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RESEARCH ARTICLE

Unravelling the Challenges of Artificial Intelligence Adoption in Construction Projects: A Comprehensive Analysis of Barriers to Acceptance

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ABSTRACT - In recent years, artificial intelligence (AI) has emerged as a key enabler of digital transformation across various industries, including construction. Despite its potential to enhance project delivery through improvements in productivity, quality, and cost-efficiency, the adoption of AI in construction remains limited, particularly in developing countries. To address this gap, this study investigates the core barriers hindering the acceptance and adoption of AI technology in construction projects and aims to identify and prioritize the most significant among them. Using a quantitative approach, data were collected through a web-based survey targeting technologists and contractors. The study employed the Analytical Hierarchy Process (AHP) to evaluate four main barrier categories—motivation, incentives, skills, and cost—each comprising several sub-factors. Findings revealed that motivation (34.40%) is the most significant barrier, followed by incentives (27.20%), skills (21.20%), and cost (17.30%). The top three sub-factors were suspicious performance (M3) at 39.10%, lack of political support (I2) at 36.43%, and poor public acceptability (M2) at 35.79%. These findings offer important insights for policymakers and construction stakeholders to develop targeted interventions that support the integration of AI technologies, aligned with Industry 4.0 initiatives.

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1. INTRODUCTION

In the new global economy, advancement has become a central issue in our daily lives. New technologies, including AI, are developed as innovative tools and capable of increasing productivity. Obviously, the significance of the revolution created by recent breakthroughs has an impact on the construction industry. According to [1], these technologies have grown by assisting in the integration of assets, people, processes, and job sites, designed to allow everything to work intelligently, improve productivity, maximize asset usage and performance, and obtain more reach into workflows. Among these technologies are Building Information Modelling (BIM), digital supply networks, green and innovative materials, predictive maintenance, prefabrication and modular construction, Augmented Reality (AR) and Virtual Reality (VR), and autonomous drones [2]. Recent developments in the field of AI technologies have heightened the need for the construction sector by modernizing the way it operates as well as applying project delivery techniques utilizing the latest technological skills. As the matter of facts, educators and practitioners across the world have acknowledged it as an efficient method of project delivery. Therefore, the use of this practice in project delivery offers numerous significant advantages in terms of time, cost, and quality. However, a major problem of embracing technologies application in the construction industry is still lacking and minimal. Practitioners are more comfortable with conventional methods and resulting resistance to change. Recent evidence claimed that the conventional contract forms prohibit the notion of construction collaboration in current construction projects [3]. Hence, this study is conducted to identify barriers to acceptance in the adoption of AI technology in construction projects. The objective of this study is to explore and evaluate the factors hindering the acceptance and integration of AI technologies within the construction industry.

The construction industry possesses a variety of challenges which hinder its growth in improving productivity [4]. The complexity is due to many interrelated processes, semi-processes, and involved players at various stages and project sites. Because of its complex nature, there is lot of risks in this sector [5]. Previous studies have reported that there are risks in any industry, but the rate of risk in the construction industry is higher both before and after construction [6]. Up to the present time, it has become undeniable that the construction sector must embrace digitalization and expeditiously enhance its technological capability [4]. However, only a small percentage of construction organizations are intent on fully utilizing digital technologies [7]. Despite this, most stakeholders recognize the long-standing culture of resistance to change [4]. As the matter of fact, a major problem with this kind of challenge is modernization. In addition to that, [8] clarified that the construction industry stumbles behind in authorizing innovative technologies instantly. The rationale of this lies in the fact that they have been continually exposed to new, innovative tools and technologies ultimately optimizing stagnant productivity [9]. Recent trends in AI technologies have led to tremendous achievements have been made in the advancement of company activities, service systems, and industry development. According to recent studies, complex challenges and decision-making for real-world problems can somehow be dealt with by practicing AI

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technology. This revolution has resulted in crucial process improvements, cost-efficiency, shorter fabrication times, greater safety, and benefited industries in achieving its sustainability goals [4].

Along with this growth in the construction industry, however, questions have been raised about the acceptance and adoption of new technologies such as AI in this era. Despite its potential, the construction industry continues to face resistance towards adopting AI due to a reliance on conventional methods and limited digital integration. While various studies have discussed digital transformation in general, there is a noticeable gap in research specifically identifying and evaluating the key barriers to AI adoption in construction projects. Hence, this study aims to address this gap by pursuing two main objectives: (1) to identify the key barrier factors affecting the acceptance of AI technology in construction projects, and (2) to evaluate and assess these barrier factors to provide a clearer understanding of the challenges faced in AI adoption.

2. LITERATURE REVIEW

The construction industry is among the world's major income generators [10]. However, the reliance on individuals input as a significant element in the construction process incurs a significant expense. The construction sector is a good contributor to the economy because it employs a comparatively high number of labours [11]. One study by [12] examined the construction projects must interact with numerous and conflicting stakeholder groups from many disciplines, producing in social complexity and most of the time, there are no long-term working relationships beyond the span of a particular project. Projects are frequently carried out by many entities, which may be geographically dispersed. In contrast to [12], [13] argued that the construction industry plays an essential role in maintaining the indigenous environment through resource consumption, revenue growth, and water use, as well as the industry contributes immensely to raising the quality of life. Traditionally, it has been argued that construction projects have been characterized by field-based production methods in which most processes are carried out onsite. Henceforth, it is difficult to endorse large-scale investments for implementing automated equipment to improve productivity due to the construction project nature that are temporary [5], [14]. Other researchers, however, who have looked at embracing technology in the construction industry towards the new normal after the Covid-19, have observed that technology is a reasonable solution for the construction industry to address the difficulties brought by COVID-19 [15].

