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Modeling AI Readiness and Adoption Intentions in Construction Management: A Technology Acceptance Model Approach

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Artificial Intelligence has emerged as a transformative force in construction management, enabling new capabilities in prediction, automation, and data-driven decision-making. Despite these advances, the industry continues to face significant barriers to widespread AI adoption, largely stemming from limited awareness, inconsistent training, and uncertainty regarding AI's perceived value. This study empirically examines the behavioral and perceptual factors that influence construction professionals' intention to adopt AI technologies. A structured survey of professionals was administered, incorporating constructs from the Technology Acceptance Model, perceived usefulness, ease of use, attitude, and behavioral intention, augmented by an awareness dimension. A total of 54 complete responses were included in the final analysis. Statistical analyses, including correlation and multiple regression modeling, were conducted to identify key predictors of adoption readiness. The results indicate that perceived usefulness and awareness are the strongest predictors of behavioral intention ($p < 0.01$), explaining 56% of its variance ($R^2 = 0.564$). Attitude exerted a positive but non-significant effect. Correlation results further confirm strong associations between usefulness, attitude, and intention, suggesting that adoption is primarily driven by perceived performance benefits. The findings highlight the need for targeted educational interventions and experiential learning opportunities that strengthen awareness and demonstrate AI's tangible value in CM practice.

Keywords: Technology Acceptance Model (TAM), Behavioral Intention, Technology Adoption

Introduction

The construction industry is entering an era defined by data-driven decision making and increasing automation. Artificial Intelligence (AI) has become central to this transition, offering capabilities that range from predictive analytics for scheduling and cost estimation to automated defect detection and progress monitoring through computer vision. Baek et al. (2024) demonstrated that deep learning-based computer vision can outperform traditional algorithms and identify site objects to enable automated productivity monitoring. A study conducted by Elmousalami et al. (2025) shows that AI applications are increasingly moving beyond proof-of-concept toward deployable solutions supporting estimating, automated quality control, and site monitoring. These studies suggest that AI is no longer peripheral to construction management (CM) but a developing component of mainstream practice.

At the same time, research on the implementation of digital and data technologies in construction consistently highlights the industry's slow diffusion of innovation. Studies on big data and digital infrastructure (Du, Hou, et al., 2024) report that although organizations are accumulating vast volumes of information through BIM, sensors, and visual data, the analytical and organizational mechanisms required to convert those data into actionable knowledge remain underdeveloped. Regona et al. (2022) further observed that the practical adoption of AI is constrained not by a lack of technical tools but by insufficient awareness, and inadequate institutional strategies for integration. Thus, while the technical potential of AI in construction is increasingly well understood, its adoption across CM functions remains fragmented and inconsistent.

This inconsistency reflects a broader knowledge gap at the intersection of technology, behavior, and education. Existing empirical research predominantly concentrates on developing or benchmarking algorithms, such as hybrid deep learning models for cost and schedule estimation (Cheng et al., 2025) or deep learning-based object detection for dynamic site management (Xu & Pan, 2024), rather than on understanding the behavioral and perceptual factors that drive whether decision-makers accept and use AI tools in practice. A notable research gap exists in the quantitative assessment of individual-level AI adoption readiness, i.e., construction professionals' awareness of AI, perceived usefulness/ease of use, attitudes, and behavioral intention to use AI, across distinct construction management (CM) functions. Moreover, prior work has not systematically compared perceptions across distinct CM functions, such as scheduling, cost control, safety monitoring, and contract administration, even though each area offers different levels of data maturity and automation potential. Without such empirical evidence, the industry lacks a clear understanding of which functional domains are most conducive to near-term AI adoption and what human or educational factors facilitate that adoption.

