

กรอบแนวคิดเชิงบริบทเพื่อทำความเข้าใจความตั้งใจเชิงพฤติกรรมในการยอมรับ
การนำปัญญาประดิษฐ์มาใช้ในโครงการก่อสร้าง

A CONTEXTUAL FRAMEWORK FOR UNDERSTANDING BEHAVIORAL INTENTION
TO ADOPT ARTIFICIAL INTELLIGENCE IN CONSTRUCTION PROJECTS

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บทคัดย่อ

งานวิจัยนี้มีวัตถุประสงค์เพื่อศึกษาปัจจัยที่มีอิทธิพลต่อความตั้งใจเชิงพฤติกรรมในการนำปัญญาประดิษฐ์ (AI) มาใช้ในอุตสาหกรรมก่อสร้างของไทย โดยอุตสาหกรรมนี้มีลักษณะเสี่ยงสูงและซับซ้อน จึงได้ขยายกรอบแนวคิดการยอมรับเทคโนโลยีให้ครอบคลุมปัจจัยด้านการสนับสนุนจากพันธมิตร ความสามารถ ความพร้อมของทรัพยากรมนุษย์ การสนับสนุนจากผู้บริหารระดับสูง ความคาดหวังด้านผลการปฏิบัติงาน ความสอดคล้อง และการตระหนักด้านความปลอดภัย การวิจัยเชิงปริมาณนี้ใช้การสำรวจจากกลุ่มตัวอย่างจำนวน 418 คน ประกอบด้วยผู้จัดการ วิศวกร และบุคลากรจากบริษัทก่อสร้าง ผลการวิเคราะห์ทางสถิติพบว่า การสนับสนุนจากพันธมิตร ความสามารถ ความพร้อมของทรัพยากรมนุษย์ การสนับสนุนจากผู้บริหารระดับสูง ความคาดหวังด้านผลการปฏิบัติงาน และการตระหนักด้านความปลอดภัย มีอิทธิพลเชิงบวกต่อความตั้งใจในการนำ AI มาใช้ ขณะที่ความสอดคล้องกลับแสดงผลเชิงลบอย่างไม่คาดคิด ทั้งนี้ การตระหนักด้านอาชีวอนามัยและความปลอดภัยเป็นปัจจัยที่มีอิทธิพลมากที่สุด โดยแบบจำลองสามารถอธิบายความแปรปรวนของความตั้งใจเชิงพฤติกรรมได้ประมาณร้อยละ 50 เชิงทฤษฎี งานวิจัยนี้ช่วยเติมเต็มองค์ความรู้ด้วยการผนวกปัจจัยด้านความปลอดภัยและปัจจัยเชิงองค์กรเข้าสู่กรอบการยอมรับเทคโนโลยี ทำให้เข้าใจการยอมรับ AI ได้รอบด้านยิ่งขึ้น ส่วนในเชิงปฏิบัติ ผลการศึกษาเสนอแนะให้ผู้จัดการโครงการก่อสร้างให้ความสำคัญกับการพัฒนาสมรรถนะบุคลากร การสร้างวัฒนธรรมความปลอดภัย และการสื่อสารที่โปร่งใส เพื่อเอื้อต่อการบูรณาการ AI อย่างมีประสิทธิภาพ งานวิจัยนี้จึงมีคุณค่าต่อทั้งนักวิชาการและผู้ปฏิบัติที่มุ่งผลักดันการนำ AI มาใช้อย่างกว้างขวางในอุตสาหกรรมก่อสร้างที่มีความเสี่ยงสูง

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ABSTRACT

This study examines the factors that influence the behavioral intention to adopt Artificial Intelligence (AI) in the Thai construction industry using an extended adoption framework. Given the industry's high-risk and complex environment, the framework was broadened to incorporate partner support, competence, human resource (HR) readiness, top management support, performance expectation, compatibility, and safety awareness. A quantitative, cross-sectional survey was conducted with 418 respondents, including managers, engineers, and staff from construction firms. Statistical analysis confirmed that partner support,