In recent years, there has been an increasing amount of literature on technology adoption in construction. The generalisability of much-published research on this issue is problematic. Barriers generally exist that hinder the execution of new ideas. Construction advancements include new equipment, machinery, and improvements that can help you attain your aim, carry out a particular role or tackle an issue [10]. It has been correspondingly considered technologies can provide the necessary strategies to achieve a better response to current and future demands and enhance performance and productivity in the construction industry [10]. Modular construction adoption formed the central focus of a study by [14] in which the author found this method increases productivity by 60% as well as can reduce the amount of waste produced by at least 70% compared to the conventional construction method. Nonetheless, in an analysis of advanced technologies usage of green building features in Hong Kong, [16] highlighted prefabrication is a waste reduction technology like precast concrete, scaffolding, and steel form and the topmost benefit not only to improve buildability yet additionally to limit waste. This includes enhanced occupant health due to improved indoor environmental quality (IEQ) and better living space, energy savings and greater long-term cost savings/profits, and most importantly the decrease of ozone-depleting substance emissions and consequently, the effect of structures on the climate [16]. Whilst [15] is more concerned with prefabrication technology in post Covid-19 since it has made an extraordinary performance in the construction industry to respond to the COVID-19 outbreak. It is widely known that Leishenshan and Huoshenshan hospitals were deployed no less than about fourteen days in Wuhan, China [15]. Thus, together these studies provide significant insights into the utilization of current technology advancement in the construction industry began to play a more critical role because of its advantages like less dependence on labor, enhanced occupational health and safety and improved efficiency.

The development of general information and communication technology (ICT) applications is increasingly being seen in a variety of areas of the construction sector [12]. Human resource and knowledge management automation, as well as document categorization, are examples of such applications, digital engineering for labour productivity, construction management data visualisation, Internet of Things, augmented and virtual reality, laser scanning, 3D printing, robotics and drones [12], [17]. His argues that her data supports [17] the view that the potential transformative impact of these technologies are arising, particularly exploring the use case scenarios where these technologies, combined with BIM can improve architecture engineering and construction (AEC) through the different phases of the project lifecycle. Some writers [13] have endeavoured to accept that the construction sector will gain from applying sustainable construction concepts by acknowledge and best practises of sustainable construction that have a positive influence on the environment, economics, and society for stakeholders to develop eco-friendly structures for economic and social welfare. In the context of safety in construction project, [11] examined the extent to which technology adoption predictors influence safety in construction. It has been proved that innovative methods have progressively gained traction owing to their potential to enhance workplace safety conditions and avert accidents and losses [11]. In this context, "safety technologies" means the use of IT, automation, and sensor technologies to track and enhance the safety compliance and control. Consideration of the social impact of safety raises the question of whether actions influenced by safety should be assessed by similar criteria with respect to other projects. Generally, there seems to be some evidence to indicate that while projects increase in complexity, it may need greater effort from employees, necessitating the incorporation of creative approaches and technological capabilities in upgrading the working environment. Much of the available literature deals with the development of technological advancement highlighting the tools that employees may utilize to educate themselves about safety protocols. Consider a VR game systems that lets students explore and operate various heavy equipment and tools used in construction, such as a tall structure cranes, movable cranes, and piling loader, as well as to create teaching tools for risky procedures like trench excavation and bricklaying.

2.1 Barriers factors to the Acceptance of AI Technology

In construction, considerable research indicates that AI technologies have a large beneficial effect on overall performance, productivity, safety, and efficiency [18]. However, there is a large volume of published studies describing the barriers to acceptance of AI technology in construction projects. Apparently, regardless of this multitude of critical endeavours, the industry is trailing other industries in the application and implementation of technological advancement. Furthermore, factor viewed to be influencing the adoption of AI technology have been explored in several studies. Cost is one of the barriers to the adoption of AI technology in construction projects. This issue had raised concerns among stakeholders in the construction industry. A study by [19] found that there was a high initial capital cost to set up the production lines and machinery and to train employees in the innovative new methods of construction. Similarly, [16] discovered that when compared to conventional buildings, it is associated with higher initial design and construction costs as well as higher maintenance costs. Likewise, [13] hold the view that a tight construction budget has existed since the procurement phase, and this is something that hinders construction organisations from considering higher costs for infrastructure project execution. [20] pointed out that many construction-related overhead expenses are incurred only if development occurs, assuming that it is difficult to deploy innovations to adapt to shifting demand. costs reduce opportunities, yet they do not constitute a primary barrier. The extent to which costs are perceived as high is influenced by the budget constraints of the organizations involved.

Skills refers to the practical capacity that individuals believe they possess to implement AI technologies in construction projects. This problem is being exacerbated by a lack of skilled construction workers to acceptance in adoption to AI technology. [20] argued that it demands qualified labors for both manufacturing component and effective on-site assembly of these parts. He also noted that the low market demand demonstrates that just a tiny number of projects use innovations, therefore relatively few or no new individuals were indeed learning about them. Similarly, [21] concluded that the lack of skilled labour on the use of AI technologies goes hand in hand with the lack of industry investment and thus could impacted to the influence of SMEs in the construction sector. Furthermore, as their expertise grew, they were able to assess, evaluate, and even design new technological approaches. In the meantime, not only they require better levels of knowledge, but also enable the learners to grasp and utilize knowledge. According to [20], university students are less introduced to new technology's organisation and design due to fewer code and standards accessible, and regulatory authorities have yet to establish many of them into planning regulations. In general, he also claimed that the lack of standards and guidance for the technical and legal elements of innovation makes national and international communication challenging. As a result of their lack of skills and experience, practitioners have a natural tendency to choose traditional approaches.

Moreover, incentives are also one of the barriers to acceptance in adoption of AI technology. Government contributes a critical role in enhancing beneficiaries' awareness of the use of AI technology in construction projects. Authorities in a country generate unique outcomes by developing proper policies. According to [22], the more government intervention there is, the more serious the public perceives innovations to be. As a result of overcoming the process of social influence, the possibility of practitioner's preference for developing technology grows [22]. Additionally, the government is urged to support construction companies interested in digital advancement by offering financial subsidies for expenditures related to innovation adoption [23]. Certainly, financial subsidies for the expenses associated with innovation adoption may help to ease their financial strain, particularly SMEs and thereby also fostering wider use of AI technology. The findings investigated that the number of manufacturers who can innovate is minimal [24]. Obviously, this implies that certain project locations may be situated a long distance from the nearest manufacturer. As a result, enormous and heavy goods must be transported across vast distances, incurring substantial transportation expenses.