The present study addresses these gaps by quantitatively examining individual-level AI adoption readiness and behavioral intentions among construction professionals. In this study, readiness is conceptualized at the individual level, a person's preparedness to embrace AI for work tasks, and is distinct from organizational AI readiness, which typically refers to firm-level conditions such as data/IT infrastructure, and implementation governance. Using constructs grounded in the Technology Acceptance Model, perceived usefulness, ease of use, attitude, and behavioral intention, augmented by an awareness dimension, the study develops an empirical profile of how professionals view AI technologies and where they anticipate applying them. Through this analysis, the research seeks to identify the construction management functions with the highest perceived potential for AI integration and to determine the perceptual variables most strongly associated with adoption (i.e., behavioral intention to use AI-enabled tools in construction management tasks).

In addition, construction education research has increasingly proposed AI-related competency needs for construction professionals. The present study contributes complementary empirical evidence on how two education-sensitive determinants, awareness and perceived usefulness, relate to professionals' behavioral intention to adopt AI, and how these perceptions vary across construction management functions. This linkage helps translate existing competency work into actionable priorities for curriculum design and professional development by indicating which perceptual levers and which CM domains may yield the largest gains in adoption intention.

Background

Artificial Intelligence in Construction

AI in construction management has evolved into a data-driven paradigm that enables managers to make informed decisions through pattern recognition, prediction, and optimization in various domains such as quality and safety management (Torres et al., 2024), risk management (Arar & Halicioglu, 2025), safety and operational efficiency (Himeur et al., 2023) and estimating (Jafary et al., 2025). Another emerging application of AI in contract administration involves the use of large language models to interpret and manage textual data such as specifications, clauses, and submittals. Zhong & Goodfellow, (2024) demonstrate how domain-specific language models can automate clause extraction and compliance checking, significantly improving efficiency in contract management workflows.

Despite these advances, the literature consistently reports that the diffusion of AI into mainstream construction management practice remains limited. Factors such as fragmented data environments, limited interpretability of AI models, insufficient training, and lack of organizational readiness continue to restrict adoption (Abioye et al., 2021; Egwim et al., 2023; Yang et al., 2024). Although AI has demonstrated significant potential across multiple management functions, its integration into daily professional practice is still at an early stage of development.

Technology Adoption in Construction

Technology adoption in construction has been widely studied across domains such as BIM, drones, virtual and augmented reality (VR/AR), and the Internet of Things. These technologies share common adoption challenges that provide a foundation for understanding AI diffusion. Prior research identifies barriers related to perceived complexity, unclear return on investment, workflow disruptions, upfront investment, and resistance to organizational change (Ma et al., 2025; Torres et al., 2024). The adoption of emerging technologies is further hindered by issues of interoperability and data governance, which are particularly critical for AI applications that depend on large datasets (Egwim et al., 2023).

A growing body of literature has focused on identifying and prioritizing adoption determinants through multi-criteria decision-making approaches. Wang et al. (2023) emphasized the importance of organizational capacity, and human readiness as the most influential enablers for AI adoption. Broader analyses of AI in construction confirm that while technical maturity is increasing, diffusion remains highly uneven across regions and project types (Abioye et al., 2021). The literature identifies recurring organizational and human determinants of technology adoption, such as cultural readiness/change-management, leadership support, and workforce skills/training, as persistent hurdles in construction's digital transformation (Torres et al., 2024). While prior studies successfully examined adoption factors for digital construction technologies, extending these frameworks to AI remain underdeveloped. The limited understanding of behavioral intention and user attitude toward AI hinders the formation of a theoretical base for predicting adoption trends. This gap highlights the need for empirical models that measure individual acceptance and behavioral intention toward AI-enabled construction management.

