployment, and system testing (Abioye, et al., 2021).

Automation in construction is increasingly being applied in both off-site and on-site contexts. Off-site, robotic prefabrication systems reduce dependency on weather conditions and manual labour by automating the production and assembly of building components in controlled environments (Regona, Yigitcanlar, Xia, & Li, 2022). These systems work alongside with task-specific on-site robots that are capable of performing structural assembly, inspection, maintenance, and finishing tasks. For example, AI-powered robots have been used on-site for bricklaying, welding, and tiling with consistent quality output (Korke, R, Shewale, & Khartode, 2023; Rafsanjani & Nabizadeh, 2023). Depending on the application, these robots function either autonomously or through teleoperation. Another example of on-site AI-enabled automation is autonomous excavation technology. These systems rely on sensor-guided machinery and pre-set geospatial parameters to perform earthmoving tasks with high precision, thereby reducing manual labour and increasing safety (Regona, Yigitcanlar, Xia, & Li, 2022). Additionally, robotic construction methods integrated with AI have shown promising results in controlled digital fabrication settings. In such environments, AI supports productivity evaluation by analysing metrics such as total cost and time per installed unit, allowing for more precise control in the construction of complex architectural forms (Egwim, et al., 2024). This technology has showed the potential to evaluate productivity, based on parameters like total cost and time per installed unit, providing improved control over the production of complex geometries (Egwim, et al., 2024).

As more AI-driven and automated robots are integrated across the construction sites, digital twin technology emerges as a complementary innovation that improves their effectiveness. A digital twin is a dynamic, real-time virtual reproduction of a physical construction site, generated with continuous streams of data from sensors, drones, and video cameras. These advanced models simulate and visualize real time ongoing site activities, such as the position and the movement of machines or equipment (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Digital twins enable data-driven decisions and adjustments, whether by human managers or autonomous systems. However, the accuracy and utility of digital twin systems can be limited by insufficient video quality and difficult weather conditions that disrupt data collection (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Companies like Komatsu and INSITE are addressing these challenges by integrating AI, computer vision, deep learning, and aerospace algorithms into their smart construction systems to improve equipment awareness and enable more accurate operational analysis (Regona, Yigitcanlar, Xia, & Li, 2022).

Complementing AI-enabled automation and monitoring systems, recent advancements in drones, sensors, and computer vision are transforming infrastructure inspection and site surveillance. These technologies offer automated, scalable alternatives to traditional, labour-intensive site observation (Korke, R, Shewale, & Khartode, 2023). For instance, convolutional neural networks (CNNs) have been trained to recognise structural defects through video feeds providing 83.22% accuracy in identifying high-level defects (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Similarly, deep learning models used in together with UAV imagery to estimate building heights by processing overlapping image segments and producing precise elevation maps (Ivanova, Kuznetsov, Zverev, & Rada, 2023). One practical example of computer vision and robotic integration is the vision-based intelligent mobile robot hoisting system, which autonomously identifies hoisting points and releases components without human intervention (Egwim, et al., 2024).

Augmented Reality (AR) has also proven to be useful for task execution and training. AR applications that combine BIM integration, 3D scanning, and gesture-based interaction help guide users through manual tasks. In an experimental setting, AR was tested for pipe assembly tasks and showed notable time-saving benefits for both professional fitters and engineering students, particularly for users with lower spatial cognition (Ivanova, Kuznetsov, Zverev, & Rada, 2023).

4.1.2 Cost Estimation and Contract Management

Artificial intelligence (AI) technologies are being increasingly applied across several domains of construction project planning and financial management. Their integration facilitates improved accuracy in forecasting costs and timeframes, enhances bidding and tendering procedures, and supports more consistent and transparent contract management.

In the area of cost estimation, AI methods have been used to develop nonparametric prediction models that provide accurate cost forecasts even with limited input data (Ivanova, Kuznetsov, Zverev, & Rada, 2023). These models can capture nonlinear dependencies within input variables to provide strong performance estimating volumes of work and accurate early-stage cost assessments (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Furthermore, hybrid approaches have been used to model water consumption costs based on variables such as concrete volume, weather, wood use, and labour input. Such models have yielded highly accurate predictions, with an average error margin of 2.66% (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Additional applications have supported the estimation of material requirements. These systems have achieved estimation accuracies with average absolute errors of 8.56% for concrete consumption and 17.31% for reinforcement usage during the early stages of civil construction planning (Ivanova, Kuznetsov, Zverev, & Rada, 2023). In the context of modular or prefabricated construction, improved models have also been applied to estimate costs related to component manufacture, transportation, and assembly, thereby contributing to the development of comprehensive pre-cost budget models (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Deep learning algorithms have also been integrated with BIM to enhance 4D (time-based scheduling) and 5D (cost estimation) planning capabilities. These integrations improve the accuracy of cost and schedule estimations by using both structured and unstructured data (Abioye, et al., 2021; Regona, Yigitcanlar, Xia, & Li, 2022; Faraji, Arya, Ghasemi, & Shiri, 2024). This approach allows for visual simulation and the dynamic re-evaluation of timelines and expenses throughout the design process.

AI has also shown potential in improving bidding and tendering processes based on influential project variables, allowing for more consistent and strategic proposal generation (Ivanova, Kuznetsov, Zverev, & Rada, 2023). In road construction procurement, machine learning techniques have been applied to datasets like bidder identity, road type, and submission cost to detect suspicious bidding patterns that may indicate collusion or bid manipulation (Ivanova, Kuznetsov, Zverev, & Rada, 2023).

Beyond pre-construction planning, AI-based prediction models have also been applied to forecast financial risks associated with accidents and delays. Deep learning models trained on historical financial loss data have enabled more reliable predictions and supported the development of tools for financial risk mitigation and sustainable cost management in ongoing construction projects (Ivanova, Kuznetsov, Zverev, & Rada, 2023). In comparison to traditional scheduling practices, deep learning techniques have outperformed legacy systems in forecasting project durations (Datta, Islam, Sobuz, Ahmed, & Kar, 2024).

In the area of contract management, AI tools have been introduced to streamline the analysis of large, complex legal documents. These tools are capable of clause identification, risk extraction, summarisation, and contract classification using natural language processing (NLP) and machine reading comprehension models (Abioye, et al., 2021). Nevertheless, early applications indicate a reduction in errors, improved accessibility to critical clauses, and enhanced compliance monitoring.

4.1.3 Data-Driven Project Management

Artificial intelligence (AI) technologies are transforming the construction industry by offering intelligent site analytics, real-time collaboration, and data-driven project control. These advancements are supported by the ongoing creation of massive amounts of data from construction sites, most of which is unstructured and difficult to handle using traditional approaches.

Construction sites are becoming smart environments through the integration of digital technologies such as Internet of Things (IoT) sensors, drones, and real-time monitoring systems. These tools continuously collect data on environmental conditions, equipment performance, and construction site activities (Faraji, Arya, Ghasemi, & Shiri, 2024; Regona, Yigitcanlar, Xia, & Li, 2022). The collected data supports the implementation of AI systems, which improve decision-making for predictive and data-driven project management (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024).

The integration of AI into project and construction management platforms enables automated data analysis, pattern recognition, and the formalisation of tacit knowledge. These capabilities help identify operational problems early and allow for real-time intervention and corrective actions (Korke, R, Shewale, & Khartode, 2023). When implemented into BIM systems, AI enhances the optimisation of planning, design, safety, quality, scheduling, and cost control (Abioye, et al., 2021). Several AI-driven optimisation techniques are already in use. For example, process mining algorithms monitor workflows to detect inefficiencies, forecast deviations, and extract collaboration patterns that improve operational control and reduce rework (Korke, R, Shewale, & Khartode, 2023). Machine learning algorithms support real-time progress tracking, predictive scheduling, and dynamic resource allocation based on data from drones, sensors, and cameras (Rafsanjani & Nabizadeh, 2023; Faraji, Arya, Ghasemi, & Shiri, 2024). Predictive models can also forecast delays and performance issues by incorporating external variables such as weather conditions, workforce availability, and supplier reliability (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024). Advanced applications of AI include convolutional neural networks (CNNs), discrete event simulation (DES), and recurrent neural networks (RNNs). These tools are used for predictive scheduling, automated timeline updates, and the analysis of equipment activity to identify inefficiencies, particularly in earthmoving operations (Aladag, Güven, & Balli, 2024; Ivanova, Kuznetsov, Zverev, & Rada, 2023).

AI also plays a key role in improving supply chain transparency and coordination, especially when combined with blockchain and IoT technologies. This integration facilitates real-time material tracking, automated contract execution, equipment monitoring, and risk detection, while also building trust across supply chain partners (Abioye, et al., 2021; Regona, Yigitcanlar, Xia, & Li, 2022).

In logistics management, AI supports inventory optimisation and autonomous coordination of warehouse and delivery operations. Sensor networks and cloud computing systems enable AI-driven inventory control, including automated rack placement and order fulfilment. Real-time data transmission to cloud platforms supports remote access and integration with transport operations, ultimately reducing resource consumption (Ivanova, Kuznetsov, Zverev, & Rada, 2023).

Site quality control is another area improved by AI. AI-powered analytics tools can detect construction defects and deviations from design specifications automatically, supporting higher quality standards and compliance (Rafsanjani & Nabizadeh, 2023).

Communication and collaboration also benefit from AI technologies. Natural Language Processing (NLP) enables chatbots and virtual assistants to support seamless information exchange, while AI-based collaboration platforms allow real-time document sharing among distributed teams (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024). These tools reduce miscommunication, improve transparency, and support centralised project tracking. Moreover, the development of Voice User Interfaces (VUIs), integrated with BIM and Industry 4.0 ecosystems, offers hands-free interaction for site workers (Abioye, et al., 2021).

Cloud-based data storage further enhances collaboration by providing scalable and secure access to project data. AI systems that utilise historical data can identify patterns, predict project outcomes, and improve planning by learning from past experiences. AI optimisation algorithms also assist in evaluating trade-offs between time, cost, and quality, supporting more effective decision-making in both architectural design and project execution (Korke, R, Shewale, & Khartode, 2023).

4.1.4 Safety and Risk Management

As one of the most hazardous industries, construction faces persistent challenges in protecting workers from injury and fatality. The introduction of AI technologies has enabled a paradigm shift in safety and risk management, offering proactive and data-driven approaches to hazard detection, prevention, and response. Through a combination of real-time monitoring, predictive analytics, and immersive training environments, AI is being leveraged to enhance worker safety across multiple dimensions. The following subsections present the key areas where AI applications are being actively deployed to reduce risk and support more resilient and secure construction sites.

Computer vision is one of the most widely applied AI technologies in construction safety. It has been utilised for real-time detection of helmet usage, posture analysis, and the identification of unsafe worker behaviour on-site (Ivanova, Kuznetsov, Zverev, & Rada, 2023; Aladag, Güven, & Balli, 2024). These applications are often developed by Convolutional Neural Networks (CNNs), which are trained on large datasets of images and videos. One system based on this approach achieved an accuracy rate of 83.89% in detecting the presence and colour classification of helmets (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Another application involved the use of a Mask Region-Based CNN (Mask R-CNN) to detect workers crossing structural supports. This model reached an accuracy of 90.35% in identifying individuals and 75.31% in detecting their interaction with structural elements (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Additionally, computer vision has also been deployed for facial recognition and motion detection to ensure only authorised individuals access specific site areas (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Other applications developed using computer vision techniques include real-time monitoring of worker-machine interactions and fatigue monitoring in crane operators (Ivanova, Kuznetsov, Zverev, & Rada, 2023).

AI technologies like ANNs and Case-Based Reasoning are used to forecast risks before they occur. These systems analyse historical data from past incidents to predict the likelihood of similar events occurring under current conditions. One model utilizing case-based reasoning was trained on past fatal accident reports and achieved a prediction accuracy of 86.31%

(Ivanova, Kuznetsov, Zverev, & Rada, 2023). Similarly, ANN models have been developed to learn patterns in past injury data and assess the risk level of present site conditions, making proactive risk management more feasible (Ivanova, Kuznetsov, Zverev, & Rada, 2023).

Building Information Modelling (BIM), when improved with AI, serves as a powerful tool for proactive safety planning. By simulating various construction phases, AI-integrated BIM can identify potential hazards, such as fall risks or machinery conflicts, before actual work begins (Abioye, et al., 2021; Faraji, Arya, Ghasemi, & Shiri, 2024; Ivanova, Kuznetsov, Zverev, & Rada, 2023). These simulations help safety managers make informed decisions during the planning stage. Furthermore, when connected to wearable devices and site sensors, BIM platforms can continuously feed real-time data into AI models, allowing for dynamic assessment of safety conditions. These models are trained to distinguish between safe and unsafe states, enabling timely intervention (Regona, Yigitcanlar, Xia, & Li, 2022; Abioye, et al., 2021).

Digital twin technology extends the utility of BIM by creating continuously updated virtual replicas of physical construction environments. These digital models are used to visualize scenarios, such as smoke dispersion in fire events and to simulate the movement of equipment and workers (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Integrated AI algorithms analyse these simulations to predict dangers and optimize responses. These systems frequently rely on networks of IoT sensors to supply dynamic data inputs for ongoing hazard analysis. For instance, in underground construction environments AI powered, IoT-connected sensors provide early warnings and alerts for hazardous conditions (Ivanova, Kuznetsov, Zverev, & Rada, 2023). The reliability and precision of such systems are directly influenced by the quality of the algorithms and the extent of investment in their development.

Unmanned Aerial Vehicles (UAVs), when combined with AI-driven object recognition capabilities, have been implemented to monitor safety compliance across road construction sites. These UAV-based systems are used to detect safety signage, construction equipment, workers, and protective barriers. While field trials indicated the viability of the technology, the performance was constrained by factors such as UAV durability, flight stability, regional regulatory compliance, and limitations in object detection algorithm efficiency (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Despite these challenges, UAVs remain a valuable asset for augmenting safety inspections from an aerial perspective.