In the history of development economics, motivation has been thought of as a barriers factor in the effort to adopt technology advancement in the construction industry. This is particularly relevant when it comes to an individual's perceptions. Perceptions are undoubtedly a classic problem that is assessed by contrasting personal understanding in the adoption of AI technology with the ideal situation [25]. In other words, it is shaped by individual experiences, social interactions with others, and cultural and historical contexts. By the same token, many construction companies are still characterized by a rather conservative company culture and mindset and are often hampered by organizational inertia. For this case, the companies need to drive organizational change including an iterative process, which requires careful alignment of company culture and goals, organizational design and incentive schemes to support their overall business goals. The willingness to learn about and apply AI technology is what motivates people to adopt it. However, there is poor public acceptability of knowledge, which is primarily shaped by the attitudes of community members and peers. According to [25] socialized and normalized behaviours are influenced by cultural and religious factors, which affect the acceptance of AI technologies. This occurs because individuals tend to compare their own perceptions of a situation with those of others. Consequently, the findings strongly suggest that when new knowledge contradicts established behaviors, initiating change can be challenging. Indeed, the adoption of new methods necessitates a shift in practice. If this change is complex, practitioners must possess a deep understanding of how to effectively implement these techniques to achieve satisfactory designs and processes. However, there must be a readiness to move away from conventional construction methods. In the same vein, [25] in his research notes that many companies and people are unwilling to change their thinking to implement new methods.

Another issue with these barriers is a suspicious performance of the adoption of technological advancement. Previous study has found that many individuals are sceptical of the performance and quality of MMCs (Modern Methods of Construction) due to prominent failures in the past [24]. This viewpoint is supported by, who stated that the ability to act entails being capable of implementing technological advancements with the available resources without devoting huge effort. All things considered satisfaction with resources is evaluated according to its quality, quantity, durability, and utility whether it is satisfying stakeholders' requirements in different ways. Up to the present time, constructing a structure in an innovative method has not been a common task for ordinary practitioners in development. Not everyone believes in their own competence to fulfil the task. On the other hand, [21] is much more concerned with lack of data security and preparedness for cyberattacks finding that it is rather unfriendly, often lacking compatibility and interoperability. According to the literature review, relatively few researches has examined technology from a social and human standpoint. Regardless matter how trustworthy, valid, generalizable, and adaptable the technology is, its execution will not appear to be legitimate if customers do not recognise and accept it. As a result, it is critical to incorporate consumers in the technology development process. Collectively, these studies outline the barriers factor influencing in the adoption of AI technology in the construction project which depend on cost, skills, incentives and motivation. Following to this, [16] claimed that the complexity of the technologies is the most significant challenge in construction project. Table 1 below shows that the past studies on Technology Barriers.

Table 1. Past studies on technology barriers

Author	Topic	Findings
[24]	Barriers of implementing modern methods of construction	Identify the importance of various barriers to wider adoption of modern methods of construction
[25]	Drivers and barriers for the adoption of hazard-resistant construction knowledge	Examine how households impacted by hazards perceive and plan to respond to hazard-resistant construction knowledge by evaluating their motivation, capacity, and opportunities (MAO).
[23]	Potential and difficulties for health and safety technologies in construction during the COVID-19 pandemic in Chinese projects	Assess the implementation of health and safety technology for handling the pandemic within the construction industry during the COVID-19 pandemic.
[22]	In what manner does the satisfaction of solar PV users augment their trust in the power grid? Evidence in rural China.	Discuss and analyse factors affecting beneficiaries' satisfaction and their trust promoting the adoption of solar PV. Methods.
[21]	Structured analysis of ICT adoption in the European construction industry	Identifies elements that pull and elements that push technology, but which need to overcome the various frictions and barriers.
[13]	Sustainable construction practices in the execution of infrastructure projects: The extent of implementation	Evaluate the means of implementing sustainable principles in the execution of infrastructure projects
[16]	Criteria and barriers for the application of green building features in Hong Kong	Determine barriers to implementation is essential to promote and enhance green building development
[18]	Understanding the usage of digital information and resources technologies in building evaluative analysis of current studies	To provide a rigorous analysis of studies about the deployment of data and resources technologies within the building construction sector and to provide a logical model outlining the many phases of the adaptation processes. Analyse deficiencies in the current studies that fail to present a comprehensive overview on innovation uptake within the building construction research.
[19]	How modern methods of construction would support to meet the sustainable construction 2025 targets; the answer is still unclear	Investigates whether a greater uptake in modern methods of construction (MMC) could help achieve sustainable construction targets.

3. METHODOLOGY

3.1 INTRODUCTION

This study aims to identify the barrier factors to the acceptance of AI technology adoption in construction projects. The questionnaire is distributed through a web-based survey platform to engage respondents involved in construction activities, particularly Technologists and Contractors. The questionnaire adopts a pair-wise comparison format derived from the Analytic Hierarchy Process (AHP) Hierarchy Diagram, which is analysed based on the various barrier factors influencing the acceptance of AI technology in the construction sector. Respondents are required to compare the significance of two paired factors and to rate the degree to which one factor presents a greater barrier than the other. The use of a web-based survey platform allows respondents to easily and quickly access and complete the questionnaire. This approach is advantageous due to its convenience, cost-effectiveness in data collection, and the ability to gather high-quality data.