Research Methodology

The theoretical framework for this study is grounded in the Technology Acceptance Model (TAM) and its extensions, which explain how individuals develop intentions to adopt new technologies. In this context, five key constructs were examined to understand AI adoption in construction management. (1) Perceived usefulness captures the belief that AI can improve efficiency, accuracy, and overall task performance. (2) Perceived ease of use reflects the extent to which AI tools are seen as intuitive and require minimal effort to operate. (3) Attitude toward AI denotes the individual's overall positive or negative evaluation of adopting AI in professional practice. (4) Intention to use indicates the individual's willingness or likelihood to adopt AI technologies in future work. Finally, (5) an additional construct (i.e., awareness) represents the degree of familiarity with AI concepts, and their applications. Construction technology adoption can be examined through several established lenses (e.g., TAM, Unified Theory of Acceptance and Use of Technology (UTAUT), Technology–Organization–

Environment framework (TOE), and Diffusion of Innovations (DOI)). We use TAM because this study is explicitly individual-level, modeling how construction professionals' awareness and perceptions relate to behavioral intention to adopt AI, and TAM provides a parsimonious, well-validated structure that aligns directly with our survey constructs (Venkatesh & Davis, 2000). In contrast, TOE primarily explain adoption via organizational/ environmental readiness, while DOI is oriented toward diffusion/adoption processes rather than the specific belief–intention mechanism. Moreover, UTAUT adds additional predictors/ moderators that would require a longer instrument and larger sample (Venkatesh et al., 2003); therefore, TAM is appropriate here and complementary to future multi-level work integrating individual acceptance with organizational readiness perspectives.

Survey Design, Participant Sample and Data Collection

The survey consisted of a combination of Likert-scale and categorical items. Likert-scale questions were measured on a seven-point scale (1 = Strongly Disagree to 7 = Strongly Agree) to assess respondents' perceptions of AI. Task-specific items, covering seven key construction management activities (e.g., scheduling, estimating, quality control), were included to assess both the perceived usefulness of AI and respondents' intentions to use AI within those functions. Categorical items gathered background information job title, years of experience, and prior exposure to AI-related tools.

Because AI is a broad umbrella term, consisting of various tools and techniques such as machine learning, computer vision, natural language processing and large language models, this study uses AI to refer to data-driven computational methods that learn patterns from data to support decision-making and automation in construction management. The survey items were framed around AI-enabled capabilities within core CM functions rather than any single commercial product or interface.

Data were collected from professionals currently employed in the construction industry, representing a variety of roles and organizational types using Qualtrics platform through two channels: (1) a direct email invitation containing the survey link, and (2) an in-person distribution of a QR code during professional interactions with construction practitioners, which respondents could scan to access and complete the survey. Participation was voluntary and anonymous, and no personally identifiable information was collected.

Data Preprocessing and Imputation

Prior to analysis, the survey responses underwent a systematic data preprocessing stage to ensure completeness and consistency. Each item in the dataset was classified as either categorical or ordinal based on a predefined schema aligned with the structure of the survey instrument. To ensure data integrity and facilitate quantitative analysis, missing values were addressed through an imputation process which allowed for the retention of a greater number of observations for statistical analysis. Categorical variables were imputed using the median value of the respective columns. Ordinal variables, were imputed using the arithmetic mean of each column, rounded to the nearest integer to maintain alignment with the original response scale. A total of 54 complete responses were included in the final analysis.

Construct Formation and Reliability

To evaluate the latent constructs underpinning the Technology Acceptance Model and its extensions, composite variables were created for each dimension using multiple survey items. The constructs included Awareness, Perceived Usefulness, Perceived Ease of Use, Attitude, and Behavioral Intention. Each construct score was computed as the means of its constituent items, all of which were measured on a consistent seven-point Likert scale. The internal consistency of each multi-item construct was assessed using Cronbach's alpha. The results indicate strong reliability for most constructs: General Behavioral Intention ($\alpha = 0.92$; 4 items), General Perceived Usefulness ($\alpha = 0.96$; 4 items), Task-Specific Behavioral Intention ($\alpha = 0.91$; 7 items), and Task-Specific Perceived Usefulness ($\alpha = 0.95$; 7 items). Attitude toward AI demonstrated acceptable reliability ($\alpha = 0.79$; 7 items). The Perceived Ease of Use construct exhibited lower internal consistency ($\alpha = 0.61$; 4 items), suggesting greater heterogeneity among its items. Because α values around 0.60 are commonly considered acceptable in exploratory research (Ait Abdelmalek & Houfaidi, 2023), the construct was retained due to its theoretical relevance within TAM and is interpreted cautiously in subsequent analyses.