Health and Safety Analytics represents another domain where AI is transforming construction safety. These systems applies machine learning models to large datasets collected from IoT devices, wearables, and digital platforms to identify patterns associated with occupational hazards (Abioye, et al., 2021; Regona, Yigitcanlar, Xia, & Li, 2022; Farhadi, 2024). Key risk-related factors include worker actions, risk management practices, immediate supervision, equipment usability, local hazards, worker capabilities, and project management conditions (Abioye, et al., 2021). Classification and optimization algorithms help safety teams pinpoint and prioritize threats, enabling more effective safety management practices.

Augmented and virtual reality technologies have also been incorporated into safety training environments. AI-based training platforms simulate real-world construction scenarios, allowing workers to engage with hazardous situations in a risk-free environment (Datta, Islam, Sobuz, Ahmed, & Kar, 2024; Egwim, et al., 2024). These tools improve learning by providing realistic, interactive experiences that improve hazard recognition and decision-making skills.

Several commercial products illustrate the real-world application of AI in construction safety, bridging the gap between academic research and on-site implementation. These tools represent a diverse set of innovations, each tailored to specific aspects of safety management, from real-time monitoring to predictive risk assessment. Their presents highlight the increasing accessibility and practical relevance of AI technologies for construction firms aiming to improve workplace safety through automation, data analytics, and proactive decision-making systems:

4.1.5 Sustainability

Artificial intelligence (AI) technologies are increasingly utilised in the construction sector to enhance resource efficiency and support sustainable practices. The application of AI spans diverse operational areas, including waste management, energy consumption monitoring, logistics, and supply chain optimisation, with the common goal of enabling data-driven decision-making and process automation.

Approximately 35% of global waste is generated by the construction industry, with particularly high figures reported in countries such as Canada (65%), Australia (50%), and Hong Kong (35%) (Datta, Islam, Sobuz, Ahmed, & Kar, 2024). The statistics underscore the need for intelligent waste-minimising design and AI-supported deconstruction planning. In the domain of waste management, AI creates a shift from reactive approaches to proactive, design-integrated strategies. Waste analytics relies on building design specifications, material properties, and construction methodologies to predict and minimise waste generation (Abioye, et al., 2021; Regona, Yigitcanlar, Xia, & Li, 2022; Faraji, Arya, Ghasemi, & Shiri, 2024). This data is processed using advanced analytics techniques to develop detailed waste profiles and inform material reuse, procurement optimisation, and deconstruction planning. By integrating AI techniques with BIM, it is possible to optimise offsite construction, select sustainable materials, and reduce waste-intensive processes throughout the project lifecycle (Abioye, et al., 2021; Aladag, Güven, & Balli, 2024). AI systems have also been applied post-construction to identify and categorise waste, enabling the selection of appropriate handling methods (Aladag, Güven, & Balli, 2024).

The use of AI in energy management further contributes to sustainability efforts. AI-enabled systems can monitor and analyse energy consumption patterns on construction sites and within buildings, providing insights that support real-time energy-saving interventions (Faraji, Arya, Ghasemi, & Shiri, 2024; Rafsanjani & Nabizadeh, 2023). These systems use sensors and control algorithms to detect inefficiencies and recommend optimisation strategies, reducing environmental impact. In parallel, AI algorithms can assess building materials for their environmental performance and suggest low-carbon alternatives to reduce embodied emissions (Datta, Islam, Sobuz, Ahmed, & Kar, 2024).

Nonetheless, the scope of AI application continues to expand, covering environmental performance, labour and carbon optimisation, material flow tracking, and supply chain resilience.

4.2 Summary of the First Analysis

Artificial Intelligence (AI) refers to the development of intelligent systems capable of mimicking human reasoning, learning, and decision-making. Today, AI is broadly understood as a system that can perceive its environment, process data, learn from experience, and act autonomously to achieve specific goals. The domain of AI is vast and constantly evolving, encompassing a wide range of subfields and applications. Its conceptual foundations are rooted in disciplines such as philosophy, computer science, and engineering, and its current capabilities span from narrow task-specific systems to hypothetical models of general and superhuman intelligence.

In the context of the construction industry, AI has begun to reshape traditional workflows and offer innovative solutions to long-standing challenges. The industry is gradually transitioning toward a more digital, data-driven, and automated future. Given the diversity of AI technologies and the complexity of construction activities, this study has introduced and categorized the current applications of AI into five thematic areas to provide a structured overview of the field: Automation and Robotics, Cost Estimation and Contract Management, Data-Driven Project Management, Safety and Risk Management, and Sustainability.

In terms of automation, AI-powered robotics and digital integration are revolutionizing both off-site and on-site construction. Robots can now perform repetitive tasks such as bricklaying, welding, and excavation with high precision and efficiency, while digital twins offer real-time virtual models of construction sites for better monitoring and control. Augmented reality tools are being used to guide manual work and training, enhancing productivity and reducing errors.

AI has also significantly improved cost estimation and contract management by introducing accurate forecasting models, automating tender analysis, and facilitating smarter contract reviews. Machine learning algorithms help identify potential financial risks early and assist in planning complex prefabricated projects with more confidence and less waste.

The integration of AI into project management platforms allows for intelligent site analytics, real-time tracking, and proactive decision-making. AI systems process data from sensors, drones, and IoT devices to optimize workflows, predict delays, and improve scheduling, logistics, and supply chain operations.

Safety and risk management in construction have also benefited from AI technologies. Through real-time monitoring, computer vision, and predictive analytics, AI systems can detect unsafe behaviours, forecast potential accidents, and simulate hazard scenarios in virtual environments. Integration with wearable devices and site sensors enables dynamic safety assessments and faster response to emerging risks.

Finally, AI supports the sustainability agenda of the construction industry by enhancing resource efficiency and minimizing environmental impact. Intelligent systems help optimize waste management, monitor energy use, and support material selection based on environmental performance. AI enables more sustainable practices throughout the construction lifecycle, from design to demolition.

To bridge the gap between academic research and practical application, this study also collected and reviewed 49 real-life AI services currently available in the construction market. These examples are compiled in Appendix III. Chapter to illustrate the diversity and maturity of AI solutions being adopted by industry players today.

V. CHAPTER

5 ANALYSIS OF THE SECOND RESEARCH QUESTION

WHAT ARE THE TECHNOLOGICAL, ORGANISATIONAL, AND ENVIRONMENTAL BARRIERS INFLUENCING AI ADOPTION IN THE CONSTRUCTION INDUSTRY?

In recent years, the Diffusion of Innovation (DOI) theory and the Technology-Organization-Environment (TOE) framework have emerged as two of the most widely used models to explain the adoption and implementation of innovation and technology within organizations (Oliveira & Martins, 2011). While DOI provide insights into how innovations spread among individuals and organizations, recent studies suggest that the TOE framework complements and extends DOI theory by addressing its contextual limitations (Alka'awneh, Abdul-Halim, & Saad, 2025).

The diffusion of innovations (DOI) theory, developed by Everett M. Rogers in 1962, provides a framework for understanding how new ideas, practices, and technologies spread through societies, organizations, and industries. Rogers identifies four major factors that influences the diffusion of innovations; the ***attributes of innovation***, ***communication channels***, ***time*** and the ***characteristics of the social system***, where diffusion is defined as,

Full use of the innovation as the best course of action available (Rogers, 1983)

DOI has proven relevant in industries like construction, where the adoption of technologies remains uneven and often slow compared to other sectors (Ara, 2024).

The TOE framework, originally proposed by Tornatzky and Fleischer in 1990, focuses on the firm-level factors of technological adoption and describes the process as influenced by three contextual domains: ***Technological***, ***Organizational***, and ***Environmental***. Each TOE parts have a distinct impact on innovation uptake (Oliveira & Martins, 2011) and covers the broader internal and external circumstances that influence the adoption process inside organisations. This model views itself as a section within an overall trajectory of innovation, spanning from technology development to its implementation in specific organisational settings (Baker, 2011).

5.1 The Technological Context

The technological context provides the primary criteria for companies evaluate the feasibility, alignment, and strategic implications of adopting new technologies. This section includes the attributes of innovation such as, Relative Advantage, Observability, Compatibility, Trialability, and Complexity, which are influencing the technology diffusion.

5.1.1 Relative Advantage

The degree to which an innovation is perceived as better than the idea that it supersedes (Rogers, 1983).

The faster and more significantly an innovation is seen to improve existing processes, whether through cost savings, productivity, accuracy, or other metrics, the more likely it is to be adopted (Rogers, 1983). However, this perceived advantage is inherently subjective and role dependent (Ara, 2024). For instance, a project manager might focus on budget and scheduling benefits, while a design engineer may assess usability or integration potential. While AI holds the potential to deliver value to a wide range of stakeholders, the decision-maker responsible for adopting the technology is often primarily focused on its financial benefits. As one interviewee pointed out, financial impact remains the primary driver behind most adoption decisions,

If people can see AI is something to help them make more money, whether it's by saving people's time, whether it's by just being faster, doing things, whether it's being able to identify risks that maybe a human wouldn't be able to see otherwise. That's what construction companies really care about is how do they make more money (Johnson, 2025)

Construction is not just a technical field but a profit-driven industry, where innovations are evaluated largely through their return on investment. As Johnson said,

Obviously construction, the reason we all are in the business is to make money. (Johnson, 2025)

An important challenge related to the perceived relative advantage of AI is the limited awareness and understanding of its tangible benefits (Parekh & Mitchell, 2024). Despite a general recognition that AI is a significant trend, many stakeholders remain unclear about what the technology can actually deliver in practice. As one interviewee explained, this lack of clarity undermines motivation to adopt,

People know AI is important, they know they should care about it, but they don't really understand the technology... They can't be truly motivated to adopt something when they don't know what the benefits are. (Jacobsen, 2025)

In addition to limited awareness, a lack of capacity and readiness to explore new technologies further inhibits the perceived value of AI. Many decision-makers are not actively seeking technological improvements, as their attention is consumed by the immediate demands of ongoing projects. As one interviewee noted, the operational pressures of the construction industry often leave little room for long-term strategic thinking or investment in innovation, *They are so busy with their business that they are not making investments... When we go to the CEO, they say: "It's not for now. We have a lot of work right now." (Serra, 2025)*

Many firms prioritize completing deliverables on time and within budget, which may result to a rejection to engage in digital experimentation or adopt innovative technology. As another interviewee put it,

Moreover, the benefits of AI adoption often take time to materialize, which poses another challenge for decision-makers focused on short-term results (Regona, Yigitcanlar, Xia, & Li, 2022). Many of AI's advantages, such as improved data quality, predictive insights, or enhanced decision-making are intangible and tend to become seen only after sustained implementation (Xu, Zhou, Sekula, & Ding, 2021).

5.1.2 Observability

One of the key reasons for the slow adoption of AI in the construction industry is the lack of observability, the extent to which the results and benefits of an innovation are visible to potential adopters. When innovation outcomes are unclear or intangible, stakeholders hesitate to take actions (Rogers, 1983). This is especially true in construction, where limited awareness and understanding of AI technologies make it difficult for firms to grasp their potential (Parekh & Mitchell, 2024). Although a variety of AI software tools already exist, many companies remain unaware of them and therefore struggle to appreciate their value (Holzmann & Lechiara, 2022).

Even though the return on investment can be significant, construction firms have not been effective at quantifying these benefits (Blanco, Rockhill, Sanghvi, & Torres, 2023), as a result, the industry struggle to build a strong business case for investments in digital technologies (Ghimire, Kim, & Acharya, 2024). This leads to hesitation among project stakeholders, who are unwilling to invest without a clear understanding of expected outcomes (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024). As one of the interviewees pointed out, the understanding of the clear value is important for adoption,

They are thinking about it, but they're not really investing much into it yet. Right now, they're cautious. They want to see clear added value before they commit. (Kouhestani, 2025)

5.1.3 Compatibility

A company's existing technological infrastructure has a major influence on the scope and speed of innovation adoption since it serves as the foundation for the integration of new technologies (Baker, 2011). This existing base can either facilitate or constrain the implementation of new systems, depending on the level of alignment and compatibility with the new technology. In the context of the construction industry, the landscape for innovation adoption is particularly challenging with traditionally low level of digital maturity (Mischke, Stokvis, & Vermeltfoort, 2024). A great example of this problem is the outdated and unstructured way of storing data, as emphasized by interviewee,

They're storing everything in Excel spreadsheets (we've had clients with hundreds of thousands of them), or maybe their master data is inconsistent and scattered across silos. (Jacobsen, 2025)

The sector has long struggled with limited digital capabilities (Blanco, Rockhill, Sanghvi, & Torres, 2023) and suffers from a weak innovation culture that inhibits the widespread and effective uptake of new technologies (Yap, Lam, Skitmore, & Talebian, 2022). A key barrier to digital transformation lies in the integration of AI technologies with existing legacy systems. Many firms still rely on manual or semi-digital methods, lacking the foundational digital infrastructure needed to support the deployment of advanced AI systems (Mischke, Stokvis, & Vermeltfoort, 2024; Blanco, Rockhill, Sanghvi, & Torres, 2023). As one interviewee explained, the absence of digital data remains a significant obstacle,

Traditionally, construction industries, they don't digitalize their records. So, you have a lot of records in paper format, if it's even available and that is a major headache. (Ayeni, 2025)

Many AI systems are not easily integrated with legacy equipment or pre-existing digital platforms, creating friction and necessitating long and expensive customization or retrofitting (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024; Regona, Yigitcanlar, Xia, & Li, 2022). Without a sufficient digital foundation, the technology encounters interoperability issues, which create data silos, limit real-time collaboration, and undermine the effectiveness of AI-driven insights (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024). This fragmentation limits the performance of AI tools and highlights the need for organization-wide digital alignment. As one of the interviewees noted,

You can't use AI in just one department while another department is still running on paper… You end up investing in something that doesn't work well because there's no reliable stream of data feeding into it. (Taammoli, 2025)

Most AI models, particularly those based on machine learning, require extensive volumes of labelled and structured data to function effectively (Xu, Zhou, Sekula, & Ding, 2021; Ivanova, Kuznetsov, Zverev, & Rada, 2023). One of the most pressing compatibility issues of AI systems is the lack of standardized, structured, and high-quality data across construction projects. As noted in multiple expert interviews,

AI is built on data, but construction companies right now simply don't have high-quality, structured data. (Jacobsen, 2025)

The greatest challenge is the availability of quality data to fuel AI innovations. (Ayeni, 2025)

The accumulation of relevant data occurs unevenly, at different stages of the construction project (Ivanova, Kuznetsov, Zverev, & Rada, 2023). Therefore, model updating is a key challenge, because the training data can quickly become outdated as materials, methods, and regulations frequently change (Ghimire, Kim, & Acharya, 2024). Without recent data, models will miss new innovations and provide unreliable guidance. For example, an AI chatbot trained before the pandemic may overlook the impacts of supply chain disruptions and labour shortages problem. As one of the interviewees pointed out, without clean, consistent, and well-maintained data, AI tools struggle to function effectively,

If you don't have clean data, if you haven't standardized your data collection processes, and if you don't maintain continuity in your data, then AI can't do much. (Taammoli, 2025)

This issue is particularly critical because the construction industry lacks formal standards for data formats, component libraries, and implementation procedures, creating significant compatibility challenges that hinder the effective integration and scaling of AI solutions (Yap, Lam, Skitmore, & Talebian, 2022). Although AI offers considerable potential and advantages, organizations often assess these innovations in relation to existing technologies. If an AI-based solution does not align with current values or operational workflows resistance to adoption is likely to occur (Na, Heo, Han, Shin, & Roh, 2022).