As illustrated in Figure 1, the conceptual framework of this study categorizes the barriers to acceptance into four major dimensions: cost, skills, incentives, and motivation. Under the cost dimension, barriers include high capital cost, high equipment cost, and high overall cost, all of which contribute to financial hesitation in adopting new technologies. The skills category highlights the necessity of skilled labour, the need for training programs, and the limited availability of standard practices for AI adoption. In terms of incentives, the lack of financial incentives, minimal political support, and a general reluctance among manufacturers to innovate serve as critical barriers. Lastly, motivation-related barriers reflect the prevailing mindset within the industry, low levels of public acceptability, and concerns about the reliability or performance of AI technologies. These identified categories and sub-factors form the core elements evaluated through the AHP methodology in this study.

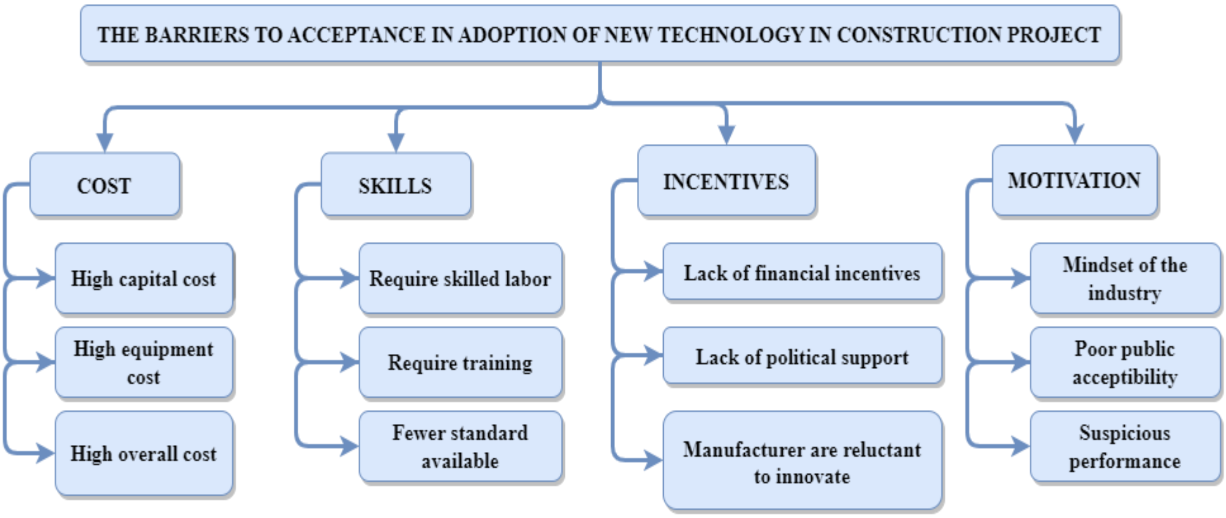

Figure 1. Conceptual framework of the barriers to acceptance in adoption of AI technology in construction project

3.2 Data Collection

Figure 2. illustrated the research methodology of this study. The sampling methods used in this study were defined based on specific criteria:

i. This study targets respondents exclusively within the construction industry.

ii. The study focuses on respondents who meet the inclusion criteria of being technologists registered with MBOT or contractors of any grade holding a CIDB license in Malaysia.

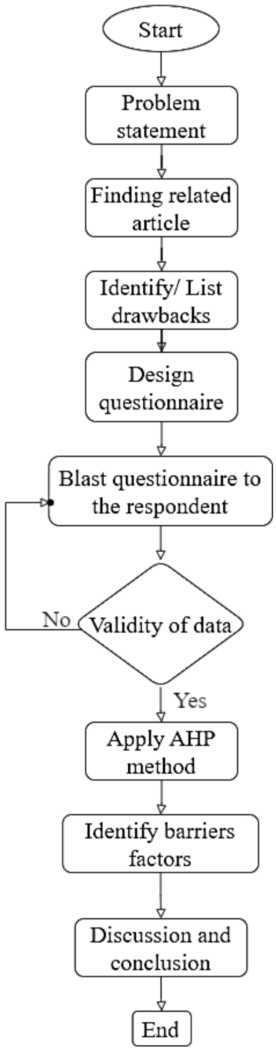

Figure 2. Research methodology

3.3 Data Analysis

3.3.1 The Analytical Hierarchy Process (AHP)

Analytical Hierarchy Process which was first introduced by Prof. Saaty provides a flexible and simple implicit way to analysing complicated dispute [26]. It is a multi-criteria decision technique that enables for the evaluation of both subjective and objective aspects in the decision-making process. It is one of the strategies designed to enhance Multicriteria Decision-Making (MCDM), which is one of the key fields of decision theory and is used to discover the optimal option from all the alternatives accessible [27]. According to [26], AHP employs a strategy that identifies pertinent information and acknowledges its significance in decision-making. Logic is useful for more than only solving tough issues and establishing relationships through deductive methods [26].

The AHP allows for the active engagement of decision-makers in achieving reconciliation and deciding on a rational basis. As a result, AHP has been regarded as one of the most effective tools since its introduction in 1988, and it has drawn enormous attention throughout the sector, including construction. Construction decision-making is often characterized as complex, ambiguous, and challenging to define clearly. Moreover, the factors involved in construction-related decisions are numerous, with intricate and frequently nonlinear interrelationships. Consequently, making informed and strategic decisions is essential for the successful execution of construction activities and operations. Thus, AHP is a convenient tool for making strategic and sound construction decisions which enables decision-makers to use several quantitative criteria to evaluate prospective alternatives and then select the most appropriate one [27].

The Analytical Hierarchy Process (AHP) is particularly valued for its capacity to incorporate the subjective perspectives of decision-makers, making it an appealing method for integration with other approaches typically oriented toward objective data [28]. Recently, it has been observed that decision-makers in construction projects—often project managers, clients, or stakeholders—have increasingly adopted AHP as a preferred tool in their decision-making processes. Consequently, AHP has become widely implemented as a component of systematic risk management strategies throughout the construction project life cycle. The subsequent section provides a detailed description of the procedural steps involved in the AHP methodology.