Statistical Analyses

The cleaned dataset was subjected to a series of statistical analyses aimed at evaluating the relationships between core constructs and identifying the key drivers of behavioral intention to adopt AI in construction management contexts. The analysis proceeded in five stages: descriptive analysis, correlation testing, index development, regression modeling, and diagnostic evaluation.

Descriptive statistics, including means and standard deviations, were first computed for all composite variables and task-specific items to establish baseline tendencies in respondents' perceptions and intentions. In addition, a composite metric, referred to as the AI Readiness Index, was developed to summarize each respondent's level of preparedness and receptiveness toward AI adoption. This index was computed as the average of three normalized components: awareness, perceived usefulness, and behavioral intention. It served as a comparative indicator used to identify trends in adoption readiness.

Bivariate relationships among the main constructs were assessed using Pearson correlation coefficients. This analysis provided insight into the interdependencies between constructs and helped verify the theoretical expectations underlying the Technology Acceptance Model. Correlation matrices were generated and visualized to highlight the strength and direction of relationships between variables.

To model the behavioral intention to use AI, multiple linear regression analysis was employed. The dependent variable was the general behavioral intention score, while the independent variables included awareness, perceived usefulness, ease of use, and attitude (Equation 1). Both unstandardized and standardized coefficients were estimated, and model fit was assessed using R-squared and adjusted R-squared values. Statistical significance was determined at the $p < 0.05$ threshold. The analysis revealed the relative contribution of each predictor to intention.

Equation 1: $\text{Intention} = \beta_0 + \beta_1(\text{Awareness}) + \beta_2(\text{Usefulness}) + \beta_3(\text{Ease of Use}) + \beta_4(\text{Attitude}) + \epsilon$

Empirical Results and Interpretation

The respondent group represented a diverse mix of professional roles and experience levels within the construction industry (Figure. 1). Most participants had one to five years of experience, followed by those with more than twenty years, indicating a balance between early-career and senior professionals. Project engineers, project managers, and executives or directors comprised the majority of respondents, with additional representation from business owners, educators, and other managerial or technical roles. This distribution reflects a broad yet industry-representative perspective on AI adoption across operational and leadership positions.

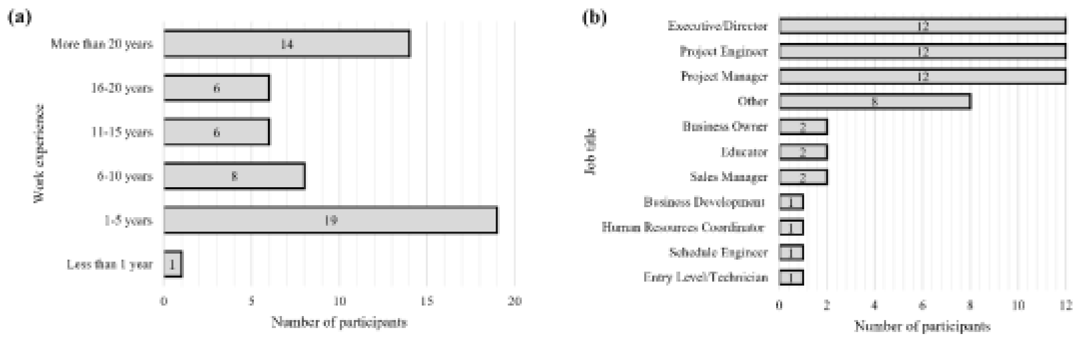

Figure 1. (a) Participants work experience, (b) Participants job title

Descriptive statistics summarize respondents' perceptions across the main constructs of the study. The analysis distinguished between general and task-specific measures to capture both overarching and contextual dimensions of AI adoption. General measures represent respondents' overall perceptions of AI usefulness, ease of use, and behavioral intention without reference to a specific function, whereas task-specific measures assess these same perceptions within distinct construction management activities such as cost estimation, scheduling, and safety monitoring.