5.1.4 Trialability

Trialability refers to the extent to which an innovation can be experimented with a limited basis (Rogers, 1983). The ability to trial an innovation helps reduce uncertainty for potential adopters, thereby increasing the likelihood of adoption, especially when the innovation also demonstrates relative advantage, compatibility, and low complexity.

Many construction firms are hesitant to invest in AI tools due to the high initial investment and risks associated with trial implementations (Egwim, et al., 2024). Pilot testing typically requires dedicated resources, extended lead times, and tolerance for uncertainty, all of which conflict with the low-risk experimentation and the short-term, risk-averse mindset prevalent in the industry (Yap, Lam, Skitmore, & Talebian, 2022). The previously discussed compatibility issues are closely tied to these trialability limitations, as the successful deployment of AI often depends on having a robust and modern technological foundation. As one interviewee explained, the process of preparing for AI adoption can be both lengthy and resource-intensive, further discouraging experimentation,

> *In many cases, they need to move to a cloud-based data platform, or even replace their ERP system altogether, and that alone can be a two- to three-year project. (Jacobsen, 2025)*

The costs associated with developing and maintaining AI models also diminish their attractiveness, especially for small and mid-sized construction firms. Training generative models requires massive computing power, specialized personnel, and ongoing investments in cloud infrastructure (Ghimire, Kim, & Acharya, 2024). As one interviewee pointed out, the cost challenge often begins at the very first step of engagement,

> *When you go to an AI company and say, "I want to integrate AI," the first thing they'll ask is, "Give me your data, in this format." And that's where the problems start. It's usually very expensive. (Taammoli, 2025)*

The high upfront development costs, combined with operational and energy expenses are growing and becoming increasingly unpredictable, especially as data and model demands evolve (Ivanova, Kuznetsov, Zverev, & Rada, 2023).

Another barrier is the immaturity of construction-specific AI technologies (Egwim, et al., 2024). Many AI tools remain in the experimental stage and are not yet optimized for practical application in unstructured, non-repetitive environments. AI's limited performance accuracy and tendency to produce hallucinated outputs further undermines trust, making firms more reluctant to engage in experimentation. As two interviewees pointed out, *Often, they don't even have many proven cases yet, and even a 2% error can be huge on a large project… They'd rather avoid using AI at all in some cases than risk those differences. (Taammoli, 2025)*

There's very little tolerance for error (Kouhestani, 2025)

Many machine learning systems, especially those intended for complex tasks, like action recognition or structural image classification, still perform poorly in real-world environments (Xu, Zhou, Sekula, & Ding, 2021; Egwim, et al., 2024). Generative AI models, trained on historical or context-specific datasets, often perform well during training but struggle to generalize to unfamiliar, real-world scenarios, such as unexpected weather delays or labour shortages, resulting in poor decision-making outcomes (Ghimire, Kim, & Acharya, 2024). For example, a GenAI system might generate inaccurate construction schedules with high confidence, which can severely disrupt project planning. These small errors can quickly escalate, triggering delays, miscommunications, and resource mismanagement and lead to significant losses (Abioye, et al., 2021). As one interviewee emphasized, even small inaccuracies can lead significant financial consequences in large-scale projects,

Then the cost of delays in projects is massive. (Johnson, 2025)

In such a high-stakes environment, decision-makers prefer to rely on familiar methods unless the benefits of innovation are clearly observable and well-documented (Abioye, et al., 2021; Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024). As one of the interviewees emphasized, construction companies don't like to take risks,

Construction companies tend to stick to their established procedures, because they trust them. Those processes have worked for them and that's why they don't take risks easily, they need to be very cautious. (Kouhestani, 2025)

Adding to these challenges is the widespread perception that AI remains a theoretical or immature concept, not yet ready for practical, day-to-day use in construction projects (Holzmann & Lechiara, 2022). Technological immaturity and the complex implementation process reinforce these concerns, making adoption seem risky and uncertain (Yap, Lam, Skitmore, & Talebian, 2022). As a result, trust in AI's reliability for critical applications is diminished, and many solutions remain experimental with limited real-world applicability, weakening their perceived advantage over traditional methods.

5.1.5 Complexity

Is the degree to which an innovation is perceived as difficult to understand, learn, and use. Technologies that are seen as intuitive and easy to adopt tend to spread more rapidly, whereas those that require significant new skills, infrastructure, or behavioural change often face resistance (Rogers, 1983).

The overall low level of digital literacy and technical familiarity among construction professionals presents a core obstacle. Many of whom have not been trained in using advanced computational tools or interpreting AI-generated outputs (Prabhakar, Xavier, & Abubeker, 2023). As a result, users often encounter challenges when trying to adapt their workflows to incorporate AI tools, as they may not fully understand how to interpret or verify AI-generated recommendations (Prabhakar, Xavier, & Abubeker, 2023). This leads to a disconnect between technological possibilities and everyday usability. When the individuals who are expected to rely on AI do not trust or understand it, the innovation fails to produce value, no matter how advanced the underlying system might be. As one interviewee said, adoption depends heavily on making these systems accessible and intuitive for non-technical users:

The main challenge is more human-centered. For example, you need to be able to enable a 50- or 60-year-old project manager to actually use and interact with that AI assistant to help "train" it. (Kouhestani, 2025)

Furthermore, if the new technology features a complex interface or has a high learning curve and disruptions to familiar processes often result in negative perceptions and users may resist its use regardless of its benefits (Na, Heo, Han, Shin, & Roh, 2022). As one interviewee pointed out, this challenge is compounded by resistance at the operational level:

When they hear that the manager wants them to fill out yet another form, daily or monthly, they naturally push back. They don't want extra work, and they often see new technologies as just more tasks rather than helpful tools. (Taammoli, 2025)

Another critical limitation lies in the lack of explainability and transparency inherent in many AI models. These systems often function as "black boxes," providing outcomes without clear explanations of how decisions were derived (Abioye, et al., 2021). Without transparent decision-making logic, construction professionals cannot understand how conclusions are drawn or verify their reliability against established engineering knowledge (Abioye, et al., 2021; Parekh & Mitchell, 2024). This opacity undermines user trust, feeds scepticism, and reduces the likelihood that construction professionals will rely on or integrate these tools into their decision-making processes. As one interviewee pointed out, the importance of developing explainable AI systems that are usable by professionals without programming expertise:

Explainable AI so can we still have an explainable AI's solutions? To allow for people who are not code based to be able to still develop and train AI, so there is that element. I mean you think about somebody who is a construction expert and not an IT specialist and you are telling the person to code. He just going to say to you I don't have time for that headache. (Ayeni, 2025)

If the new technology features a complex interface or requires significant changes to long-standing routines, users may resist its use regardless of its benefits (Na, Heo, Han, Shin, & Roh, 2022).

5.2 The Organizational Context

The organizational context refers the internal characteristics of a firm that influence the adoption and implementation of technological innovations. These include Organizational Structure, Culture and Leadership, Communication, and Firm Size and Resources which all influence how new technologies are evaluated, implemented, and used.

5.2.1 Organizational Structure

One of the most prominent organizational barriers lies in the low degree of standardization and industrialization across teams, projects, and business units. Construction projects typically operate in isolation, each with its own methods, tools, and management practices. This fragmentation has limited the scaling of improvement initiatives and discouraged firms from investing in long-term digital strategies (Blanco, Rockhill, Sanghvi, & Torres, 2023). Even when AI solutions are successfully implemented in one project, they are rarely scaled across multiple projects within the same company (Mischke, Stokvis, & Vermeltfoort, 2024). As one interviewee noted, even within the same organization, innovation often remains isolated:

> *Construction companies aren't structured for efficiency. They operate in silos, so even if you implement something smart on one project, it won't automatically be adopted across other projects in the same company. (Jacobsen, 2025)*

This isolation means that digitalization in construction is not just a matter of adopting new tools, it demands a shift in how businesses are structured and managed. Effective digital transformation requires coordinated changes across organizational structures, workflows, and job roles (Samuelson & Stehn, 2023). Organic and decentralized structures, known for flexible roles, team orientation, and informal interaction, are often associated with the early stages of adoption because they encourage openness to experimentation and the exchange of innovative idea (Oliveira & Martins, 2011). However, as innovation moves from experimentation to implementation, more mechanistic structures may be beneficial. These structures, marked by centralized decision-making, defined hierarchies, and standardized procedures, can provide the necessary coordination, accountability, and control to operationalize innovation at scale (Baker, 2011). Still, excessive bureaucracy can become a barrier. As one interviewee pointed out, rigid organisational layers in big companies can be problematic,

> *The really big companies have so much bureaucracy, and it's so hard to start implementation with them. (Serra, 2025)*

Many construction companies lack the organizational flexibility, open mindset, and long-term strategic vision needed to effectively introduce and integrate innovative technologies like AI (Holzmann & Lechiara, 2022). Successful AI implementation requires more than just adopting new tools, it requires a restructuring of internal systems and processes, reconfiguring existing workflows to accommodate AI-driven solutions, which often deeply rooted in traditional practices.

5.2.2 Culture and Leadership

A culture that encourages learning and risk-taking, without blaming failure, can help innovations get accepted and used more quickly (Na, Heo, Han, Shin, & Roh, 2022). In this context, organizational support in the form of policies, cultural reinforcements, and tangible resources are key elements. Employees are more willing to engage with new technologies, such as AI-based systems, when they feel that the organisation acknowledges their efforts, provides enough resources, and cultivates an environment in which learning and adaptation are rewarded rather than punished (Na, Heo, Han, Shin, & Roh, 2022). As one interviewee pointed out, applying modern technology is also becoming a competitive advantage in attracting younger talent,

> *Also all the young people that are coming into the industry. They want to use tech. They don't want to use Excel and e-mail and that's it. Like some people just refuse to work at those types of companies. I think they're also seeing it as a way to attract employees with. (Johnson, 2025)*

Still, many companies are resistant to change, which is undergoing technological transformation. Traditionally known ways of doing things are favoured above the new but un-trusted technologies promising to deliver great rewards (Abioye, et al., 2021; Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024), which highlights the effects of the industry's weak innovation culture (Yap, Lam, Skitmore, & Talebian, 2022). One of the underlying reasons for this resistance can be the increased transparency that digital technologies, tend to bring into workflows. As one interviewee observed, change is not only resisted due to unfamiliarity, but also because of the visibility and accountability it imposes on individuals and teams. For some, new technologies threaten their control over how information is presented or decisions are justified, which can generate friction,

> *Maybe one person is open to change and trying new things than someone else sees it as something that they don't want on their project because for whatever reason, they're just don't like change… It becomes more difficult for them to then control the narrative of the story they want to tell… It's bringing a lot of transparency into things which sometimes create some friction because people don't always want everyone to know everything that's happening right now (Johnson, 2025).*

Furthermore, executive support and a clear digital strategy are essential for successful integration. Leaders must champion innovation, allocate resources, and communicate the strategic value of AI initiatives, yet many construction firms fall short in this regard (Yap, Lam, Skitmore, & Talebian, 2022). Decision-makers may underestimate the extent of organizational change required or may perceive AI as too complex or expensive to prioritize in current business cycles (Holzmann & Lechiara, 2022). Typically, project outcomes are strictly managed with tight budgets, which discourages team leaders from piloting improvements (Mischke, Stokvis, & Vermeltfoort, 2024). As one interviewee emphasized, without genuine buy-in from top leadership, implementation efforts are likely to fail,

> *When we detect that a C-level person, who has to make the decision for the company to go forward with the implementation is not interested, we leave that project, because it's impossible without alignment from the C-level. (Serra, 2025)*

The absence of visible leadership commitment often translates into inadequate communication across departments. Communication channels are frequently informal, uncoordinated, and disconnected from strategic objectives. When employees lack clarity about the purpose, scope, and benefits of AI technologies, engagement drops, and scepticism grows (Holzmann & Lechiara, 2022). Without clear messages from leadership and continuous two-way communication with staff, digital transformation risks becoming fragmented, underfunded, or misunderstood. As one interviewee said, implementation can be failed if the leadership support is missing,

Where the management is laid back and don't give a hoot about what AI is all about. There's nothing the employees are going to do about it. (Ayeni, 2025)

However, effective communication from top management, also influences organizational openness to innovation. Leaders who express a compelling vision of technological transformation, integrate innovation with the firm's central goal, and give both formal and informal rewards for innovative behaviour contribute to an internal atmosphere that is ideal to change (Oliveira & Martins, 2011). As one interviewee explained, motivating change within such an environment often requires strong incentives and proactive effort:

People don't want to change these workflows… people don't want to learn unless you really incentivize them. (Serra, 2025)

Employee attitudes towards new technologies are largely influenced by senior management's commitment and ability to integrate innovation into strategic objectives (Baker, 2011; Na, Heo, Han, Shin, & Roh, 2022). In such environments, innovation is actively encouraged, and failure is viewed as a learning opportunity rather than a responsibility (Baker, 2011). As one interviewee noted, cultural alignment often follows the direction set by leadership,

Organisational management posture drives several outcomes… So if the management is taking a strong position in the adoption of AI, you'd expect that the employees behaviour and culture will move in that direction. (Ayeni, 2025)

5.2.3 Communication

Diffusion is a social process, relying heavily on interpersonal communication (Rogers, 1983). Central to this process are communication channels, which is between the source (typically change agents) and the receiver (potential adopters). These channels can be mass media or interpersonal interactions and can originate from either cosmopolite (external) or local sources. While mass media and cosmopolite sources are generally more effective in generating awareness and knowledge about an innovation, interpersonal channels and local sources play a more influential role in shaping attitudes and influencing adoption decisions (Irfan, 2021).