3.3.2 Procedural / Steps in AHP Method

The Analytical Hierarchy Process (AHP) involves several key calculation steps: hierarchical development, relative assessment matrices, normality, value aggregation, and coherence evaluation. The method employs the assessments of decision-makers to arrange intricate choice problems into a hierarchical framework. A nine-point scale (1–9) is employed to represent the logical preferences of decision-makers [26]. By arranging each pair of decision items in a matrix, AHP facilitates the ranking of alternatives through pairwise comparisons, which generate weighted scores to assess the comparative significance of items and criteria. Matrix algebra is then utilized to enhance these values and ascertain the ideal solution.

The phases of the AHP technique comprise:

Step 1: Construct the factor matrix. This step involves decomposing the problem into a hierarchical structure comprising the overall goal, factors, and sub-factors, as illustrated in Figure 1.

Step 2: Conduct pairwise comparisons of alternatives using a qualitative scale. This scale ranges from 1 to 9, allowing decision-makers to assign relative weights based on the significance of each activity in relation to the overarching objective. At the lower end, a score of 1, "Equal Importance," suggests that two activities are equally important in achieving the goal. Progressing up the scale, a score of 3, "Moderate Importance," is applied when experience or judgment slightly favors one activity over another.

The scale further intensifies with a score of 5, representing "Essential or Strong Importance," where one activity is strongly preferred based on the decision-maker’s experience and judgment. A score of 7, termed "Very Strong Importance," indicates a clear preference for one activity, backed by demonstrable dominance in practical scenarios. At the highest intensity, a score of 9, "Extreme Importance," signifies that the evidence supporting one activity over another is of the utmost certainty and relevance. Intermediate values (2, 4, 6, and 8) provide flexibility in the scale, allowing decision-makers to assign nuanced preferences when an absolute decision is not feasible, and a compromise rating is necessary. This scale, with its structured approach to quantifying subjective judgments, supports the rigorous comparative assessment required in the AHP process.

Step 3: The results from the comparative analyses of varied factors being compiled transformed into a square matrix format. If C={Ci|j=1,2, 3,…,n} represent the parameters given. Eqn. 2 illustrates the paired comparison employing a square, reciprocal matrix:[26]

$$A = aij = \begin{Bmatrix} a11 & \dots & a1n \\ \vdots & \ddots & \vdots \\ an1 & \cdots & ann \end{Bmatrix} \tag{1}$$

Step 4: The major eigenvalue and its associated normalized right eigenvector of the comparison matrix indicate the relative significance of each assessed element. The components of the normalized eigenvector function as weights for each factor or sub-factor, as well as ratings for alternatives. Equation (3) delineates the normalization formula applicable to each matrix:

$$Aw = \lambda max.\ W \tag{2}$$

According to [26], a necessary and sufficient condition for consistency is λmax=n. Inconsistency arises when λmax differs from n, which can happen due to variations in pairwise comparisons. Thus, [26] suggests a method for assessing inconsistency by calculating the consistency index (CI) using Equation (3). The consistency ratio (CR) is then obtained by dividing CI by the random consistency index (RI), as shown in Equation (4), where RI values are listed in Table 3. A CR value exceeding 0.1 indicates that the pairwise comparison should be reconsidered:

$$CI = \frac{(\lambda_{max} - n)}{(n - 1)} \tag{3}$$

$$CR = \frac{CI}{RI} \tag{4}$$

The Random Consistency Index (RI) values, which correspond to the number of factors used in the Analytic Hierarchy Process (AHP) for assessing consistency in decision matrices. The RI values are crucial for determining the Consistency Ratio (CR) in AHP, which evaluates the logical consistency of pairwise comparisons. For matrices with 1 or 2 factors, the RI value is 0, indicating that no random inconsistency is present due to the simplicity of the decision-making scenario. For a 3-factor matrix, the RI value is 0.58, reflecting a low inconsistency level, as fewer comparisons are needed. As the number of factors increases, the RI value grows to reflect the increased chance of inconsistency: 4 factors yield an RI of 0.90, 5 factors have an RI of 1.12, 6 factors result in an RI of 1.24, 7 factors have an RI of 1.32, 8 factors yield an RI of 1.41, 9 factors show an RI of 1.45.

The increasing RI values align with the complexity added by each additional factor. For matrices with 9 factors, the highest RI value of 1.45 indicates the maximum allowable random inconsistency for matrices of this size in the AHP framework. These values provide a basis for comparing the actual consistency of judgments to a randomly generated matrix, thereby ensuring that decision-making processes remain rational and dependable even in complex scenarios.

4. RESULTS

4.1 Questionnaire

The questionnaire is distributed through a web-based survey platform to get respondents involved in construction projects, especially Technologists and Contractors. This questionnaire employs a pair-wise question format derived from the AHP Hierarchy Diagram, which was analysed based on barriers factors to AI technology acceptance in construction projects. Respondents were asked to compare the relevance of two paired factors and to rate the scale of the barrier factor as dominating over the other factors. Because respondents may quickly access their responses, this questionnaire is disseminated using web-based surveys. The benefits of web-based surveys may be connected to the convenience and low cost of data collection, as well as the quality of the data.

4.2 Demographic Data Analysis

Table 2. shows the demographic data that covers the gender of respondents, working sector, profession, contractor grade, and years of experience. Demographic data provides a valuable basis for examining diverse viewpoints on technology adoption within the construction sector. The gender distribution, with 63% male and 37% female, reflects current industry trends but also underscores the potential for incorporating more women's perspectives, which could foster novel ideas and approaches to embracing technology. The substantial representation from the private sector (77%) offers deep insights into market-oriented attitudes, while the public sector's input (23%) sheds light on how regulatory frameworks influence innovation. The variety of professional roles, notably among engineers and main contractors, captures the perspectives of those integral to project implementation. Moreover, with over half of the respondents identified as professionals rather than specific contractor grades, the data encompasses both strategic and operational viewpoints. A range of experience levels, from early-career to seasoned professionals, further enriches the analysis, balancing openness to innovation with established industry insights. This demographic diversity provides a solid foundation for understanding technological readiness in construction and highlights specific areas with strong potential for innovation.