competency, HR readiness, top management support, performance expectation, and compatibility positively influenced AI adoption intention, although compatibility unexpectedly showed a negative effect. Among all factors, occupational health and safety awareness emerged as the most influential predictor, emphasizing the central role of safety in shaping adoption behavior. Conversely, barriers such as unclear communication about project compatibility, misaligned team collaboration, and inconsistent employee attitudes hindered adoption. The proposed model explained approximately 50% of the variance in behavioral intention, demonstrating strong explanatory power. Theoretically, this research enriches existing knowledge by extending adoption frameworks with safety- and organization-oriented constructs, offering a more holistic perspective on AI adoption in construction. Practically, the findings underscore the importance of leadership commitment, employee readiness, and transparent communication. Construction managers are encouraged to strengthen workforce competency, promote a strong safety culture, and ensure effective communication to facilitate the integration of AI. Overall, this study provides valuable implications for both scholars and practitioners seeking to advance AI adoption in high-risk industries.

Keywords: Artificial Intelligence, Construction Projects, Behavioral Intention, Technology Adoption, Organizational Context

INTRODUCTION

The construction industry is increasingly experiencing a paradigm shift through the integration of artificial intelligence (AI). Applications such as predictive analytics, computer vision for safety monitoring, automated scheduling, and intelligent resource management have shown great potential to enhance productivity, efficiency, and sustainability in construction projects (Pan & Zhang, 2021; Zheng et al., 2022). Despite these advantages, AI adoption in the construction sector has been slower compared to other industries, largely due to challenges related to organizational readiness, managerial support, workforce competency, and concerns regarding safety and compatibility (Davies & Harty, 2020; Li et al., 2021). Previous research has often relied on established models of technology adoption that focus on user perceptions and organizational or environmental contexts to explain adoption behavior. While these perspectives emphasize the role of usefulness, ease of use, and organizational factors, they may not fully capture the complexities of construction projects, which are highly dynamic and risk-prone.

To address this gap, the present study proposes an extended adoption framework that incorporates partner support, competency, human resource (HR) readiness, top management support, performance expectations, compatibility, and safety awareness as additional constructs. Safety awareness, in particular, is a critical factor in construction, as

employees' willingness to adopt AI technologies is shaped by their perceptions of occupational health and risk management (Lingard et al., 2014). Therefore, the purpose of this study is to examine the factors influencing behavioral intention to adopt AI in the Thai construction industry through a broader, industry-specific lens. By integrating both general adoption variables and construction-related factors, the study provides theoretical contributions to technology adoption research and practical guidance for promoting AI integration in construction enterprises.

RESEARCH OBJECTIVES

1. To examine the critical factors influencing the behavioral intention to adopt Artificial Intelligence (AI) in the Thai construction industry.
2. To analyze the role of organizational readiness, leadership support, and safety awareness in shaping AI adoption behavior within construction projects.
3. To provide theoretical and practical insights for developing a comprehensive framework that promotes effective AI adoption in high-risk industries.

LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into the construction industry requires a comprehensive understanding of the factors influencing both organizational and individual acceptance. This study employs an extended conceptual framework that captures determinants at multiple levels to explain behavioral intention to adopt AI. At the individual level, perceived usefulness (PU) and perceived ease of use (PEOU) are highlighted as key drivers shaping attitudes toward technology adoption and subsequent behavioral intention (Davis, 1989; Venkatesh & Davis, 2000). These constructs have been widely applied in technology adoption studies across industries due to their strong explanatory power (Venkatesh & Bala, 2008). However, given the complexity of construction projects and organizational settings, focusing solely on individual perceptions is insufficient to fully explain adoption behavior.

To address this gap, the framework integrates broader contextual dimensions, including technological, organizational, and environmental factors, which have been shown to influence innovation adoption at the firm level (Oliveira & Martins, 2011; Baker, 2012). Building on these foundations, this study incorporates additional constructs tailored to the construction industry. Partner support and organizational competency reflect the importance of external collaboration and internal capability in facilitating AI adoption (Zhu et al., 2006). HR readiness and top management support capture the role of skilled personnel and executive leadership in overcoming barriers (Haffke et al., 2016). Performance expectation emphasizes the perceived benefits in terms of efficiency and productivity, consistent with prior research on technology adoption (Venkatesh et al., 2003). Compatibility refers to the alignment between AI systems

and existing organizational processes, which is crucial for successful integration (Chau & Tam, 1997). Finally, safety awareness highlights the importance of occupational health and safety considerations, which are particularly significant in construction, as they significantly influence employee trust and willingness to adopt AI systems (Lingard et al., 2014).