Internal communication mechanisms play a crucial role in the effectiveness of AI adoption. Clear, consistent, and targeted communication ensures that all stakeholders understand the purpose, benefits, and expectations associated with AI initiatives. Unfortunately, construction firms often lack formal communication plans that align technical language with user-friendly messaging (Holzmann & Lechiara, 2022). As one interviewee noted, building alignment through open discussion is important:

We make a point to meet with everyone involved, tech staff, project managers, operations people. If the owner needs to be involved, we'll meet with them too. If the owner wants subtrades included, we'll bring them in. The goal is to make sure everyone is part of the conversation. (Johnson, 2025)

However, within the firm there is no guarantee that these alignments are there,

Often, we're approached by someone in a tech or VDC (Virtual Design and Construction) role who's really enthusiastic about innovation. But that interest doesn't always translate to the project team. (Johnson, 2025)

Within these interpersonal networks, there are opinion leaders, who influence the opinions or behaviours of others. These people have a significant impact on how innovations are perceived and has a role in boosting the outreach process through targeted involvement. Informal connecting agents, such as, product champions, gatekeepers, and cross-functional teams, help to bridge information gaps and promote organizational alignment, supporting the spread of new ideas and facilitating technology adoption decision-making processes (Baker, 2011). An effective approach to overcoming communication barriers, as described by Johnson, is leveraging internal champions, colleagues who have successfully used the innovation and can speak credibly to its value in practice,

What we've found helpful is leveraging internal champions. If someone in the company has already used Buildots successfully on a previous project, like a site superintendent, we encourage new teams to speak directly with them. We'll say, "Don't just take our word for it, talk to your colleague. He has used Buildots on two projects already. Ask him whatever you want." That makes people feel like they're buying into something that's already been tested by someone in their own role, not just listening to an outside vendor trying to sell them something new. These kinds of user stories, whether from within their company or from other similar companies, go a lot further than us just saying, "This will help you." It builds trust. (Johnson, 2025)

Another important factor in these diffusion networks is heterophily, the degree to which individuals differ in attributes such as knowledge or background. Rogers argues that when communication occurs only among similar individuals (homophily), the spread of new ideas is limited (Rogers, 1983). Heterophilous interactions, on the other hand, expose people to new perspectives and encourage the exchange of unfamiliar knowledge, which can accelerate innovation diffusion. In the context of AI adoption, the diversity of stakeholders in construction, ranging from engineers and project managers to superintendents and executives, creates a highly heterophilous environment. However, this diversity can also pose challenges, as differing priorities, personalities, and attitudes may slow down consensus and create friction in decision-making. As one interviewee observed, even individuals with the same role and experience can approach innovation very differently,

There's been many different types of people that we talked to, different roles have different priorities, even if you have two site superintendents, they have the same role, same level of experience, you're just dealing with different personalities. (Johnson, 2025)

5.2.4 Firm Size and Resources

Firm size plays a crucial role in shaping an organization's ability to adopt and integrate AI technologies. Larger construction companies typically benefit from greater access to capital, robust technical infrastructure, and specialized personnel, allowing them to pilot new technologies and absorb the risks associated with experimentation (Yap, Lam, Skitmore, & Talebian, 2022). This phenomenon is frequently used as a metaphor for more important underlying characteristics, such as access to skilled staff, digital systems, and infrastructure (Baker, 2011; Oliveira & Martins, 2011). Firms with high levels of uncommitted resources, and interconnected structures are more capable of experimenting with new solutions (Oliveira & Martins, 2011). As one expert simply stated, the ability to adopt AI at scale is often concentrated among those with the resource to do so,

It's a game for the big players. (Taammoli, 2025)

In contrast, small and mid-sized enterprises (SMEs) often struggle with resource limitations such as, tight profit margins, fluctuating project schedules, and limited access to external funding, all of which reduce their capacity to make long-term strategic investments in AI (Abioye, et al., 2021; Parekh & Mitchell, 2024; Holzmann & Lechiara, 2022; Regona, Yigitcanlar, Xia, & Li, 2022). These firms are typically focused on meeting immediate operational demands, leaving little room for experimentation or digital transformation. The disparity between large and small firms becomes evident in the kinds of clients and collaborators that AI providers and consultancies tend to work with. As one interviewee noted, their engagements often centre around the industry's biggest players,

We're working with a very large client, one of the top five biggest contractors in Denmark. (Jacobsen, 2025)

Deploying AI technologies requires extensive financial and human capital. The initial investments cover hardware acquisition, AI software licensing, systems integration, and training programs to educate and develop skills among workers for a more automated workplace (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024). These costs are compounded by ongoing maintenance and the need to continually update systems as technologies evolve (Abioye, et al., 2021; Yap, Lam, Skitmore, & Talebian, 2022; Parekh & Mitchell, 2024). As one of the interviewees said, his clients are typically mid-sized to large firms with the budgets to absorb these investments because these cumulative costs are simply unaffordable for many SMEs,

Our customers are companies that are in the middle, they are not little companies because the little ones have no budget for that. (Serra, 2025)

In addition to budget constraints, there is a pronounced shortage of human capital with the dual skillsets of AI literacy and domain-specific construction knowledge. While general AI developers may be available, few have experience navigating the unique requirements of construction projects (Yap, Lam, Skitmore, & Talebian, 2022). As a result, firms are forced to either recruit expensive external consultants or postpone integration altogether (Abioye, et al., 2021; Parekh & Mitchell, 2024). As one interviewee noted, the industry must focus on developing professionals who can bridge the technical and operational divide, *There is definitely skills and knowledge gap that needs to be filled or bridged for the industry. (Ayeni, 2025)*

The skill deficit is twofold. On one hand, existing construction personnel often lack the necessary expertise to effectively operate AI platforms and interpret their outputs (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024; Holzmann & Lechiara, 2022). Furthermore, the resistance can be due to workers fear that automation could threaten their employment, limiting openness to AI integration (Regona, Yigitcanlar, Xia, & Li, 2022; Prabhakar, Xavier, & Abubeker, 2023). On the other hand, the global shortage of qualified AI engineers, with specific experience in the construction domain (Abioye, et al., 2021; Regona, Yigitcanlar, Xia, & Li, 2022), such as prompt engineering and data interpretation skills, which are currently rare in construction (Ghimire, Kim, & Acharya, 2024; Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024). AI implementation is not merely a technical task; it requires a committed team with both the know-how and the organizational will to drive change and coordinate efforts across departments (Holzmann & Lechiara, 2022).

These challenges are compounded by the nature of the construction workforce. The industry frequently relies on temporary or inexperienced labour to meet tight project deadlines, which disrupts the flow of institutional knowledge required for sustained innovation (Mischke, Stokvis, & Vermeltfoort, 2024). Temporary employment arrangements hinder knowledge accumulation, reduce continuity in system use, and stall initiatives that require iterative testing and gradual refinement. When labour demands are urgent, firms are often forced to compromise on skill requirements, accepting suboptimal matches just to keep projects on schedule, which reduces productivity and undermines the long-term success of digitalization efforts (Mischke, Stokvis, & Vermeltfoort, 2024). AI systems thrive on consistent user input, feedback loops, and adaptation. A transient workforce unable to maintain continuity in system engagement severely limits the effectiveness of such tools and the organization’s capacity for digital learning over time (Regona, Yigitcanlar, Xia, & Li, 2022; Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024).

5.3 The Environmental Context

The environmental context refers to the external setting in which a firm operates, including Industry Characteristics and External Technology, Regulatory Environment, Social and Stakeholder Dynamics, and Time. These elements significantly shape the ability and motivation of construction firms to adopt and implement artificial intelligence.

5.3.1 Industry Characteristics and External Technology

Innovation diffusion is profoundly shaped by the characteristics of the social system in which it occurs. A social system is a set of interrelated units engaged in joint problem solving to accomplish a common goal (Rogers, 1983). In the construction industry, this system is notably fragmented, operating as a "loosely coupled system" with multiple semi-autonomous subsystems (Irfan, 2021). This structural complexity poses considerable challenges for systemic change, making innovation diffusion heavily dependent on both dominant actors and external technological forces. In this ecosystem, dominant firms within the value chain have significant influence over their upstream and downstream partners, effectively setting the pace and direction of innovation (Baker, 2011). Such dynamics create a vendor-driven innovation environment. As one interviewee noted, market leaders like have significant power over innovation trajectories,

Autodesk is basically dominating the design field… and major breakthroughs are depend on them, they're leading the way. (Kouhestani, 2025)

This monopolistic influence leads to an innovation landscape that hinges on a few powerful technology providers, limiting the autonomy of smaller firms. Despite this, meaningful systemic transformation in construction remains rare without broad collaboration among stakeholders such as regulators, clients, and contractors. The industry's project-based nature and short-term delivery pressures further undermine long-term strategic alignment (Samuelson & Stehn, 2023). Competitive pressure is a significant external force that pushes technological development. In the construction industry, firms often adopt new technologies not out of strategic foresight but due to fear of being outpaced by competitors (Na, Heo, Han, Shin, & Roh, 2022; Alka'awneh, Abdul-Halim, & Saad, 2025). As interviewees emphasized,

I think everyone's just kind of knows they need to use AI at some point and they know that if they're not going to, they're going to be left behind. (Johnson, 2025)

One of my colleagues put it nicely "The reason they want to implement AI is because they're afraid of being left behind." (Jacobsen, 2025)

This reactive mindset illustrates a broader absence of long-term, AI-specific roadmaps within organizations. Rather than being guided by a proactive digital vision, innovation is frequently a defensive response to external pressures.

The maturity of the sector also influences its approach to innovation. Construction is typically categorized as a mature industry, where innovation tends to be reactive and driven by cost reduction imperatives rather than growth (Baker, 2011). Many firms continue to rely on legacy systems, struggling with foundational elements of Industry 4.0, while other sectors are transitioning toward Industry 5.0 (Prabhakar, Xavier, & Abubeker, 2023). As one interviewee observed, *They never went through digitalization or anything like that. (Serra, 2025)*

Moreover, the variable and unpredictable nature of construction projects prevents the deployment of AI technologies that depend on consistency and replicability. Predictive models and process automation tools often fail to generalize across projects due to the unique conditions at each site (Holzmann & Lechiara, 2022). In underground construction, for instance, unpredictability and high adaptivity requirements often necessitate ad hoc AI solutions that are neither scalable nor feasible across multiple projects (Holzmann & Lechiara, 2022).

External technological developments significantly shape organizational strategies. These innovations, although not yet implemented, redefine what is technologically possible and serve as aspirational benchmarks (Na, Heo, Han, Shin, & Roh, 2022). AI integration in construction encompasses a spectrum of innovation types. Incremental innovations, such as AI-enabled scheduling tools, offer low-risk, gradual improvements (Ghimire, Kim, & Acharya, 2024). Synthetic innovations emerge from combining technologies like BIM, IoT, and machine learning to enhance decision-making. Discontinuous innovations, meanwhile, introduce radical shifts from conventional practices, posing both opportunity and risk (Oliveira & Martins, 2011; Baker, 2011). However, a major hurdle to scalable AI implementation lies in the industry's project-centric structure. Each construction project operates as a unique prototype, with distinct teams, budgets, and contexts. As one interviewee put it,

Each department in a construction company tends to work differently, and each construction site usually has its own setup… It's always a prototype. Even if you build exactly the same project just one kilometre away, there will still be new uncertainties. (Taammoli, 2025)

This level of customization leads to inefficiencies and prevents the accumulation of institutional knowledge. Digital investments and AI tools are often limited to individual projects, limiting their long-term utility and internal diffusion (Samuelson & Stehn, 2023; Mischke, Stokvis, & Vermeltfoort, 2024). Purchasing decisions are frequently made at the project level rather than the organizational level, further complicating standardization and scalability (Blanco, Rockhill, Sanghvi, & Torres, 2023).

Physical infrastructure also constrains AI adoption. Many construction sites lack reliable internet and power, both essential for cloud-based AI platforms (Abioye, et al., 2021; Yap, Lam, Skitmore, & Talebian, 2022). Real-time feedback loops and adaptive AI capabilities are struggle in environments with limited bandwidth and unreliable connectivity (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024; Parekh & Mitchell, 2024). AI applications such as 3D scanning, remote sensing, or generative design are particularly affected by these constraints.

The digital landscape is further fragmented by inconsistent software usage across firms and projects. Practitioners frequently switch tools based on client requirements or project scale, creating steep learning curves and undermining knowledge continuity. This inconsistency limits the cumulative value of AI investments and hinders cross-project integration (Blanco, Rockhill, Sanghvi, & Torres, 2023).