Table 2. Demographic data

Demographic Variable	Category	Number of Respondents	Percentage (%)
Gender	Male	19	63
	Female	11	37
Working Sector	Private	23	77
	Public	7	23
Profession	Engineer	10	34
	Main Contractor	8	27
	Consultant	7	23
	Supplier	1	3
	Others (Senior Lecturer, Assistant Engineer, Project Manager)	4	13
Contractor Grade	Grade 7	11	37
	Grade 3	2	7
	Grade 2	1	3
	Not Applicable	16	53
Years of Experience	1-4 Years	13	43
	5-9 Years	3	10
	10-14 Years	6	20
	Over 15 Years	8	27

4.3 Barriers Factors Analyse Using AHP Method

The purpose of this study is to identify the barrier factors affecting the acceptance of AI technology adoption in construction projects using the AHP approach. A hierarchical model was developed, consisting of four primary factors, each further broken down into sub-factors. Reciprocal matrices were then created to facilitate experts in performing pairwise comparisons within the hierarchy. The geometric mean was utilized due to its compatibility with reciprocal values in the matrices. Additionally, when local priorities are aggregated using the arithmetic mean, global priority ratios vary, whereas they remain consistent when the geometric mean is used [29]. Table 3 presents the list of prioritized weight factors. Table 3 shows the priority weights of the four main barrier factors and their corresponding sub-factors in the adoption of AI technology in construction projects, as determined through the AHP method. The weights indicate the relative importance of each factor and sub-factor based on expert judgment, helping to identify which barriers have the most significant impact on AI acceptance.

Table 3. List of prioritized weight factor

Main Factors	Factors (Local Weighted, %), Rank	Sub-Factors (Local Weighted, %)	Global Weighted (%)	Ranking
Barriers Factor	Cost (17.30), 4	C1, (40.51)	7.01	9
		C2, (40.12)	6.94	10
		C3, (19.37)	3.35	12
	Skills (21.20), 3	S1, (37.47)	7.94	5
		S2, (21.11)	4.48	11
		S3, (41.42)	8.78	4
	Incentives (27.20), 2	I1, (34.79)	7.38	7
		I2, (36.43)	9.91	2
		I3, (28.79)	7.83	6
	Motivation (34.40), 1	M1, (25.91)	7.05	8
		M2, (35.79)	9.73	3
		M3, (39.10)	13.45	1

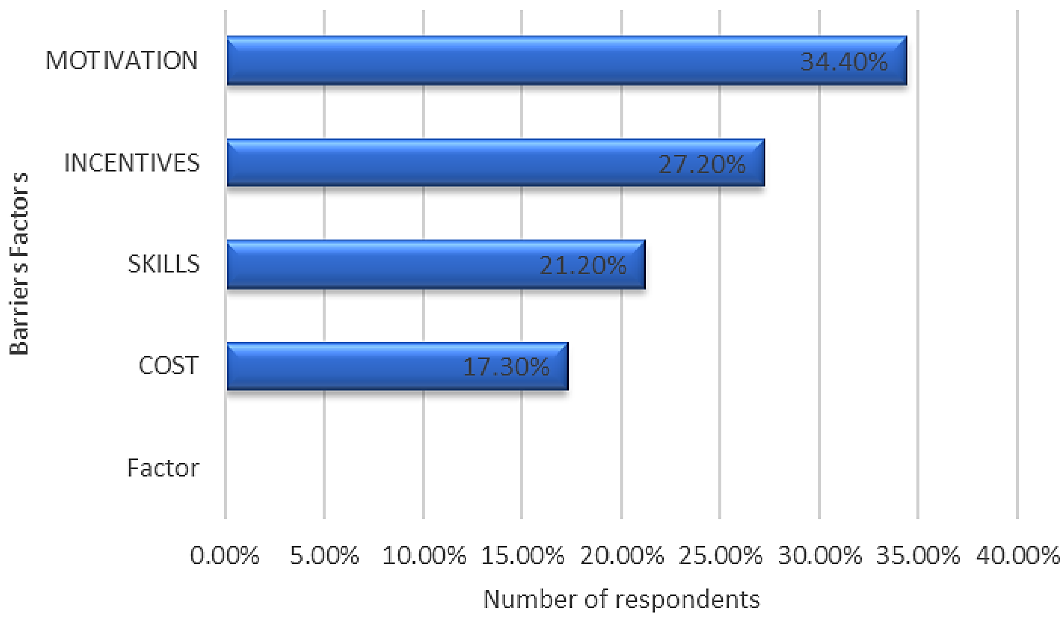

Figure 3. Prioritized of barriers factor elements

Figure 3 shows the most prioritized barriers factors to the acceptance of AI technology adoption in construction project are motivation (34.40%), followed by incentives (27.20%), and skills (21.20%). The least factor is cost (17.30%). Motivation dominated the ranks largely due to individual's perceptions. As stated in the literature review, perceptions are unquestionably a classic issue that is evaluated by comparing individual perceptions with the ideal circumstance [25]. This study produced results which corroborate the findings a great deal of the previous work in this field. A possible explanation for these outcomes will be a low level of motivation in many individuals and companies [24]. They do not intend to change their mentality in the hopes of embracing any new techniques. This assertion demonstrates that if the necessary change is sophisticated, it may be difficult to elicit change. This occurs because practitioners necessitate a high level of expertise of AI technology to fulfil the requirements of stakeholders.