Across all constructs, respondents expressed generally positive attitudes toward AI adoption (Table 1: Panel A). Perceived usefulness recorded the highest mean score (5.48 ± 1.33), followed by attitude (5.08 ± 0.96) and intention (4.99 ± 1.59), indicating that participants largely recognize the potential benefits of AI and are inclined toward its use. Task-specific usefulness (5.19 ± 1.35) and intention (4.96 ± 1.34) exhibited similar levels, suggesting consistent perceptions across both general and applied contexts. Ease of use yielded a comparatively lower mean (4.34 ± 1.06), reflecting some uncertainty regarding the effort required to integrate AI into daily workflows. Awareness averaged 0.57 ($\sigma = 0.26$) [on a scale of 0 to 1], signifying moderate familiarity with AI concepts among construction professionals. The distribution of the AI Readiness Index (ARI) shown in Figure 2(a) further supports these findings, with most respondents clustered in the moderate-to-high readiness range, indicating a broadly positive orientation toward AI adoption within the industry.

Table 1. Summary of survey constructs and task-specific measures

Panel A: Construct Descriptive Statistics			**Panel B. Task-specific intention and usefulness ratings**		
Construct	Mean	σ	Task	Intention	Usefulness
Usefulness General	5.48	1.33	Contract & Legal Compliance	5.30	5.31
Usefulness Tasks	5.19	1.35	Cost Estimating & Control	5.26	5.41
Attitude	5.08	0.96	Supply Chain & Logistics	5.09	5.17
Intention General	4.99	1.59	Project Planning & Scheduling	4.96	5.41
Intention Tasks	4.96	1.34	Risk Management	4.83	5.04
Ease of Use	4.34	1.06	Safety Monitoring	4.67	4.89
Awareness	0.57	0.26	Quality Control & Inspection	4.59	5.07

Among task-specific measures Contract and Legal Compliance (Intention = 5.30; Usefulness = 5.31) and Cost Estimating and Control (Intention = 5.26; Usefulness = 5.41) emerged as the most promising domains for near-term AI adoption (Table 1: Panel B). These tasks involve structured data and repeatable decision processes, which are likely to enhance their suitability for automation. Conversely, Safety Monitoring and Quality Control exhibited relatively lower intention scores (4.59–4.67), suggesting that despite their recognized usefulness, practitioners may perceive higher implementation complexity or data uncertainty in these areas.

The relationships among the principal constructs were examined using Pearson correlation coefficients (Figure. 2(b)). Overall, the results demonstrate patterns of association consistent with technology adoption theory, with most constructs exhibiting positive intercorrelations that align with theoretical expectations from technology adoption research. Among all relationships, perceived usefulness emerged as a central construct, showing the strongest correlations with attitude ($r = 0.76$) and intention ($r = 0.69$). This indicates that construction professionals who perceive AI as valuable for improving project outcomes also tend to hold more favorable attitudes toward its use and are more inclined to adopt it. This finding reinforces the core tenet of the Technology Acceptance Model, where perceived usefulness is typically the most powerful predictor of behavioral intention. The strong relationship between attitude and intention ($r = 0.61$) further underscores the role of positive affective evaluations in shaping adoption decisions. Ease of use displayed moderate correlations with usefulness ($r = 0.39$) and attitude ($r = 0.43$), but only a weak association with intention ($r = 0.24$). This pattern suggests that while ease of use contributes to forming positive perceptions of AI, it exerts a more indirect influence on adoption behavior. Practically, this implies that professionals may accept minor usability challenges if the perceived benefits of AI applications are sufficiently high, a perspective often observed in complex, technology-intensive sectors such as construction management (Du, Hashim, et al., 2024). In contrast, awareness showed comparatively weak associations with usefulness ($r = 0.16$) and attitude ($r = 0.16$), and only a modest correlation with intention ($r = 0.36$). This indicates that simple exposure to AI technologies does not necessarily translate into strong perceptions of their value or into behavioral intention to adopt them. Many respondents may recognize AI conceptually but lack hands-on experience or a clear understanding of its operational benefits. These results highlight a potential gap between awareness and meaningful engagement, an insight that suggests targeted training or experiential learning opportunities could be essential for converting awareness into adoption.