This extended framework provides a comprehensive theoretical foundation for examining the multifaceted factors influencing AI adoption in the construction industry. It enables a holistic assessment that considers both individual perceptions and organizational readiness while addressing industry-specific issues such as safety and collaboration.

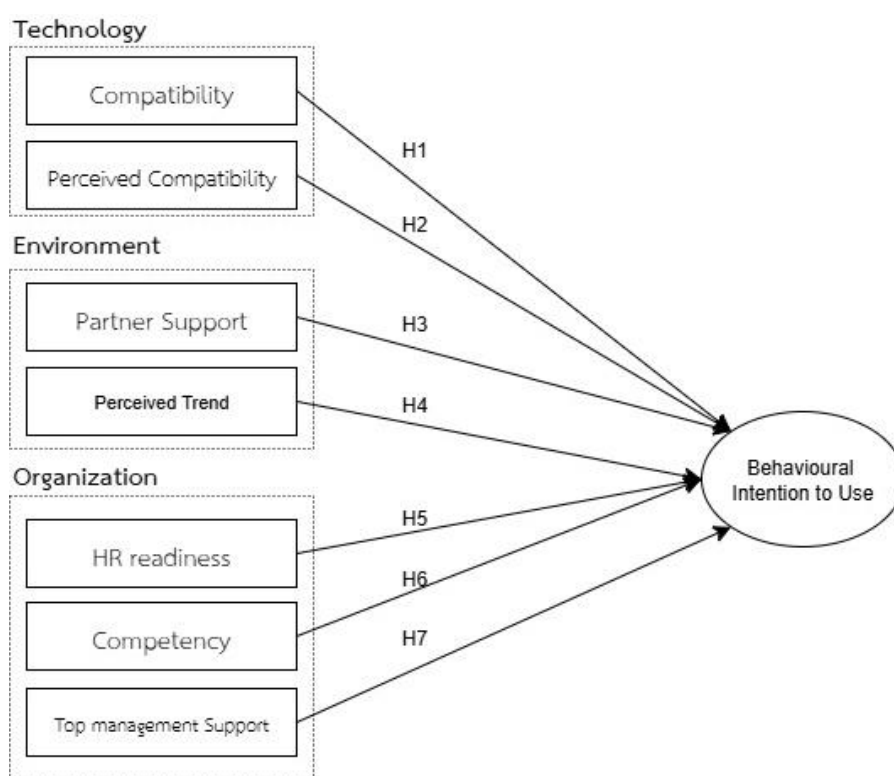


Figure 1 Regression-Based Framework of AI Adoption in Construction

The adoption of Artificial Intelligence (AI) in construction projects is shaped by technological, environmental, and organizational factors.

In the Technology dimension, compatibility refers to the degree to which AI systems align with existing processes and workflows, while perceived compatibility reflects employees' subjective assessment of fit; differences between these two perceptions may result in resistance or uncertainty toward adoption.

In the Environment dimension, partner support highlights the importance of collaboration with external stakeholders, while perceived trend captures the influence of industry-wide movements and market dynamics that create pressure for adoption.

In the Organization dimension, HR readiness emphasizes the preparedness of human resources to embrace AI technologies, competency underscores the skills and capabilities within the organization, and top management support reflects leadership engagement in driving adoption.

Together, these seven predictors converge on Behavioral Intention to Use AI, illustrating how technological perceptions, external influences, and organizational resources jointly determine adoption decisions in the construction industry.

H1: Compatibility has a significant positive effect on the behavioral intention to use AI in construction projects.

H2: Perceived compatibility has a significant positive effect on the behavioral intention to use AI in construction projects.

H3: Partner support has a significant positive effect on the behavioral intention to use AI in construction projects.

H4: Perceived trend has a significant positive effect on the behavioral intention to use AI in construction projects.

H5: HR readiness has a significant positive effect on the behavioral intention to use AI in construction projects.

H6: Competency has a significant positive effect on the behavioral intention to use AI in construction projects.