Incentives are the next most barrier factor to be prioritized. Prior studies that highlighted the need for government intervention played an important part in persuading the public to take a more serious interest in implementing new technological growth in construction projects [22]. According to the findings of this survey, respondents believe that, to encourage industry practitioners to take the lead in digitalizing the construction industry, parties in government agencies and the private sector should tackle difficulties among industry practitioners. It can therefore be assumed that the results suggest that these parties should support construction companies engaged in digital advancement by offering financial incentives for innovation adoption expenditures [23]. This is because financial subsidies for the expenses associated with innovation adoption may help to ease their financial strain. As somewhat from the outcome, it is possible to predict that the number of companies capable of innovating is growing [24]. Skills ranked second-to-last among the barriers to AI technology adoption because they necessitate highly skilled labour as well as requires training to boost practical skills. This is consistent with our previous findings, which indicated that individuals with a background in a construction-related profession would prefer skilled labour in the adoption of AI technologies. This argument underlines the importance of skilled labour in both the production of components and modular parts in factories and the proper on-site assembly of these parts on the construction site [24]. Other authors have speculated that, a shortage of trained labour for the use of AI technology goes hand in hand with a lack of industrial growth [21].

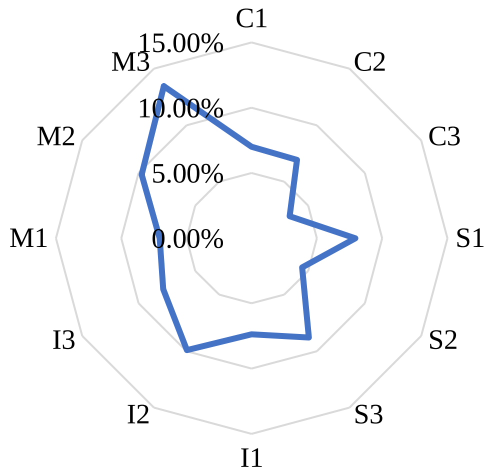

Figure 4. Prioritized of barriers sub factor elements

Furthermore, the sub-factors were ranked, and the top and bottom three (3) sub-factors will be discussed further. Figure 4 shows that 39.10% of the barriers to AI technology adoption are due to suspicious performance (M3). This study is parallel with Rahman (2014) findings. Many individuals are sceptical of the performance and quality of innovations because of significant failures in the past. There are, however, other possible explanations. Producing a structure employing an innovative approach has not been a common task for ordinary industry practitioners. Not everyone is confident in their ability to fulfil the tasks. These results match those observed in earlier studies. However, Turk (2021) was found to be significantly more concerned with a lack of data security and preparation for cyberattacks throughout this survey, believing it to be quite unfriendly, typically lacking compatibility and interoperability.

Next, lack of political support (I2) that falls under the incentives factor are also one of the top sub-factors (36.43%). This finding may be explained by the fact that the majority of respondents appear to be in agreement to encourage support from the parties concerned, most notably by granting political support connected to the adoption of innovation in the construction sector [23]. It is assumed that, with this intention in mind, the political influence associated with innovation adoption may serve to alleviate their stress and, as a result, promote greater acceptance of AI technologies. It is therefore proposed that an award be given to a candidate who meets the award criteria as a political supporter. Further studies, which take these variables into account, will need to be undertaken. The observed rise in supportive action might be related to the process of social influence being transcended, which increases the potential of practitioners' favour for advancing technology [22]. Further work is required to establish this.

Following that, poor public acceptability (M2) is assessed on the motivational constraints' component, with 35.79% being emphasised. This is because individuals are motivated to accept AI technology by their willingness to learn about and utilise it. However, public acceptance of knowledge is low, owing mostly to the attitudes of community members and peers. The current study's findings are compatible with those of [25], who state that socialised and normalised behaviour is influenced by culture and religion, and hence impacts the acceptability of AI technology. This is because people prefer to compare their own perception of the circumstance with other people's. Indeed, new requirements need a transformation in practice. If the necessary change is complex, practitioners must have a thorough grasp of how they should apply the approach to develop good designs and procedures. But they ought to be willing to set aside conventional construction methods. In accordance with the findings obtained, an earlier study has shown that [24] research indicates that many organisations and individuals are reluctant to alter their mentality in order to accept any new approaches.

However, the findings of the current study about high equipment costs (C2) does not parallel to past studies. The cost of setting up manufacturing lines and machinery for inventive modern building methods was expensive [19]. This problem had caused alarm among construction industry players. Although our findings differ from those of other published research [24], they are consistent with the belief that many site-based overhead costs are paid only if construction occurs, assuming that it is difficult to employ innovations to adapt to shifting demand. Costs, strictly speaking, reduce opportunity, but this is not the primary obstacle. The second bottom sub-factor is required training (S2) for construction workers to work under the new environments with 21.11% to prioritized. This study was unable to demonstrate that manufacturing components and modular in factories required highly skilled workers, therefore the efficiency of assembly work on-site of these parts is secure [24]. There is some evidence to suggest according to Rahman (2014) hold the view that this issue resulted in poor market demand since just a slight number of projects exploited an invention, implying that few or no newcomers were learning about innovations. Nonetheless, these finding do not parallel with the current study since S2 is on the bottom of the ranking.

Finally, contrary to expectations, this study did not identify a significant difference between barriers factors to acceptance in AI technology adoption and higher total cost to execute the innovation was ranked last with a result of 19.37%. When compared to the conventional way, this statistic is promising. [16] revealed that it is tied to greater start-up and installation expenses, as well as higher maintenance expenditures. Similarly, [13] believe that a restricted construction budget has persisted since the procurement phase, which prevents construction companies from pursuing greater prices for infrastructure project implementation. Another significant result was that, as [24] pointed out, many site-based overhead expenses are only incurred if a building occurs, implying that it is difficult to deploy innovations to adapt to uncertainty. However, these outcomes were not encouraging. Further studies, which take these variables into account, will need to be undertaken. These findings will doubtless be much scrutinized, but there are some immediately dependable conclusions for the fewest number of respondents with lower contractor grades. Thus, the cost constraints have no effect on the higher contractor grade.