5.3.2 Regulatory Environment

Government regulation represents a double-edged sword in the domain of technological innovation. It can serve either as a catalyst or a barrier, depending on how legal frameworks are designed, enforced, and interpreted (Oliveira & Martins, 2011). Within the construction industry, a sector has strict safety standards, jurisdictional fragmentation, and localized operations, which pose critical external barriers to AI adoption. On one hand, environmental and safety compliance can drive technological advancement by mandating the use of modern systems. On the other hand, innovations that require extensive testing or formal approval often encounter delays and added costs due to regulatory rigidity (Baker, 2011). The situation is exacerbated by the lack of uniformity in regulatory environments. As an interviewee emphasized,

Construction is highly customized and localized, it's based on each specific project, geography, and team. (Taammoli, 2025)

This localization undermines efforts to develop standardized practices for AI implementation, even within multinational firms. Furthermore, the rapid evolution of AI technology introduces legal issues around risk, compliance, and accountability, many of which remain inadequately addressed by existing construction law.

AI technologies, particularly those reliant on cloud infrastructure and real-time data, raise new concerns regarding cybersecurity and data privacy. These systems frequently process sensitive personal and project-related information, making them attractive targets for cyberattacks (Regona, Yigitcanlar, Xia, & Li, 2022). Unauthorised access or data breaches might harm intellectual property or even threaten on-site worker safety by interrupting AI-driven automation (Yap, Lam, Skitmore, & Talebian, 2022). Despite these threats, most construction firms lack formal internal policies on AI usage, and regulatory bodies have yet to offer comprehensive guidance (Ghimire, Kim, & Acharya, 2024). The regulatory gaps become especially dangerous as generative AI begins to produce complex project outputs such as safety plans and construction schedules. In these situations, even minor errors in AI-generated outputs can result in significant consequences, including construction delays, safety hazards, or financial losses. However, there is currently no clear legal framework that defines who is responsible when such failures occur, leaving accountability in a state of legal uncertainty (Ghimire, Kim, & Acharya, 2024).

Compounding this challenge are ethical concerns surrounding automated surveillance and data processing. IoT-based systems often collect personal data through cameras, sensors, and wearable devices. This introduces questions about worker autonomy, privacy, and the ethical treatment of recorded information (Yap, Lam, Skitmore, & Talebian, 2022). While AI can improve safety by detecting anomalies and hazards, it also presents new risks related to bias, discrimination, and excessive reliance on opaque algorithms (Parekh & Mitchell, 2024).

International construction projects present another challenge in the deployment of AI tools. While AI adoption might be supported in a firm's home country, it can face resistance abroad due to weaker regulatory infrastructures or the influence of local partners. No matter how open the culture of the home country is toward change, AI use is not always guaranteed if the international market is not ready for it (Holzmann & Lechiara, 2022). Furthermore, the need to comply with regulations like the EU's General Data Protection Regulation (GDPR) complicates cross-border AI deployment. Firms must navigate a tangled web of legal obligations regarding data protection, intellectual property, and ethical usage (Obiuto, Adebayo, Olajiga, & Festus-Ikhuoria, 2024).

Another major barrier is the absence of institutional support structures to facilitate AI integration. Most firms lack access to specialized training programs in AI ethics, prompt engineering, and privacy compliance (Yap, Lam, Skitmore, & Talebian, 2022). There are also no widely recognized third-party organizations to vet, certify, or benchmark AI tools for construction-specific applications. This institutional void reduces confidence among firms and inhibits strategic decision-making around AI adoption (Ghimire, Kim, & Acharya, 2024).

5.3.3 Social and Stakeholder Dynamics

Social and stakeholder dynamics are a minor but significant component of the environmental context around AI adoption in the construction industry. These dynamics includes the behaviours, expectations, and interactions among clients, contractors, consultants, regulators, and end-users, as well as broader societal values concerning trust, accountability, and technological responsibility. Despite the sector's strong technical and commercial orientation, its decentralised structure and short project lifecycles make it particularly sensitive to social impact (Samuelson & Stehn, 2023). The industry operates through fragmented and temporary networks of collaboration, involving shifting partnerships between contractors, subcontractors, consultants, and clients. This results in limited organizational memory and a lack of standardized processes, which together complicate innovation diffusion (Mischke, Stokvis, & Vermeltfoort, 2024). The decision-making power for AI adoption is often unclear and responsibility could end up with a procurement lead, a site manager, or a digital transformation officer, causing uncertainty and delays (Blanco, Rockhill, Sanghvi, & Torres, 2023).

Power imbalances further shape adoption behaviour. Large clients or dominant contractors often set the technology agenda, while smaller stakeholders, such as subcontractors, are sidelined from strategic innovation decisions (Na, Heo, Han, Shin, & Roh, 2022). Many clients still favour traditional methods and do not actively request AI-enabled solutions. In the absence of client-driven demand, firms lack motivation to prioritize AI initiatives (Holzmann & Lechiara, 2022). As a result, AI is often introduced as a compliance item or performance enhancer rather than as a transformative strategy, reducing its overall impact and integration.

Stakeholder dynamics also overlap with economic interest. Construction firms typically operate with low margins, and gains from productivity-enhancing tools like AI are often absorbed elsewhere in the value chain. Upstream suppliers and downstream clients often capture the financial benefits of digital innovation, while contractors, who bear the cost and risk, see little return (Mischke, Stokvis, & Vermeltfoort, 2024). This dynamic suppresses innovation motivation, especially in tendering processes, where competition is fierce and bids are evaluated primarily on cost. Firms frequently underbid in hopes of recovering margin through assumed productivity gains, but this rarely translates into long-term investment in digital tools. The lowest bid is often the winning bid, but too often it comes from the player with the grandest underestimation of risks rather than the most productive one (Mischke, Stokvis, & Vermeltfoort, 2024)

5.3.4 Time

The dimension of time is a key element in understanding how innovations like artificial intelligence (AI) diffuse within the construction industry. The innovation decision process comprises five stages: knowledge, persuasion, decision, implementation, and confirmation (Rogers, 1983). These stages require awareness, understanding and time for experimentation, feedback, and institutionalization. However, the fast-paced, delivery-driven nature of construction projects offers little room for such iterative cycles (Oliveira & Martins, 2011).

Construction projects are typically short-term and delivery-focused, emphasizing completion over iteration. Teams are assembled temporarily, and disbanded at the end of a project, which undermines continuity and learning across projects. This temporal fragmentation means that innovations like AI rarely benefit from long-term organizational commitment. The lack of sustained interaction with the technology inhibits the full progression through Rogers' five stages, particularly the later stages of implementation and confirmation, where learning and adaptation are critical. Moreover, each project tends to function as a self-contained prototype, further complicating the reuse and refinement of AI tools across organizational boundaries. As a result, successful AI implementations remain isolated and unscaled, unable to create cumulative organizational memory or momentum for broader transformation (Mischke, Stokvis, & Vermeltfoort, 2024). Rogers' model also classifies adopters into five categories: innovators, early adopters, early majority, late majority, and laggards. Innovators are risk-takers who introduce new ideas, followed by early adopters, respected opinion leaders who reduce uncertainty for others. The early majority are pragmatic and adopt only with proven benefits. The late majority are sceptical and adopt due to necessity or peer pressure. Laggards are the most traditional, adopting only when an innovation has clearly been established. When AI in the construction industry is placed within Rogers' adopter classification, the technology appears to be moving from the early adopter phase to the early majority. Innovators and early adopters have already initiated conversations and trials regarding AI usage, and there is a growing awareness of its potential,

I can see what's been going on over the last eight years, and honestly, not a lot has happened… Some of the front-runners in the construction industry right now are starting to have the conversations, what should they actually do about AI. The process of implementation has very slowly started (Jacobsen, 2025)

On a scale of 1 to 10, I'd put it around 4 in terms of preparedness and motivation for AI adoption. (Ayeni, 2025)

Just looking back over the past year and a half, the progress has been incredible. So imagine what the next five years will bring. (Johnson, 2025)

These observations suggest that AI in construction is still in the early phase of the S-curve diffusion model, where awareness and experimentation dominate but mainstream integration is yet to occur. The industry, at present, is transitioning between early adopters and the early majority, meaning that AI adoption is still not widespread but gaining traction among more pragmatic firms seeking proven value.

5.4 Summary of the Second Analysis

The adoption of Artificial Intelligence (AI) in the construction industry is heavily influenced by a wide range of technological, organizational, and environmental challenges. The analysis applies the Diffusion of Innovation (DOI) theory and the Technology-Organization-Environment (TOE) framework to structure these barriers comprehensively.

Key technological challenges include limited perceived relative advantage, a lack of observability, poor compatibility with legacy systems, restricted trialability, and high complexity. Many firms do not clearly understand AI's practical benefits, and decision-makers often prioritize short-term gains over strategic innovation. Compatibility issues are exacerbated by fragmented data, outdated infrastructure, and low digital maturity. Trialability is constrained by cost, lack of skills, and long implementation timelines. Complexity arises from AI's non-intuitive interfaces, lack of explainability, and low digital literacy among construction professionals.

Internally, construction firms face fragmented organizational structures, weak innovation cultures, and insufficient leadership support. Projects are siloed, preventing the scaling of successful innovations. Cultural resistance to change, often rooted in fear of increased transparency or job disruption, further hinders adoption. Leadership plays a crucial role, without strong C-level commitment and a clear strategy, digital transformation fails. Internal communication is often fragmented, limiting shared understanding. Firm size and resources also matter, larger firms are better equipped for AI experimentation, while SMEs lack financial and human capital and suffer from skills shortages.

Externally, the fragmented nature of the construction industry, dominance by large technology vendors, and a reactive innovation culture impede systemic change. Firms often adopt AI out of fear of falling behind rather than strategic vision. Regulatory environments, though potentially supportive, are inconsistent and underdeveloped, especially regarding AI-specific standards, cybersecurity, and accountability. Social dynamics among stakeholders, such as power imbalances, lack of client demand, and unclear decision-making authority, also complicate adoption. Time is a major constraint, project-based, short-term operations hinder long-term learning, experimentation, and scaling.

Overall, AI adoption in construction is in the early adopters' section closer to the early majority's one but remains limited by multi-level resistance and a fragmented ecosystem.

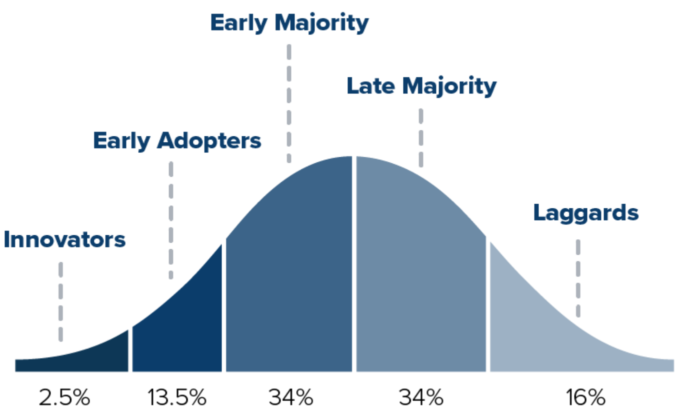

Figure 2, Innovation adoption lifecycle

VI. CHAPTER

6 ANALYSIS OF THE THIRD RESEARCH QUESTION

Based on the previous findings:
HOW CAN AN AI CONSULTANCY BUSINESS OPPORTUNITY BE DEVELOPED, USING THE DISCOVERY-DRIVEN PLANNING FRAMEWORK?

To explore how an AI consultancy business opportunity can be developed in the construction sector, this section combines entrepreneurial opportunity theory with the Discovery-Driven Planning (DDP) framework. The entrepreneurial opportunity lens was selected to explain how the business idea can be evolved from recognizing unmet needs and underutilized resources into a viable, structured concept. This theoretical perspective is particularly suitable for dynamic, emerging markets like AI in construction, where opportunities are often not immediately visible but need to be shaped and refined through continuous engagement with industry signals.

Given the high level of uncertainty surrounding AI adoption, especially among small and medium-sized construction firms, traditional business planning tools would be insufficient. Therefore, the DDP framework was applied to structure the development process. It enables low-risk experimentation by focusing on assumptions rather than fixed forecasts and supports learning-based iteration rather than rigid execution. This approach is ideal for ventures in early stages of validation, where both client readiness and the feasibility of the business model are still evolving.

Together, these methods were chosen to ensure a systematic, flexible, and evidence-based approach to turning early insights and barriers into a real-world business opportunity, while remaining adaptable to unexpected findings and market feedback.

6.1 Entrepreneurial Opportunity Theory

In the context of entrepreneurship, opportunities are not simply discovered, they are actively developed, through a dynamic and iterative process that transforms vague market needs or underutilized resources into viable business concepts (Ardichvili, Cardozo, & Ray, 2003). This process is about opportunity recognition and accurately opportunity development. Entrepreneurs play an active and creative role in shaping opportunities by interpreting market signals, identifying inefficiencies, and recombining resources to generate novel solutions (Ardichvili, Cardozo, & Ray, 2003).

Opportunity development begins when an individual's entrepreneurial alertness exceeds a certain threshold (Ardichvili, Cardozo, & Ray, 2003). From this point, entrepreneurs engage in cycles of evaluation and refinement, where market needs and available resources are continuously redefined and aligned to create value for targeted users. Opportunities, in their initial state, may appear as imprecisely defined market gaps or idle capabilities. Over time, as the entrepreneur gains more clarity on customer needs and resource potential, these vague notions evolve into concrete business concepts, which eventually grow into well-defined business models.

Five major factors shape this opportunity development process: (1) entrepreneurial alertness, (2) information asymmetry and prior knowledge, (3) social networks, (4) personality traits such as optimism and self-efficacy, and (5) the nature of the opportunity itself (Ardichvili, Cardozo, & Ray, 2003). These elements influence how entrepreneurs perceive and shape value creation opportunities, especially in emerging or underdeveloped markets.

6.1.1 Opportunity Recognition

Opportunities develop as individuals shape elemental ideas into full-blown business plans. But the process of opportunity development is conceptually distinct from opportunity recognition or identification. What most literature in entrepreneurship calls ‘‘opportunity recognition'' appears to include three distinct processes: perception, discovery, and creation.

The perception of entrepreneurial opportunities often begins with sensing or identifying unmet market needs or underutilized resources. Individuals vary in their sensitivity to such signals due to differences in experience, knowledge, and cognitive framing (Ardichvili, Cardozo, & Ray, 2003). These variations influence who is able to perceive the potential for value creation in a given context.