H7: Top management support has a significant positive effect on the behavioral intention to use AI in construction projects.

METHODOLOGY

1. Population and Sample

The population of this study encompassed employees and stakeholders within the Thai construction industry. This included executives, project managers, engineers, foremen, architects, design staff, and general employees. All were directly involved in planning, managing, and executing construction projects. A purposive sampling technique was employed to ensure that respondents possessed relevant knowledge and experience with construction operations and emerging technologies, such as BIM and AI applications. The survey used a quantitative, cross-sectional design. Data were collected over a six-month period through both online and paper-based questionnaires. Ethical approval was obtained from the Human Research Ethics Committee of the University of the Thai Chamber of Commerce. Informed consent was secured from all participants. A total of 418 valid responses were obtained. This sample size exceeded the minimum recommended size for multivariate analysis and structural equation modeling (Hair et al., 2019). Respondents represented a wide range of organizational roles and demographics: 32.11% were managers or executives, 20.87% general staff, and 20.64% engineers or foremen. Smaller proportions included architects/designers, business owners, and partners. Most held at least a

bachelor's degree (68.35%), followed by a master's (23.62%), and a doctoral degree (2.52%). This indicated a workforce with a high level of professional training. In terms of organization size, 60.92% of respondents came from firms with more than 200 employees, and 17.70% from firms with 101–200 employees. Additionally, 66.51% of the firms worked in companies operating for more than 15 years, indicating maturity and stability within the sample. This heterogeneity in roles, firm sizes, and organizational experience ensured the dataset was sufficiently representative of the Thai construction industry. This diversity strengthened the explanatory power of the study's findings and enhanced their theoretical and practical relevance for the adoption of AI in high-risk industries.

2. Research Instruments

The research instrument employed in this study was a structured questionnaire designed to capture relevant data from participants in the Thai construction industry. The questionnaire consisted of three major sections. The first section gathered demographic information, including respondents' position, education level, company size, and years of business operation. The second section measured independent variables, covering aspects of technology, organization, environment, personnel, and leadership support, along with extended adoption constructs such as partner support, competency, human resource (HR) readiness, top management support, performance expectation, compatibility, and safety awareness. The third section addressed dependent variables, focusing on perceived usefulness, perceived ease of use, attitude, and behavioral intention. All measurement items were drawn and adapted from validated instruments in prior studies (Davis, 1989; Venkatesh & Bala, 2008; Oliveira & Martins, 2011) to ensure academic rigor and conceptual consistency. Responses were measured using a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). To confirm the appropriateness of the instrument, construct validity was assessed through confirmatory factor analysis (CFA), ensuring that both convergent and discriminant validity were achieved following established criteria (Fornell & Larcker, 1981).

3. Data Collection

Data for this study were collected through a structured questionnaire administered to employees and stakeholders in the Thai construction industry. A quantitative, cross-sectional survey design was applied, and data collection was conducted over a six-month period using both online and paper-based formats to ensure accessibility and broader participation across different organizational sizes and regions. Prior to data collection, the research received ethical approval from the Human Research Ethics Committee of the University of the Thai Chamber of Commerce (UTCC), and informed consent was obtained from all respondents. A purposive sampling method was used to target individuals with relevant experience in construction projects and familiarity with digital technologies, particularly applications of Artificial Intelligence (AI). The questionnaire was

distributed via professional networks, organizational contacts, and industry associations, with follow-ups conducted to maximize response rates. Out of the distributed questionnaires, a total of 418 valid responses were obtained and included in the analysis. This sample size exceeded the minimum recommended threshold for multivariate analysis and structural equation modeling, ensuring statistical robustness and reliability of the findings.

4. Data Analysis

The collected data were analyzed using multivariate statistical techniques. Descriptive statistics were first employed to summarize demographic information and provide an overview of respondents' characteristics. The measurement model was then evaluated to assess the reliability and validity of the constructs through Confirmatory Factor Analysis (CFA). Convergent and discriminant validity were examined following the criteria established by Fornell and Larcker (1981), ensuring that the constructs were both theoretically and empirically sound. After validating the measurement model, the structural model was tested to examine the hypothesized relationships among constructs. Regression-based analyses were employed to identify the influence of partner support, competency, HR readiness, top management support, performance expectation, compatibility, and safety awareness on behavioral intention to adopt AI in the construction industry. Model fit was assessed using multiple indices, including CFI, TLI, RMSEA, and χ^2/df , in line with established guidelines (Hair et al., 2019). Furthermore, explanatory power was evaluated through R-squared values, and additional analyses were conducted at the item level to identify the most influential predictors of AI adoption.