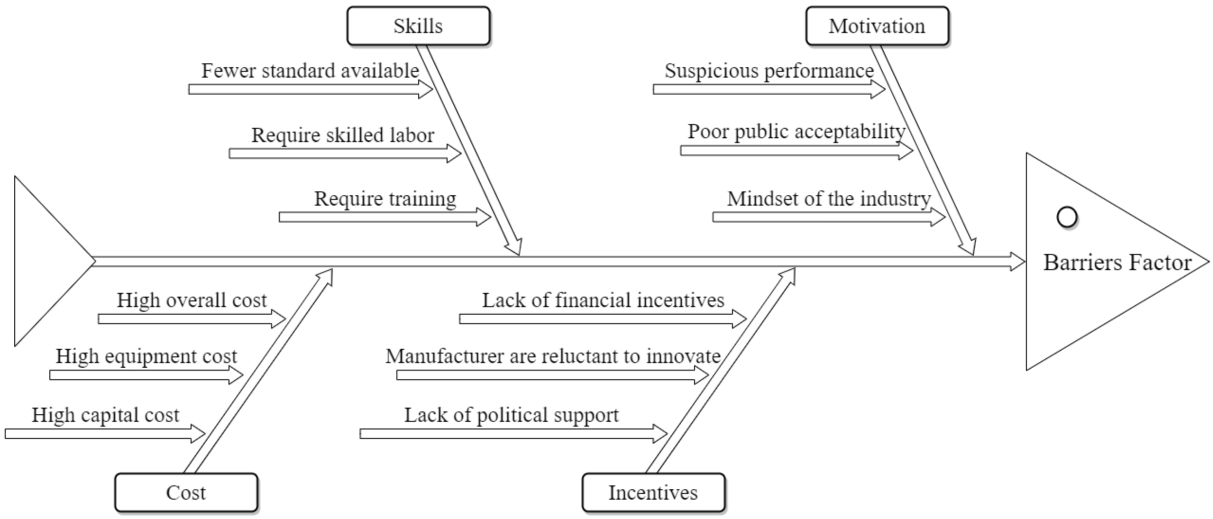

Figure 5. Model of barriers to acceptance in adoption to AI technology in construction project

Figure 5 presents a cause-and-effect diagram (often referred to as a fishbone or Ishikawa diagram) that visually illustrates the key categories contributing to barriers in the acceptance and adoption of AI technology within construction projects. The model categorizes the primary barrier factors into four main dimensions: Cost, Skills, Incentives, and Motivation. These categories represent the major causes feeding into the central issue, identified as the Barriers Factor, which hinders the effective implementation of AI technologies in the construction sector. The Cost dimension includes sub-factors such as high capital costs, high equipment costs, and high overall project costs. These financial burdens can discourage firms from investing in advanced AI solutions due to budget constraints or perceived lack of return on investment.The Skills dimension highlights the need for specialized human resources and training. Sub-factors in this category include the requirement for skilled labour, the necessity of targeted training programs, and the limited availability of established standards or guidelines. These elements point to the knowledge and competency gaps within the workforce that act as significant adoption barriers. The Incentives dimension addresses external support mechanisms and innovation drivers. This includes the lack of financial incentives, insufficient political or institutional support, and a general reluctance among manufacturers and industry players to innovate. Without proper support structures, organizations may find little motivation to transition toward AI-based methods.

Finally, the Motivation dimension encompasses behavioural and perceptual factors. Sub-factors include the prevailing mindset within the construction industry, low levels of public or stakeholder acceptability, and concerns over the reliability or perceived risks of AI performance. These factors reflect resistance to change and scepticism toward the outcomes of AI integration. Collectively, the diagram serves as a structured representation of how these various contributing elements interconnect and ultimately result in resistance or delays in AI technology adoption in construction projects. It also provides a useful framework for identifying which specific areas require intervention or policy focus to improve acceptance levels.

CONCLUSIONS

In summary, this study offers a comprehensive evaluation of the obstacles impeding AI adoption in construction projects, providing essential insights to support the industry's shift from conventional construction practices—which often rely heavily on manual processes and legacy systems—to AI-driven approaches that enable automation, predictive analytics, and enhanced decision-making. By identifying critical barriers such as motivation, incentives, skills, and cost, the research reveals the complex and interrelated challenges that continue to slow the construction sector's digital transformation. Among these, motivation—shaped by individual perceptions, trust in technology, and organizational culture—emerges as the most significant barrier. This highlights the need for targeted initiatives that promote awareness, build trust, and encourage a mindset open to technological change. The study's emphasis on incentives also underscores the critical role of governmental support, policy frameworks, and financial aid in mitigating initial adoption risks, particularly for small and medium-sized enterprises. Furthermore, the findings stress the importance of skill development, pointing to notable gaps in AI-related knowledge that affect both design and on-site implementation. Interestingly, although cost remains a concern, it was ranked lowest among the barriers, suggesting that non-financial factors—such as workforce readiness and industry perception—play a more decisive role in AI adoption.

However, this study is not without limitations. The sample was limited to technologists and contractors in a specific regional context, which may affect the generalizability of the findings to other stakeholders or geographic areas. Additionally, the use of AHP, while effective for prioritization, relies on subjective judgments, which may introduce bias despite efforts to ensure data reliability. Future research should explore a broader and more diverse set of stakeholders, including clients, consultants, and policymakers, across various countries and construction environments. Longitudinal studies could also assess how barrier perceptions evolve over time as AI technologies mature. Moreover, qualitative investigations may provide deeper insights into the behavioral and organizational factors behind resistance to AI adoption, complementing the quantitative approach used in this study. This study offers valuable direction for policymakers, industry leaders, and researchers, recommending collaborative efforts to formulate policies, training programs, and support systems that enhance the accessibility, relevance, and practical implementation of AI technologies across different segments of the construction industry.

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AUTHOR CONTRIBUTIONS

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Noram Irwan Ramli.: Data Collection

Putri Zulaiha Razi: Supervision and Data Validation

Mohammad Syamsul Hairi and Omar Jamaludin.: Writing- Reviewing and Editing.

Mohamad Idris Ali: Formal Analysis

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DATA AVAILABILITY STATEMENT

The data used to support the findings of this study are included within the article.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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