The recurring challenges outlined in the problem statement indicate a latent demand within the construction industry for innovative, technology-driven solutions. In this regard, artificial intelligence has been suggested as a possible response to these systemic issues. Although the potential of AI has been acknowledged in scientific and professional articles, its limited adoption across the sector could be interpreted as an indication of underutilized technological capacity. Taken together, these patterns may represent the early signals of an entrepreneurial opportunity, an emerging convergence of market need and underemployed technological resources, visible primarily to actors with the relevant alertness and contextual insight.

The recognition of a fit between identified market needs and available capabilities is key in the opportunity discovery process. Rather than focusing solely on offering a product or service, entrepreneurs often bring forward the ability to combine knowledge and resources in a way that reveals untapped potential within a specific industry context (Ardichvili, Cardozo, & Ray, 2003). This stage involves shifting attention from analysing the current state to envisioning what is possible.

In the construction industry, identifying the barriers to AI implementation contributes to a more precise understanding of existing gaps between technological potential and operational reality. These gaps may be interpreted as problems that require targeted support and structured intervention. As a result, the concept of a consultancy emerges as a potential opportunity for addressing adoption challenges. Such a service could function as a critical intermediary, aligning market demands with the underutilised potential of AI technologies.

Creation of opportunity moves beyond recognition or discovery; it involves actively constructing a business concept that reconfigures existing capabilities to meet unfulfilled market needs (Ardichvili, Cardozo, & Ray, 2003). This stage may require aligning needs and resources as well as introducing unique combinations or approaches that result in value delivery that outperforms current offerings.

Previous findings indicate that many construction firms face significant constraints in adopting AI technologies, particularly due to limitations in time, financial flexibility, awareness, and digital readiness. These barriers preventing many firms from even initiating transformation. While many digital consultancies operating in the construction sector provide support for AI implementation, their services are often tailored to firms that have already committed to transformation. As a result, consultancies rarely participate in raising awareness, identifying latent demand, or initiating adoption among hesitant firms and their offering are frequently tied to promoting in-house developed solutions. As one of the interviewees said,

But we don't advertise it because it's not scalable. It's only a few of us, and we do it for selected clients, not just anyone. (Taammoli, 2025)

We're building software not only for the current generation of construction managers, but with future generations in mind. (Taammoli, 2025)

In contrast, the proposed consultancy concept aims to serve as an independent enabler of AI adoption. The consultancy would focus on reaching firms at the pre-adoption stage, those interested but constrained, by raising awareness, building capacity, and enabling access to external resources such as public funding, government support programs, and industry partnerships. In addition, rather than developing or selling proprietary tools, it aims to analyse and implement existing technologies that are best suited to the client's needs. This neutrality enables a broader and more flexible range of solutions. In this way, the consultancy creates a new and necessary fit between the persistent needs of firms within the construction sector and the underutilised potential of AI, therefore contributing to broader industry development.

6.1.2 Type of Opportunity

To further clarify the nature of the entrepreneurial opportunity identified, it is useful to consider how opportunities differ based on the degree of definition of both the value sought (market need) and the value creation capability (available solution). The opportunities categorized into two dimensions: whether the market need is known or unknown, and whether the resources or capabilities to create value are defined or undefined (Ardichvili, Cardozo, & Ray, 2003).

It distinguishes between idea-driven innovation, problem-solving, technology transfer, and match-making opportunities, depending on which elements are defined or undefined.

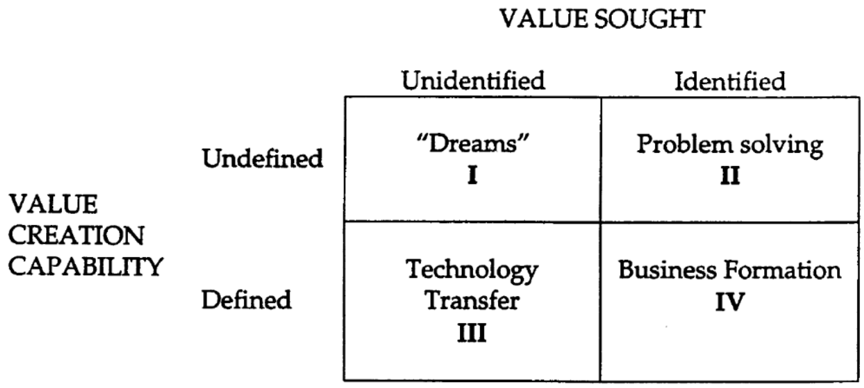

Figure 3, Types of opportunities (Ardichvili, Cardozo, & Ray, 2003)

In this framework, the opportunity addressed by the proposed AI consultancy service occupies the lower-right quadrant of the matrix: both the value sought and the value creation capabilities are known. Construction firms are increasingly aware of their inefficiencies and digitalization gaps, particularly regarding AI adoption. These constitute well-identified needs or "problems." Simultaneously, there is a growing repository of technological tools, frameworks, and support systems, both public and private, that can facilitate AI adoption, representing known "solutions" or capabilities.

However, the persistent challenge lies not in the absence of awareness about the problem or solution, but in connecting the two in a way that is accessible, actionable, and tailored to the realities of hesitant or digitally immature firms. The consultancy, therefore, plays the role of an enabler, matching existing needs with existing capabilities through advisory, implementation planning, capacity-building, and navigation of external resources such as funding or partnerships. This type of opportunity is categorized as a "match-making" opportunity, where value is created not by inventing new technologies or discovering unknown problems, but by creating a more effective alignment between what is already recognized as needed and what is already available as possible.

From a developmental standpoint, this quadrant represents a relatively mature opportunity. As Businesses formed where both problem and solution are known tend to exhibit higher chances of success compared to those built on speculative assumptions (Ardichvili, Cardozo, & Ray, 2003). This is particularly relevant in the construction sector, where innovation tends to be incremental and risk-averse, making the reliability of both the need and the solution critical for adoption.

Nevertheless, it is important to note that while both sides of the opportunity are known in general terms, the specific configuration that makes adoption feasible for each firm is often undefined. Each client may face unique constraints in time, skills, funding, or awareness. Thus, the entrepreneurial work lies in customizing the match, identifying the appropriate technology, tailoring the implementation roadmap, and overcoming firm-specific barriers.

By operating in this space, the proposed consultancy fulfils a bridging function that is currently underdeveloped in the market. Rather than pushing proprietary tools, it creates value by offering strategic intermediation, translating broad market knowledge and available technological solutions into individualized adoption strategies. This approach supports firms in realizing existing potentials as well as contributes to wider systemic change by accelerating digital transformation across a traditionally lagging industry.

6.1.3 Opportunity Development

The business idea behind this thesis, an independent AI consultancy for the construction industry, has developed step by step from a basic recognition of a market need into a more concrete and structured opportunity. The idea emerged by observing problems and gaps within the industry, rather than from having a specific technology or resource looking for a market. There are already many AI tools, digital frameworks, and support programs available, but most firms don't know how to access or implement them effectively. This clear gap between what firms need and what is available became the starting point for the business idea.

- The business concept centres around offering independent advice, planning, and hands-on support to construction companies that are curious about AI but uncertain about how to proceed. Many firms are experimenting informally without proper strategies or integration plans. One of the interviewees shares similar concerns from a subcontractor perspective within the industry,

Everyone I talk to is just like, "Oh yeah, I'm just playing around with it." But no one has actually learned how to integrate it properly into their business, at least not anyone I've spoken to (Gaffey, 2025)

As it was also discussed in the earlier analysis, this illustrates the widespread lack of internal capabilities for AI adoption, particularly in small and medium-sized enterprises (SMEs). These firms often have limited time, resources, or digital maturity, which hinders their ability to explore AI alternatives. In many cases, curiosity exists but is rarely followed by initiating structured effort or financial commitment.

- A key differentiator of this business concept is its intentional focus on SMEs, a customer base that is often left out by other consultancy services or software providers, which typically concentrate on large-scale projects. As several interviewees pointed out, existing consultancies often bypass smaller firms,

If it's a small project where you know everyone by name and can walk around the site in 10 minutes, our services aren't necessary. (Taammoli, 2025)

However, this does not mean smaller firms cannot benefit, even without comprehensive datasets or models, AI can still be valuable. Opportunities exist to use simpler tools for practical improvements, such as progress tracking or financial control. As interviews stated,

AI can help track the actual progress on site, determining whether a project is ahead or behind schedule, just by analysing images or video. It can also be used to estimate how much money has been spent versus actual progress. This can help identify whether subcontractors are being overpaid or underpaid relative to the work completed. Another area is estimating unit prices. For example, using AI to forecast price fluctuations of materials, so you can optimize the supply chain by buying materials when they're cheapest, instead of reacting too late. So there are a lot of possible use cases for AI. (Jacobsen, 2025)

Regardless of how developed a company is, there's something they can be doing with AI to help them. (Johnson, 2025)

- This consultancy's value proposition lies in helping SMEs bridge the gap between AI availability and applicability by offering tailored support. This includes identifying suitable tools, preparing firms for AI adoption, guiding implementation, and connecting them with external enablers such as public funding or strategic partners. Importantly, the consultancy does not aim to sell proprietary software, it remains technology-neutral and selects solutions objectively based on each client's needs.

The current technological landscape supports this approach. Some AI domains, like computer vision, are already mature and accessible. As one interviewee pointed out,

Computer vision has a relatively low in complexity. There are already a lot of well-developed algorithms in this area, computer vision has been part of the tech industry for 20+ years. (Jacobsen, 2025)

Others, like generative AI or intelligent agents, are beginning to show promise for solving widespread industry pain points such as documentation and communication. As interviewees noted these tools could address inefficiencies particularly common across construction firms,

With agents and generative AI, we can handle the problem of documentation and conversations. (Serra, 2025)

I'm especially looking forward to breakthroughs in project scheduling and cost forecasting. (Ayeni, 2025)

As the consultancy also focuses on supporting implementation, training will be also part of the service offering. Making sure that teams not just receive the technology but know how to use them in their specific context. Interviewees emphasized the importance of the necessary skills,

I think training is a must when you're introducing AI tools. (Gaffey, 2025)

One interviewee also pointed out that, from an entrepreneurial perspective, there is still a significant gap between the solutions available and how well they fit the unique identity of each business,

That's the real gap, finding and fitting the right digital solutions to each unique business identity. (Banerje, 2025)

In conclusion, the consultancy aims to act as a trusted AI transformation partner for SMEs in construction. It builds upon observed gaps, aligns with firm needs, leverages accessible technologies, and focuses on enabling AI innovation where it's most needed, not where it's most advanced. Initially, the consultancy's focus will be on improving project management through technologies such as computer vision, sensors, and algorithms. These tools will help gather and structure site data, enabling more accurate decision-making, improving resource efficiency, and boosting overall productivity. This positions the consultancy as a meaningful response to unmet demand in the sector, especially among the under-served segment of small and medium construction firms.

6.1.4 Opportunity Evaluation

Opportunity evaluation is a continuous and iterative process that begins informally and becomes increasingly structured as commitment of resources intensifies (Ardichvili, Cardozo, & Ray, 2003). In the early stages, individuals may explore perceived market needs or available capabilities through intuitive or experience-based judgments, without explicitly articulating their evaluation criteria. This informal investigation allows for low-risk exploration, during which potential opportunities may be quietly abandoned or pursued further, depending on perceived alignment and promise.

In the context of the proposed consultancy, the early signs, such as insights from interviews, and literature, have undergone this type of preliminary evaluation. The persistent digitalization gap in construction, coupled with an abundance of tools and frameworks designed to close that gap, present an entrepreneurial opportunity worth exploring. The consultancy concept is now in the phase where more formal evaluation is necessary to justify continued development and potential resource commitment.

This transition from informal to formal evaluation requires looking at the opportunity through a more systematic lens: Is there a real and unmet need? Is the solution feasible and attractive to the target audience? Can it deliver sufficient value to drive adoption and justify payment? In this case, several indicators suggest that the answers may be yes.

The literature consistently highlights how digital transformation remains a challenge for SMEs in the construction sector. Interviews pointing to a widespread curiosity about AI tools, but also confusion and hesitation when it comes to actual implementation. However, even in firms with low digital maturity, innovation can still occur, as long as solutions are practical and deliver value. As one subcontractor, a possible future customer said,

I think if it saves time, reduces risk, or improves profit, then I'll give it a look. (Gaffey, 2025)

From an entrepreneurial standpoint, clear, understandable and simply formulated,

Use AI to save time and become more efficient (Banerje, 2025)

From a consultant's perspective, the potential scope of AI in construction is wide,

Honestly, every aspect of construction could benefit from AI. (Kouhestani, 2025)

This early field validation enhances the reasons to continue the development of the consultancy. These quotes highlight a clear interest from potential customers, and confidence from experts. Moreover, broader market trends also support the viability of this opportunity. The global AI in construction market size was valued at USD 3.93 billion in 2024, and it is projected to grow to USD 22.68 billion by 2032, with a compound annual growth rate (CAGR) of 24.6% (Fortune Business Insights, 2025). This rapid growth demonstrates the increasing demand for AI-driven solutions as well as the timing and importance of entering this market.

6.2 Discovery-Driven Planning of the AI Consultancy Venture

In an environment of high uncertainty, traditional planning approaches are often inadequate (McGrath & MacMillan, 1995). This is especially true in under-digitized industries like construction, where the practical use of artificial intelligence still in its early stage, fragmented, and highly reliant on assumptions. Unlike established organisations that can plan based on well-documented prior experiences, entrepreneurial initiatives in developing industries face a high level of uncertainty, including market needs and customer readiness to the feasibility of delivering the intended value proposition (McGrath & MacMillan, 1995). As a result, Discovery-Driven Planning is an effective framework because it takes into account the fact that little is known and much is assumed. This tool supports the systematic collection of assumptions and their transformation into knowledge. When new data is discovered, it is integrated into the evolving strategy.