RESULTS

A total of 418 respondents participated in the study. The majority were in the position of Manager/Executive (32.11%), followed by General Staff (20.87%) and Engineer/Foreman (20.64%). Regarding company size, most respondents (60.92%) reported working in organizations with more than 200 employees, while 17.70% were in companies with 101–200 employees. In terms of educational attainment, the majority (68.35%) held a bachelor's degree, followed by 23.62% with a master's degree. For years of business operation, most respondents (66.51%) indicated that their organizations had been in operation for more than 15 years, while 15.60% reported 5–10 years of operation (Table 1).

Table 1. Demographic Characteristics of Respondents

Demographic Characteristics	Frequency	Percentage
Current Position in the Company		
Manager/Executive	140	33.49%
General Staff	91	21.77%
Engineer/Foreman	90	21.53%
Architect/Design Department	36	8.61%
Business Owner	28	6.70%
Partner	17	4.07%
Employee	8	1.91%
Other	8	1.91%
Highest Education Level		
Bachelor's Degree	285	68.18%
Master's Degree	103	24.64%
Below bachelor's degree	19	4.55%
Doctoral Degree	11	2.63%
Years of Business Operation		
More than 15 Years	290	65.55%
5–10 Years	68	16.27%
11–15 Years	52	12.44%
Less than 5 Years	24	5.74%

The respondents reported overall positive perceptions toward the constructs examined. Technology, organization, and environment demonstrated relatively high mean scores ($M = 4.623$, $SD = 1.361$; $M = 4.546$, $SD = 1.126$; and $M = 4.696$, $SD = 1.006$, respectively), indicating favorable readiness levels. Specifically, technology was associated with high perceived readiness, the organization reflected moderate-to-high readiness, and the environment showed strong external influence supporting adoption. These results suggest that contextual and structural conditions are conducive to the integration of AI in construction projects, with external drivers playing a particularly influential role (Table 2).

Table 2. Descriptive Statistics and Interpretation of Main Variables

Variables	No. of Items	Mean	SD	Interpretation
Technology	20	4.623	1.361	High perceived readiness.
Organization	28	4.546	1.126	Moderate-to-high readiness.
Environment	19	4.696	1.006	Strong external influence.

This study conducted a regression analysis to examine the factors influencing behavioral intention to adopt AI in the construction industry. As shown in Table 3, several significant predictors were identified: Partner Support ($\beta = 0.204$, $p < 0.001$), Competency ($\beta = 0.140$, $p = 0.003$), HR Readiness ($\beta = 0.239$, $p < 0.001$), Top Management Support ($\beta = 0.205$, p

< 0.001), Performance Expectation ($\beta = 0.125$, $p < 0.001$), and Compatibility ($\beta = 0.128$, $p = 0.007$). Perceived Compatibility ($\beta = -0.135$, $p = 0.002$) was found to have a negative influence on behavioral intention to adopt AI. Collectively, these findings highlight that individual, organizational, and external collaboration factors play critical roles in shaping the adoption behavior of AI in the construction sector (Table 3).

Table 3. Regression Analysis of Factors Influencing Behavioral Intention to Adopt AI in the Construction Industry

Variable	B	SE(b)	Beta	T	p-Value
Partner Support	0.217	0.055	0.204	3.966	0.000
Competency	0.182	0.061	0.140	2.968	0.003
HR readiness	0.227	0.049	0.239	4.620	0.000
Top management Support	0.200	0.049	0.205	4.078	0.000
Perceived Trend	0.150	0.043	0.125	3.512	0.000
Compatibility	0.173	0.064	0.128	2.706	0.007
Perceived Compatibility	-0.132	0.042	-0.135	3.171	0.002

The regression model predicting Behavioral Intention to Adopt AI in the Construction Industry demonstrated satisfactory explanatory power. The coefficient of determination (R^2) was 0.486, indicating that approximately 48.6% of the variance in behavioral intention could be explained by the independent variables included in the model. The adjusted value was 0.477, confirming the model's robustness after accounting for the number of predictors. Furthermore, the Durbin–Watson statistic was 2.039, suggesting no serious issue of autocorrelation in the residuals, thereby supporting the model's validity.