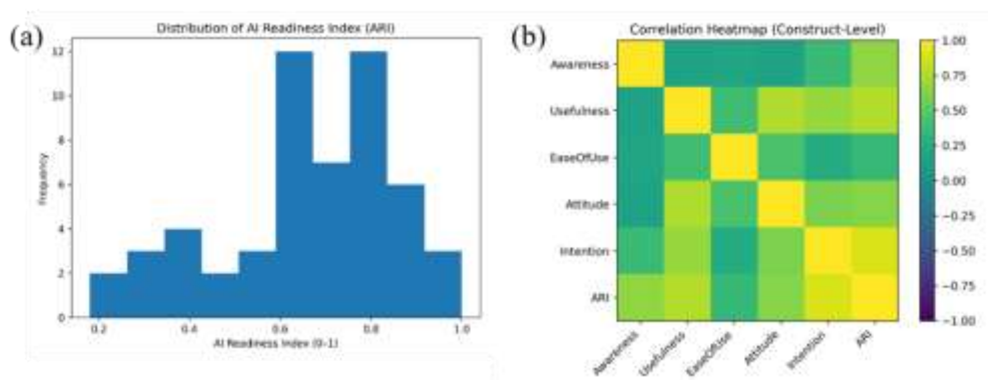

Figure 2. (a) AI Readiness Index, (b) Correlation analysis results

A multiple linear regression analysis was conducted to examine the extent to which awareness, perceived usefulness, ease of use, and attitude predict behavioral intention to adopt AI in construction management. As shown in Table 2, the overall model was statistically significant ($F= 15.84$, $p < 0.001$) and explained approximately 56 % of the variance in behavioral intention ($R^2 = 0.564$), indicating a strong explanatory capacity for a behavioral study of this nature (Al-hawari & Mouakket, 2010; Venkatesh & Davis, 2000). Diagnostic tests confirmed the robustness of the model. Residuals were approximately normal (Omnibus $p = 0.146$; JB $p = 0.246$) and showed no evidence of autocorrelation (Durbin–Watson = 2.03). Variance Inflation Factors (VIFs) were low for all predictors (Awareness =

1.04; Usefulness = 2.39; Ease of Use = 1.25; Attitude = 2.49), indicating minimal multicollinearity and stable parameter estimates.

Among the predictors, perceived usefulness ($\beta = 0.64$, $p = 0.001$) and awareness ($\beta = 1.66$, $p = 0.008$) emerged as significant determinants of adoption intention. This finding reinforces the notion that both perceived value and familiarity are central to professionals' motivation to adopt new technologies. In practical terms, respondents who view AI to improve decision-making, productivity, or project outcomes are more likely to express strong adoption intentions. Likewise, those already exposed to AI concepts, through prior training or general familiarity, demonstrate greater readiness to integrate such technologies into their workflows. This pattern underscores that adoption behavior in construction is not only driven by perceptions of efficiency or performance enhancement but also by the degree of cognitive comfort with technology. It suggests that awareness-building initiatives (e.g., workshops, pilot projects) may be as critical as technical improvements in accelerating AI across the industry.