In this section the four key document is developed, namely a ***reverse income statement***, which models the basic economics of the business; ***pro forma operations specifications***, which lay out the operations needed to run the business; a ***key assumptions checklist***, which is used to ensure that assumptions are checked; and a ***milestone planning chart***, which specifies the assumptions to be tested at each project milestone.

6.2.1 Reverse Income Statement

The purpose of creating a reverse income statement is to determine what level of revenue the AI consultancy must generate in order to achieve a desired profit while staying within reasonable cost limits. Unlike traditional planning approaches that begin with projected revenues and work downward to estimate profits, the reverse income statement starts from the bottom line. It begins by setting a target profit and then works upward to identify the maximum allowable costs and the revenue required to meet those targets. This method ensures that profitability is built into the business model from the start and helps establish clear financial constraints in an environment full of uncertainty. In the case of this consultancy, where both demand and delivery models are still unproven, this approach provides a structured way to understand what scale of operations and pricing will be necessary to make the venture financially viable.

To reflect a realistic financial goal for the early stages of the venture, the target annual profit was set to 400,000 DKK *(Assumption 1)*. This amount represents a modest and achievable income level for a solo consultancy, allowing for both personal compensation and limited reinvestment, while reducing pressure on pricing and workload during the initial market entry phase.

To justify the choice of profit margin for the consultancy, industry-level profitability benchmarks were considered. According to the European Construction Sector Observatory, the gross operating rate of the Danish broad construction sector stood at 30.2% in 2018. (European Commission, 2021) However, since the AI consultancy described in this thesis is a new venture operating with greater risk and uncertainty a more conservative profit margin of 20% was selected *(Assumption 2)*. This provides room for flexibility, learning, and reinvestment, while maintaining a viable financial structure.

The required annual revenue was calculated using the reverse income formula.

$$Revenue = \frac{Profit}{Profit\ margin} = \frac{400{,}000}{0.20} = 2{,}000{,}000\ DKK$$

This ensures that the business can meet its financial target while operating within defined cost limits. From this, the allowable costs are derived.

$$Allowable\ Costs = Revenue - Profit = 2{,}000{,}000 - 400{,}000 = 1{,}600{,}000\ DKK$$

The business model assumes the completion of 10 client projects per year *(Assumption 3)*, which reflects a realistic workload for a solo consultant given the complexity, duration, and client interaction typically involved in AI-related advisory services for the construction industry. The followings are per-project breakdown.

$$Price\ per\ Project = \frac{Revenue}{Project\ Annually} = \frac{2{,}000{,}000}{10} = 200{,}000\ DKK\ \textit{(Assumption 4)}$$

$$Profit\ per\ Project = \frac{Target\ Profit}{Project\ Annually} = \frac{400{,}000}{10} = 40{,}000\ DKK$$

$$Allowable\ Cost\ per\ Project = \frac{Allowable\ Costs}{Project\ Annually} = \frac{1{,}600{,}000}{10} = 160{,}000\ DKK$$

These figures are based on a set of embedded assumptions regarding project volume, pricing, and delivery model. While the actual market conditions and client willingness to pay may vary, these assumptions provide a structured starting point for evaluating whether the venture's goals are financially achievable. All key assumptions are further detailed and tested in the subsequent Pro Forma Operations Specifications and Assumptions Checklist. These figures are not treated as fixed forecasts but as working assumptions to be tested, refined, or adjusted as new data emerges during the venture's early operations (McGrath & MacMillan, 1995).

These assumptions and their corresponding calculations are summarised in the table below.

Target Profit	*Assumption 1*	400,000	*DKK*
Profit margin	*Assumption 2*	20%	
Revenue		2,000,000	*DKK*
Allowable Costs		1,600,000	*DKK*
Project Annually	*Assumption 3*	10	
Price per Project	*Assumption 4*	200,000	*DKK*
Profit per Project		40,000	*DKK*
Allowable Costs per Project		160,000	*DKK*

Table 1, Reverse income statement

6.2.2 Pro Forma Operations Specifications

This phase focuses on identifying and structuring all the activities required to produce, deliver, and support the product or service offered by the venture. These activities collectively determine the venture's allowable cost structure and lay the groundwork for validating its feasibility.

Unlike traditional business planning, which often relies on fixed projections and industry templates, discovery-driven operations planning uses iteration, estimation, and adaptation. At this early stage, the objective is not to achieve precision, but rather to construct a realistic model of the venture's logistics and resource needs. Simple spreadsheets and assumptions are sufficient to begin outlining what the business must do to function (McGrath & MacMillan, 1995). This approach allows founders to spot critical flaws in the business concept early, before major investments are made. It also supports the incremental correction of assumptions as new data is gathered through market interaction, testing, and stakeholder engagement. Every industry operates under its own set of standards and expectations, such as profit margins, cost structures, or client interaction cycles, and these must be considered to build a viable operational model.

The primary goal at this stage is to translate strategic intentions into practical actions, defining the capabilities, partnerships, processes, and resources necessary to operate the venture. This step is essential for aligning projected activities and costs with the reverse income statement, while also ensuring that all underlying assumptions remain visible, challengeable, and testable (McGrath & MacMillan, 1995).

In the context of this AI consultancy, the following section outlines the key operational activities, delivery methods, and resource requirements that shape the logistics of running the business. By formally framing these operational challenges, the model becomes more actionable and more adaptable to change.

Service Offering

The consultancy will focus on providing four core services to construction firms, which are designed to provide strategic value without requiring in-house development work, enabling a lean consultancy structure.

- AI Readiness Assessments – Evaluating the digital maturity of clients and identifying gaps in data, processes, and culture.
- Tech Scouting – Identifying suitable AI tools and technologies
- Strategic Roadmap Development – Designing phased implementation plans for AI use cases that align with each client's operational realities and goals.

As one interviewee said these are crucial first steps to understand the core elements,

> *So, when a client comes to us and says, "We're interested in implementing AI," the first thing we usually do is suggest running the AI Readiness Assessment. The goal of this process is to help them understand three things: how ready they are for AI, what the potential use cases could be in their organization, and what their roadmap might look like to get there. (Jacobsen, 2025)*

- Funding and Partnership Support – Assisting clients in identifying public funding opportunities and preparing grant applications that can fully cover the cost of the consultancy service, while also connecting them with relevant technology providers, when applicable.

Delivery Method

Services will primarily be delivered in a hybrid format, combining remote delivery, like online meetings, cloud-based tools, and digital collaboration platforms (e.g., Notion, Miro, Microsoft Teams) and on-site visits, such as, diagnostics, training, or workshops. Technical implementation tasks may be partially outsourced to trusted freelance specialists or external partners.

Capabilities and Resources

To win stakeholders on board it is fundamental to communicate the clear value that the technology can bring to the firm. As one interviewee pointed out, presenting the benefits is the first step,

The first step would be to develop a business case for deploying it within the organization. You need to clearly justify why you want to implement that solution and what specific benefits it will bring to the organization. (Ayeni, 2025)

After that, to deliver the above mentioned service offerings effectively, the consultancy requires a combination of strategic, relational, and domain-specific capabilities. These include a broad understanding of artificial intelligence concepts, tools, and integration requirements; strong familiarity with construction sector processes; and the ability to identify and evaluate digital opportunities within client organizations. Equally important are the skills to engage diverse stakeholders, facilitate communication between technical and non-technical actors, and coordinate change management within the firm. Furthermore, awareness and knowledge to find funding opportunities and write applications. Core tools will include online collaboration platforms, assessment templates, broad AI software offerings, roadmap templates, and grant application templates. Technical development work and grant applications may be partially supported through partnerships or freelance collaborations as needed, allowing the consultancy to focus on navigation, integration, and strategic alignment.

Operational Assumptions

The operational model of the consultancy is built on a set of assumptions related to time, cost, and workload across four core areas: Client Work, Sales, Funding, and Operations. An additional 16 key assumptions were identified to estimate the resources required to deliver services effectively within a delivery model of 10 projects per year. These assumptions are based on initial estimations, personal judgment, and exploratory thinking rather than formal industry benchmarks. They are intended to create a realistic starting point for modelling the venture's operations and identifying which areas may require further validation or adjustment as the business develops.

The average project duration is estimated at 4 weeks *(Assumption 5)*, requiring approximately 100 active consultant hours per project *(Assumption 6)*. This includes research, meetings, reporting, coordination with external experts, and client communication. Annually, this results in around 1000 hours, which is realistic for a solo consultant operating full-time.

The consultancy is not based on traditional direct selling, but rather on building relationships and guiding clients toward grant-funded innovation. Based on this, each signed client is assumed to require outreach to approximately 5 contacts *(Assumption 7)*, and 5 hours of pre-sales work *(Assumption 8)* for meetings, scoping, and proposal preparation. Furthermore, in-person presence carries strong credibility and is highly valued by professionals. Participating in industry events and conferences is a powerful learning opportunity and a strategic marketing approach to build visibility and trust. Therefore, 30,000 DKK / year is allocated for attending relevant trade fairs *(Assumption 9)*, conferences, and networking forums, along with 300 hours / year dedicated to preparation, travel, and active participation *(Assumption 10)*. This visibility will become a key channel for attracting clients once the consultancy is market ready.

The consultancy operates under a grant-funded model, where the consultancy fee is integrated into the funding application *(Assumption 20)*. This reduces the financial barrier for construction firms while ensuring that the venture can operate without requiring direct payments from clients. Approximately 100 hours per year *(Assumption 11)* are allocated for identifying relevant funding calls and aligning client cases with available opportunities. An additional 100 hours per year *(Assumption 12)* are allocated to preparing grant proposals, whether independently or in collaboration with an external grant writer. In cases where external support is required, the consultant may delegate parts of the writing process. These collaborations are estimated to cost 10,000 DKK / application *(Assumption 13)*, resulting in a total annual expense of 100,000 DKK, depending on the number of externally supported proposals. This reflects the depth of work needed to prepare 10 applications per year, integrated into project delivery.

Several operational costs and time allocations were included to ensure the business can function smoothly. External experts who may support in AI tool evaluations or pilot designs a budget of 40,000 DKK / year *(Assumption 14)* is allocated. With an average of one on-site visit per project, the travel cost is estimated at 3,000 DKK / project *(Assumption 15)*, totalling 30,000 DKK / year. Access to platforms like Notion, ChatGPT Pro, and project management tools is budgeted at 20,000 DKK / year *(Assumption 16)*. Covering accounting, compliance, and legal consultation, this is estimated at 15,000 DKK / year *(Assumption 17)*.

To further reduce the financial barrier for construction firms, the consultancy also assumes that the hardware and software required for AI implementation, such as jobsite cameras and AI analytics platforms, can be covered as part of the funding application *(Assumption 21)*. This ensures that clients can adopt AI without upfront capital investment. The average cost of an AI tool package is estimated at 100,000 DKK / project *(Assumption 18)*, depending on project scope and tool complexity. This package typically includes cameras for data collection, AI software licenses, and where necessary, technical setup or integration support. For the consultancy, this results in an annual projected cost of 1,000,000 DKK, to be included in project funding proposals alongside the consultancy fee.

A 10% buffer is added to the available working time, ~160 hours / year *(Assumption 19)*, accounting for unexpected delays, illness, or overrun on client work.

These assumptions are designed to be both practical and testable, and they will be revised as more data is gathered through real client engagements. Together, they form a realistic picture of what the consultancy requires to operate sustainably under a grant-funded model.

6.2.3 Key Assumptions Checklist

The third discipline in the Discovery-Driven Planning process is to identify and track the key assumptions upon which the business concept relies. These assumptions, often embedded in strategic and operational thinking, must be explicitly stated so they can be tested, refined, or rejected as the venture evolves (McGrath & MacMillan, 1995). By examining each assumption and feeding the results back into the reverse income statement and operational model, the business can adapt in response to reality, ensuring that viability is not based on optimism, but on evidence.

Assumption 1	Target Profit	400,000	*DKK*
Assumption 2	Profit margin	20%	
	Revenue	2,000,000	*DKK*
	Allowable Costs	1,600,000	*DKK*
Assumption 3	Project Annually	10	*DKK*
Assumption 4	Price per Project	200,000	*DKK*
	Profit per Project	40,000	*DKK*
	Allowable Costs per Project	160,000	*DKK*

Category	***Assumption***	**Operation**	**Project**	**Annually**	**Unit**
Client Work	*Assumption 5*	Project Duration	4	40	*Weeks*
	Assumption 6	Active Consultancy	100	1000	*Hours*
Sales	*Assumption 7*	Client Outreach	5	50	*Contact*
	Assumption 8	Pre-Sales Work	5	50	*Hours*
	Assumption 9	Marketing & Visibility		300,000	*DKK*
	Assumption 10	Personal Development		300	*Hours*
Funding	*Assumption 11*	Funding Scouting		100	*Hours*
	Assumption 12	Funding Applications		100	*Hours*
	Assumption 13	External Grant Writer Support	10,000	100,000	*DKK*
Operations	*Assumption 14*	Tech Freelancers Costs		40,000	*DKK*
	Assumption 15	Travel Costs	3,000	30,000	*DKK*
	Assumption 16	Software & Tools Costs		20,000	*DKK*
	Assumption 17	Admin & Legal Costs		15,000	*DKK*
	Assumption 18	AI Tool Package Cost	100,000	1,000,000	*DKK*
	Assumption 19	Contingency Buffer 10%		160	*Hours*
	Overall	**Costs Spent**		**1,505,000**	***DKK***
	Overall	**Time Spent (8 hours / day)**		**208**	***Days***

Assumption 20	The Consultancy Fee is integrated into the funding
Assumption 21	AI Tool Package Cost is integrated into the funding

Table 2, Key assumptions checklist

6.2.4 Milestone Planning and Learning Loop

The consultancy's strategic development based on predetermined plan and disciplined process of transforming critical assumptions into validated knowledge. In a venture where uncertainty is high and many operational elements remain untested, milestone planning provides a structured mechanism to guide resource allocation, reduce risk, and maximize learning over time (McGrath & MacMillan, 1995). This approach ensures that major investments, whether in time, money, or strategic direction, are made only after gaining evidence that justifies the next step. Rather than attempting to meet the plan at all costs, this model recognizes the importance of iterative discovery and adaptation (McGrath & MacMillan, 1995). Each milestone represents a checkpoint for testing key assumptions across the business model: client willingness to pay, value perception, funding feasibility, cost structures, tool deployment, and scalability potential.