Table 4. Regression Analysis of Item-Level Predictors Influencing Behavioral Intention to Adopt AI in the Construction Industry

Item	B	SE	Sig.	T value	P value
EGP1	0.142	0.037	0.166	3.817	0.000
EPT2	0.187	0.053	0.157	3.560	0.000
OCM3	0.157	0.036	0.194	4.429	0.000
OHR1	0.255	0.036	0.303	6.987	0.000
TCPB4	0.218	0.043	0.210	5.119	0.000
TCPL8	0.130	0.028	0.163	4.647	0.000
TOB2	-0.111	0.048	-0.100	2.315	0.021
TPC1	-0.106	0.039	-0.108	2.732	0.007

The regression analysis identified several item-level factors that significantly influenced behavioral intention to adopt AI in the construction industry.

EGP1 (The organization has adequate budgets to support AI adoption) ($\beta = 0.166$, $p < 0.001$) indicates that sufficient financial resources positively contribute to the intention to adopt AI. EPT2 (Employees can easily learn and adapt to new AI technologies) ($\beta = 0.157$, $p < 0.001$) demonstrates that employees' learning ability and adaptability enhance the likelihood of adoption. OCM3 (The company's management policies are supportive of AI implementation) ($\beta = 0.194$, $p < 0.001$) reflects the positive role of supportive management policies in driving AI adoption. OHR1 (Employees are aware of occupational health and safety risks) ($\beta = 0.303$, $p < 0.001$) emerged as the strongest predictor, underscoring the crucial role of health and safety awareness in shaping adoption behavior. TCPB4 (Technology and processes can be integrated smoothly within the construction environment) ($\beta = 0.210$, $p < 0.001$) highlights the importance of seamless technological and process integration in supporting adoption. TCPL8 (Leadership provides continuous support for adopting new technology) ($\beta = 0.163$, $p < 0.001$) reinforces the critical role of leadership commitment and sustained support. TOB2 (Employees have positive attitudes toward the use of AI technology) ($\beta = -0.100$, $p = 0.021$) unexpectedly showed a negative effect, which may indicate discrepancies between reported attitudes and actual behavioral intention. TPC1 (Team collaboration is essential for successful AI adoption in projects) ($\beta = -0.108$, $p = 0.007$) also had a negative impact, suggesting that ineffective or poorly aligned collaboration may become a barrier to adoption.

The findings indicate that organizational resources, management support, safety awareness, and leadership are strong positive drivers of AI adoption intention, with OHR1 (occupational health and safety awareness) being the most influential factor among them. In contrast, the negative effects of TOB2 and TPC1 highlight potential weaknesses in organizational alignment and collaboration that must be addressed to enhance successful AI adoption in the construction industry.

The regression model predicting behavioral intention to adopt AI (BIA) demonstrated satisfactory explanatory power. The R-square value was 0.502, indicating that approximately 50.2% of the variance in BIA could be explained by the independent variables included in the model. After adjusting for the number of predictors, the adjusted R-squared value was 0.489, confirming stable explanatory capability. Moreover, the Durbin-Watson statistic was 2.044, which falls within the acceptable range (1.5–2.5), confirming the absence of autocorrelation in the residuals and supporting the validity of the regression results.

DISCUSSION

The results of this study offer valuable insights into the factors that influence behavioral intention to adopt AI in the construction industry. At the construct level, partner support, competency, HR readiness, top management support, performance expectation, and compatibility were found to be significant positive predictors. These findings align with previous studies that emphasize the role of organizational readiness and managerial commitment in fostering technology adoption (Venkatesh & Davis, 2000; Oliveira & Martins, 2011). In particular, HR readiness and top management support indicate that the availability of skilled personnel and executive guidance are crucial to overcoming barriers to adoption, consistent with research highlighting leadership as a determinant of digital transformation (Haffke et al., 2016).