Table 2. Model Fit Parameters

Parameter	Value	Parameter	Value
R-squared	0.564	Omnibus	3.848
F-statistic	15.84	Prob(Omnibus)	0.146
Prob (F-statistic)	2.18E-08	Skew	-0.474
Log-Likelihood	-78.902	Kurtosis	3.592
AIC	167.8	Durbin-Watson	2.028
BIC	177.7	Jarque-Bera (JB)	2.808
		Prob(JB)	0.246

Although attitude exerted a positive but non-significant effect ($\beta = 0.33$, $p = 0.189$), its directionality indicates that favorable affective evaluations toward AI still play a supporting role (Table 3). The lack of statistical significance may stem from overlapping variance shared with perceived usefulness, a common pattern in TAM-based analyses where perceived usefulness often dominates behavioral intention once entered simultaneously. This suggests that professionals' enthusiasm for AI tends to be anchored less in abstract optimism and more in tangible evidence of usefulness. Conversely, ease of use displayed a small negative and non-significant coefficient ($\beta = -0.15$, $p = 0.354$). Given the moderate internal consistency of the ease-of-use scale ($\alpha = 0.61$), this finding is interpreted cautiously. Construction professionals may perceive AI as inherently complex but still worthwhile if it yields measurable performance benefits. This pragmatic stance aligns with prior findings in technology adoption research, where skilled practitioners often prioritize outcome utility over simplicity (Du, Hashim, et al., 2024), particularly for sophisticated systems that enhance planning, estimation, or risk management.

Table 3. Regression analysis results

	coef	**SE.**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-0.5176	0.886	-0.584	0.562	-2.298	1.263
Awareness	1.6574	0.6	2.764	0.008	0.452	2.862
Usefulness	0.6447	0.175	3.675	0.001	0.292	0.997
Ease of Use	-0.1493	0.16	-0.936	0.354	-0.47	0.171
Attitude	0.3304	0.248	1.333	0.189	-0.168	0.829

The results of this study carry important implications for construction management (CM) education, particularly regarding how academic programs can align with the industry's evolving digital landscape. Specifically, awareness and perceived usefulness are the most significant predictors of professionals' intention to adopt AI, suggesting that knowledge exposure and practical relevance are the primary levers through which education can drive adoption readiness. This implies that CM curricula should not treat AI as an abstract or purely technical subject but as an applied competency integrated into existing domains such as cost estimating, scheduling, quality control, and risk management. Embedding AI-focused modules that emphasize hands-on experience, problem-based learning, and demonstration of tangible benefits, for instance, through case studies, simulations, or collaborative projects with industry partners, can enhance both cognitive familiarity and perceived value among students. The relatively weaker observed influence of ease of use suggests that professionals may tolerate technological complexity when perceived benefits are clear; however, this interpretation should be viewed cautiously given the lower reliability of the ease-of-use scale. Therefore, educational strategies should prioritize developing students' conceptual understanding of AI's capabilities, critical interpretation of AI-generated insights, and confidence in managing data-driven tools rather than merely simplifying software interfaces.

Conclusions

This study contributes empirical evidence on the behavioral foundations of AI adoption in construction management, revealing how professionals perceive, evaluate, and intend to use emerging intelligent technologies. The results demonstrate that perceived usefulness and awareness jointly form the most influential determinants of behavioral intention, underscoring that readiness to adopt AI is shaped as much by informed familiarity as by perceived performance gains. Attitude and ease of use played less decisive roles, indicating that professionals prioritize tangible outcomes over simplicity when assessing new digital tools. These insights suggest that AI diffusion within the construction sector will likely depend on the visibility of successful use cases, hands-on exposure to applications, and continued efforts to articulate measurable benefits in productivity, accuracy, and safety.

From an educational standpoint, the findings emphasize the need for construction management programs to evolve beyond passive instruction toward experiential learning environments that cultivate both awareness and applied competence. Embedding AI literacy across core CM courses, such as cost estimating, scheduling, and project control, can help students develop the contextual understanding and critical reasoning required to evaluate and implement intelligent systems effectively. Industry partnerships and project-based learning can further bridge the gap between theory and practice, offering students opportunities to engage with real-world datasets, algorithms, and automation workflows. Ultimately, the study supports the view that preparing the next generation of construction professionals requires not only teaching the technical operation of AI tools but also fostering the mindset necessary to lead their integration strategically and ethically across diverse construction management functions.

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