To coordinate this process, a "Keeper of the Assumptions" is appointed, the founder and consultant. This role involves tracking which assumptions are being tested, collecting feedback, revising data in light of results, and updating the venture's planning documents. Without a formal mechanism for assumption tracking, the risk is high that critical learnings will be lost.

Milestone	Goal	Key Assumptions Tested	Learning Outcome
M1-A Explore the AI Tool Landscape	Engage with 3–5 AI tool providers in the construction industry to gather insights on available solutions	A14: External technical expertise is required for tool evaluation and integration A18: The AI tool package (hardware and software) has a predictable and affordable cost structure	Gain an understanding of the core features, pricing models, implementation requirements, and potential partnership opportunities offered by AI tool providers. This will help assess the feasibility of integrating these tools into the consultancy's service model
M1-B Validate the Funding Path	Engage with grant consultants and innovation funding agencies to evaluate the feasibility of the funding-based business model	A11: Time investment in funding scouting is realistic and sufficient A13: External grant writing support is available and affordable A20: The consultancy fee can be included in relevant public funding schemes A21: The cost of the AI tool package (hardware/software) can be covered by funding programs	Determine whether bundling consultancy services and AI tools into a single funding application is accepted and realistic. This will validate the viability of the "no direct cost to client" model and help define the structure and scope of future applications
M1-C Prepare for Internal Operations	Begin setting up the essential internal systems and tools needed to manage the consultancy's operations effectively	A16: The estimated cost and choice of software tools for project management, communication, and collaboration platforms are sufficient for solo operations	Identify and secure the necessary digital tools to support day-to-day consultancy activities, ensuring operational readiness for future client work
M2 Build and Test Initial Value Proposition	Develop and test an early version of the value proposition by creating a one-pager and elevator pitch. Conduct interviews with 3–5 decision-makers in SME construction firms to gather feedback	A7: Construction firms can be reached effectively through direct contact and are open to exploratory discussions	Identify who the key decision-makers are, what pain points they face, and how they perceive AI-driven consultancy services. Assess their willingness to engage with AI and determine whether they see value in a bundled offer that includes both consultancy and AI tool implementation. Use the insights to refine your outreach approach and improve the clarity and appeal of your communication strategy

Table 3, Milestone planning first stage

Milestone	**Goal**	**Key Assumptions Tested**	**Learning Outcome**
M3 Test a Real Case	Run a full pilot engagement with one SME construction firm. This includes conducting an initial assessment, delivering a tailored AI roadmap, and supporting the firm in applying for relevant grant funding	A5: The average project duration is 4 weeks A6: The project requires approximately 100 active consultant hours A8: 5 hours of pre-sales work is sufficient for initial scoping and proposal development A12: Time allocated to funding applications is realistic and manageable A15: Estimated travel costs for the project are accurate	Validate the structure and time requirements of the 4-week delivery model, including actual consultant hours and pre-sales effort. Assess how the client perceives the value of the AI roadmap and overall consultancy support. Additionally, test the practicality of supporting a firm through a full funding application and gain insight into the application process and outcomes
M4 Review Operations & Cost Structure	Analyse the actual costs and time investments from completed pilot projects and compare them against the original assumptions	A4: The proposed price per project is viable and aligned with actual delivery costs A17: Administrative and legal expenses are accurately estimated	Refine the business model based on real-world data. This includes adjusting pricing, consultant hours, and overhead cost estimates to ensure financial sustainability and improve the accuracy of future projections
M5 Establish Industry Presence and In-Person Marketing	Actively participate in construction and technology-related industry events, fairs, and networking forums. Position the consultancy as a credible and engaged thought partner by initiating conversations, showcasing the concept, and delivering short talks or presentations	A7: Construction firms are reachable and responsive through direct personal engagement A9: The allocated marketing budget is sufficient to support in-person activities such as event attendance and networking A10: Industry presence through events and conferences is an effective channel for building visibility, credibility, and generating client interest	Build meaningful relationships and raise awareness of the consultancy within the construction industry. Test whether face-to-face engagement at events results in stronger credibility, client conversations, and lead generation compared to passive online channels. Identify which events offer the most value for both professional learning and business development
M6 Plan for Scale	Interview industry experts to explore potential partnership or subcontracting models that could support future growth. Assess the feasibility of expanding delivery capacity while preserving quality and flexibility	A1: The target annual profit is achievable A2: The expected profit margin is realistic given delivery costs A3: The number of projects per year is scalable A6: A solo consultant has capacity limitations A18: The contingency buffer accounts for delays or overruns when scaling	Identify viable strategies for scaling the consultancy beyond solo capacity, such as collaborating with freelancers, forming strategic partnerships, or subcontracting. Clarify the trade-offs between cost, control, and delivery quality as the business grows

Table 4, Milestone planning second stage

Milestone	Goal	Key Assumptions Tested	Learning Outcome
M0 Gain Practical Experience	Seek traineeship-style collaboration or temporary involvement with existing consultancies operating in the construction or digital innovation space. The aim is to observe real project workflows, understand internal operations, and gain hands-on exposure to implementation processes	A5: Typical project duration is manageable and allows for involvement in meaningful project phases A6: Active consultant hours can be realistically estimated based on observed work A13: External tech support may be required depending on the firm's structure A15: Software tools used in real projects align with assumed licensing and cost structures. A16: Administrative and legal workflows are comparable to assumed operational requirements	Build a foundational portfolio and gain credibility through real-world exposure. Develop technical and operational insight into how similar consultancies operate, including their use of legal, administrative, and software systems. This experience will inform the planning and strengthen the value proposition through firsthand understanding

Table 5, Milestone planning optional path

The first stage focuses on gaining sufficient industry knowledge and testing early assumptions through low-cost, high-impact interactions with relevant stakeholders. Milestones M1-A, M1-B, and M1-C are pursued simultaneously to explore AI tool offerings, validate funding opportunities, and set up internal operations. These activities lay the essential groundwork by providing clarity on available solutions, implementation feasibility, funding structure, and operational readiness. Once this foundational knowledge is secured, Milestone M2 builds on it by engaging directly with potential clients to test and refine the initial value proposition. This phase prepares the consultancy for real-world application and its first successful deal.

The second stage represents the transition from idea to real-world execution, covering the consultancy's first operational year. Beginning with a pilot project (M3), key business assumptions are tested in practice, including delivery timelines, effort estimates, and the funding process. Subsequent milestones focus on reviewing actual costs (M4), establishing a credible in-person presence in the industry (M5), and exploring strategies for future scaling (M6). These activities provide valuable insight into operational realities, client perception, and market positioning. The combined learnings form the basis for refining the business model and preparing the consultancy for sustainable growth.

The third table is an optional path focuses on gaining practical experience through traineeship-style collaboration with an established consultancy. If such an opportunity emerges early, it enables hands-on exposure to real project workflows and allows key operational assumptions to be tested in practice. Direct observation of delivery methods, internal systems, and support structures helps reduce uncertainty and inform future planning. This stage also creates time for independent study and strategic refinement of the consultancy concept. Serves as a low-risk, high-learning entry point before launching full operations.

6.3 Summary of the Third Analysis

This section builds upon the insights generated through the previous research questions to propose and plan a viable AI consultancy business for the construction industry. The idea emerged not from having a specific product to push, but from recognizing a persistent problem in the sector: despite growing awareness of artificial intelligence and its potential, many construction SMEs remain stuck at the pre-adoption stage due to a lack of time, resources, digital readiness, or knowledge.

The opportunity was identified through a process of entrepreneurial alertness, interviews, and literature review. Repeated patterns, such as informal experimentation with AI tools, confusion around implementation, and hesitancy among smaller firms, revealed a latent market need. Simultaneously, a growing ecosystem of AI tools, software providers, and public support programs signalled underutilized resources. By interpreting these signals and recognizing the disconnect between available solutions and actual adoption, a match-making opportunity was identified: bridging well-known problems with existing but inaccessible solutions.

Unlike existing consultancies that typically support firms already committed to digital transformation, this business concept focuses on those at the pre-adoption stage. It aims to raise awareness, assess readiness, and facilitate adoption by acting as an independent and technology-neutral advisor. Public funding is considered a strategic enabler to reduce the financial barrier to entry for clients. The consultancy would assist firms in navigating and applying for these funds where possible, but the model remains adaptable to other funding mechanisms or client payment structures.

Discovery-Driven Planning framework was applied to systematically test and develop this idea under conditions of high uncertainty. The summary of the steps were the followings:

- A reverse income statement to define financial viability, setting a target profit of 400,000 DKK and deriving necessary revenues and allowable costs based on 10 annual projects.
- Pro forma operations to outline service offerings, such as AI readiness assessments, roadmap planning, tech scouting, and funding application support; delivery methods; required capabilities; and cost assumptions.
- A key assumptions checklist to explicitly track unknowns related to pricing, effort, funding feasibility, outreach efficiency, and client engagement.
- A milestone-based learning plan, with staged goals such as exploring the AI tool landscape, validating funding paths, piloting the service, and refining operations based on real-world data.

This approach supports iterative learning and strategic flexibility. Instead of making rigid forecasts, the plan emphasizes testing assumptions, learning from the market, and adapting accordingly. The proposed consultancy doesn't seek to invent new technologies, but rather to enable better alignment between already identified needs and proven solutions, something many firms struggle to achieve on their own.

In conclusion, this business opportunity was not “discovered”, but rather developed through cycles of observation, framing, and planning. By applying the DDP framework, the venture is positioned for low-risk, evidence-based growth, with a clear value proposition for an underserved segment of the construction market.

VII. CHAPTER

7 DISCUSSION

This discussion offers a critical reflection on the thesis findings and outlines future recommendations. AI adoption in the construction industry is still in its early stages within the innovation lifecycle and its overall impact remains limited. Moreover, the technology itself still requires further development and refinement to deliver significant value to the industry. Currently, only major players in the industry are experimenting with AI. However, construction projects typically involve multiple stakeholders, and if only a few adopt the technology, widespread implementation is unlikely to occur.

AI is not a one-size-fits-all solution and cannot be seamlessly integrated into construction firms without careful consideration due to its highly contextual characteristics. The research reveals that external support most of the times are required for successful technology adoption and utilisation. This creates both a need and an opportunity for tailored consultancy services that helps innovate the construction industry. Currently, most digital transformation consultancies cater to large firms, leaving small and medium-sized enterprises (SMEs) underserved. This points to a significant market gap: the transition from awareness to actionable implementation among SMEs remains largely unsupported.

Although many technology providers exist, their solutions are often too expensive or complex for smaller firms. In this context, a technology-neutral, implementation-focused consultancy model, one that emphasizes accessibility, guidance, and practical support, could help increase AI uptake. Such a model has the potential to improve SMEs' overall productivity and competitiveness across the construction industry.

The consultancy model proposed in this thesis was developed with a validation roadmap, but it has not yet been tested under real-world market conditions. Further research is needed to assess its practical viability and long-term impact on innovation outcomes at the firm level. Given the limitations of relying solely on external sources, incorporating a real-world use case or practical experimentation would greatly enhance the development of this idea, especially by addressing geographic and construction-specific attributes.

This thesis identifies only one potential business opportunity arising from implementation barriers, with a primary focus on aligning the author's personal interests with what was perceived as the most promising and impactful solution for advancing digital transformation in construction. However, it is acknowledged that additional opportunities may also emerge from these adoption barriers.

VIII. CHAPTER

8 CONCLUSION

This thesis set out to explore the challenges and opportunities surrounding the adoption of artificial intelligence in the construction industry. Through a multi-theoretical lens combining the Technology-Organization-Environment (TOE) framework, Diffusion of Innovation (DOI) theory, Entrepreneurial Opportunity theory, and Discovery-Driven Planning (DDP), the study provides a holistic understanding of both the barriers to AI adoption and a practical business model designed to address them.

The first part of the study mapped current AI applications in construction. Five main categories were identified: Automation and Robotics, Cost Estimation and Contract Management, Data-Driven Project Management, Safety and Risk Management, and Sustainability. These use cases demonstrate the transformative potential of AI to improve productivity, safety, and efficiency throughout the construction lifecycle.

Despite these promising applications, adoption remains limited. Using the TOE framework with the integration of the DOI theory, this thesis analysed the technological, organizational, and environmental barriers that hinder widespread implementation. Key technological challenges include lack of perceived relative advantage due to limited awareness and interest in ROI as well as low observability, poor compatibility with existing systems and stakeholder workflows, low trialability resulting in high initial investment requirements, and high complexity in understanding, applying and utilizing the technology. Organizational constraints, such as fragmented structures, weak innovation cultures, resistance to change among employees, limited leadership support, and lack of internal resources further slowdown the innovation uptake. Environmental obstacles, including industry fragmentation, regulatory ambiguity, and limited client demand for advanced technology also limit the diffusion. Collectively, these factors position the construction industry in the early stage of the innovation adoption lifecycle, with SMEs particularly underserved.

In response to these findings, an entrepreneurial opportunity was identified: the development of an independent, technology-neutral AI consultancy service tailored to support SMEs at the pre-adoption stage. Drawing on Entrepreneurial Opportunity theory, the thesis framed this gap as a “match-making” opportunity, connecting well-known industry needs with existing but underutilized AI capabilities. To structure this business opportunity in a realistic and flexible way, the Discovery-Driven Planning (DDP) framework was employed due to the high uncertainty around operational specifications. This included the creation of a reverse income statement, pro forma operational specifications, a key assumptions checklist, and a milestone-based learning loop. These tools enable low-risk experimentation and iterative refinement of the consultancy model based on real-world market feedback.

In conclusion, this thesis contributes to the understanding of AI applications currently used and their adoption challenges in the construction industry and proposes a practical pathway forward through entrepreneurship. By developing targeted support mechanisms for SMEs, AI adoption could become more advanced and refined as more experiments are carried out.

IX. CHAPTER

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