Interestingly, perceived compatibility was negatively associated with behavioral intention. This unexpected result suggests that when employees perceive discrepancies between existing processes and AI solutions, it may reduce their willingness to adopt, echoing prior work that underscores the challenges of misaligned technology integration (Chau & Tam, 1997).

The item level, OHR1 (Occupational Health and Safety Awareness), emerged as the strongest positive predictor, indicating that safety considerations are central to AI acceptance in construction. This aligns with studies that emphasize the importance of perceived risk reduction in enhancing adoption (Davis, 1989; Ifinedo, 2012). Other positive predictors, such as PPE1 (personal protective equipment awareness), TCPB4 (technology and process integration), and TCPL8 (leadership support) reinforce the importance of organizational safety culture and continuous support in shaping adoption behavior (Lingard et al., 2014).

Items such as PPC1 (communication of project compatibility), TOB2 (employee attitudes), and TPC1 (team collaboration) were negatively associated with adoption. These findings highlight potential organizational weaknesses in communication and alignment, suggesting that even with strong leadership and resources, inconsistent communication and ineffective collaboration may hinder adoption. This observation aligns with studies that identify cultural and communication gaps as significant barriers to technological innovation in the construction industry (Liu et al., 2021).

The findings underscore that AI adoption in construction requires not only technological readiness but also a strong emphasis on safety, leadership, and communication. Future strategies should address misalignments in perception and improve collaboration to ensure the successful implementation of AI technologies.

Theoretical Implications

This study contributes to the body of knowledge on technology adoption in the construction industry by extending existing adoption frameworks with additional constructs, such as partner support, competency, HR readiness, and safety awareness. The significant role of OHR1 (occupational health and safety awareness) as the strongest predictor underscores the importance

of integrating safety-related constructs into adoption models, which have been underexplored in prior research. Moreover, the unexpected negative effects of perceived compatibility and team collaboration highlight the complex dynamics of adoption behavior, suggesting that alignment between organizational processes, communication, and employee perceptions is critical. These findings advance theoretical understanding by demonstrating that behavioral intention is shaped not only by perceived usefulness and ease of use, but also by organizational culture, leadership, and safety factors.

Practical Implications

From a managerial perspective, the results offer actionable insights for enhancing AI adoption in the construction industry. First, organizations should prioritize employee training and HR readiness, ensuring that staff possess the necessary competencies to adapt to AI technologies. Second, leadership must play an active role in providing continuous support and fostering a safety-conscious culture, as both leadership support and safety awareness were found to significantly drive adoption. Third, communication strategies need to be improved to avoid misperceptions about compatibility and project integration. Finally, since team collaboration has been shown to have a negative effect, project managers should carefully align roles, responsibilities, and expectations to ensure that collaboration supports, rather than hinders, AI adoption. Collectively, these implications suggest that successful adoption requires not only technological investment but also organizational alignment, clear communication, and a strong safety culture.

SUGGESTIONS FOR FUTURE RESEARCH

1. Suggestions for Practical Implementation

For practical implementation, construction firms should prioritize strengthening workforce competency through continuous training and development programs. Meanwhile, top management must demonstrate a strong commitment by providing resources, setting clear strategic directions, and fostering a culture of innovation. At the same time, a safety-oriented culture should be integrated into AI adoption strategies to ensure that risk management remains central to the implementation of technology in high-risk environments. Clear and transparent communication channels are essential for minimizing misunderstandings about compatibility and enhancing team collaboration. Partnerships with technology providers, academic institutions, and industry associations can further support and accelerate the integration of AI solutions in the construction sector.

2. Suggestions for Future Research

Future research should extend this study by employing longitudinal or mixed-method approaches to capture changes in perceptions and adoption behaviors over time, as the cross-sectional design used here limits causal interpretation. Additional constructs such as

regulatory frameworks, ethical considerations, sustainability, and environmental impacts should be incorporated to enrich the adoption framework and provide a more holistic understanding of AI integration in construction. Comparative studies across different cultural and industrial contexts would enhance the generalizability of findings, while qualitative approaches, such as in-depth interviews and case studies, could offer richer insights into organizational dynamics, leadership practices, and employee perceptions. These directions will advance theoretical contributions and provide practical guidance for the effective adoption of AI in high-risk industries.

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