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Personal Innovativeness and Initial Trust in AI-Enabled BIM Adoption Using UTAUT in Malaysia

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ABSTRACT

The construction industry is undergoing a significant digital transformation driven by Construction 4.0 technologies, with Building Information Modeling (BIM) and Artificial Intelligence (AI) emerging as key enablers of improved productivity, collaboration, and decision-making. The integration of AI with BIM has given rise to AI-enabled BIM systems, which combine BIM's data-rich environment with advanced capabilities such as machine learning, predictive analytics, natural language processing, and intelligent automation. Despite the potential benefits of AI-enabled BIM, its adoption within the Malaysian construction industry remains limited, and empirical evidence on the factors influencing its acceptance is scarce.

This study examines the determinants of behavioral intention to adopt AI-enabled BIM systems among construction professionals in Malaysia. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT), the study extends the model by incorporating personal innovativeness and initial trust as additional predictors. Data were collected from 261 professionals employed by CIDB Grade 7 (G7) construction firms randomly selected using probability sampling and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

The results indicate that performance expectancy, effort expectancy, social influence, and personal innovativeness have significant positive effects on behavioral intention to adopt AI-enabled BIM systems. Personal innovativeness was a particularly important predictor, exerting both direct effects on behavioral intention and indirect effects through performance expectancy and effort expectancy. Initial trust did not directly influence behavioral intention; however, it significantly enhanced perceptions of usefulness and ease of use, which in turn indirectly affected adoption intention through these mediating constructs. The model demonstrated satisfactory explanatory and predictive power.

This study contributes to the literature by extending UTAUT to the emerging context of AI-enabled BIM adoption and by providing one of the first empirical investigations of this technology in Malaysia. The findings offer practical implications for construction firms, policymakers, and software developers seeking to accelerate AI-enabled BIM adoption through user-centered design, digital skills development, organizational support, and targeted policy interventions.

Keywords: AI, Building Information Modeling, Personal Innovativeness, Initial Trust, UTAUT.

INTRODUCTION

The global construction industry is undergoing a profound transformation as it responds to increasing project complexity, fragmented workflows, productivity pressures, sustainability demands, and the need for more integrated decision-making (Datta et al., 2024; Dagou et al., 2024; Egwim et al., 2023; Nnaji et al., 2023; Rahim, Ismail et al., 2023). Historically reliant on manual labor and conventional project delivery methods, the sector is now moving toward Construction 4.0, where digital technologies such as Building Information Modeling (BIM), artificial intelligence (AI), cloud computing, big data analytics, the Internet of Things, drones, laser scanning,

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blockchain, augmented reality, and 3D printing are reshaping how built assets are designed, constructed, operated, and maintained (Faraji et al., 2024; García de Soto et al., 2022; Srivastava et al., 2022). Among these technologies, BIM has emerged as one of the most widely promoted and strategically important tools because it enables the creation, management, and exchange of reliable digital information across the entire lifecycle of a built asset.

BIM represents a shift from traditional two-dimensional computer-aided design toward an intelligent, collaborative, and data-rich model-based process. It supports design coordination, clash detection, cost estimation, schedule planning, construction monitoring, facility management, and lifecycle asset maintenance (Heidari et al., 2024; Lee et al., 2022; Pan & Zhang, 2023; Zawada et al., 2024). By integrating geometric and non-geometric project information into a shared digital environment, BIM enhances communication, improves coordination among stakeholders, reduces errors and rework, supports more accurate cost and time estimation, and contributes to greater productivity and sustainability. Nevertheless, BIM adoption remains uneven across countries and regions, shaped largely by institutional support, economic capacity, government policy, technological readiness, and user acceptance (Oyuga et al., 2023; Yizing et al., 2025).

Recent advances in AI have further expanded the potential of BIM. AI technologies, including machine learning, natural language processing, predictive analytics, computer vision, and generative AI, enable construction systems to learn from data, identify patterns, automate complex tasks, and support intelligent decision-making (Adebayo et al., 2025; Ghimire et al., 2024; Omotayo et al., 2025; Pan & Zhang, 2023). When integrated with BIM, AI transforms BIM from a descriptive digital representation into an intelligent, predictive, and prescriptive decision-support system. AI-enabled BIM systems can facilitate generative design, automated documentation, real-time project monitoring, predictive risk and safety management, natural-language interaction with BIM data, issue detection, conflict resolution, stakeholder training, and cross-disciplinary collaboration (Dagou et al., 2024; Heidari et al., 2024; Li et al., 2024; Zawada et al., 2024). This convergence offers significant potential to improve project performance, enhance sustainability, reduce uncertainty, and strengthen knowledge management throughout the construction project lifecycle.

In Malaysia, the construction sector is central to national socio-economic development and has been increasingly encouraged to adopt digital technologies through policy initiatives such as the Construction Industry Transformation Program and CIDB's Construction 4.0 Strategic Plan (2021–2025). These initiatives position BIM and other IR 4.0 technologies as key enablers of productivity, competitiveness, and modernization. However, despite policy support and the availability of BIM implementation guidelines, BIM adoption in Malaysia remains lower than in several developed economies, with reported adoption at approximately 55% as of 2021 (Yizing et al., 2025). More importantly, empirical evidence on AI-enabled BIM adoption in Malaysia is extremely limited, and no substantial research has yet examined the factors influencing construction professionals' intention to adopt this integrated technology.

This gap is significant because the successful implementation of AI-enabled BIM depends not only on technological availability but also on users' perceptions, organizational readiness, trust, skills, innovativeness, and social influence. Existing studies have examined BIM or AI adoption separately, yet have given limited attention to their convergence as an integrated system, particularly in Malaysia's construction context. Addressing this gap is essential for guiding policymakers, construction firms, software developers, and technology vendors in promoting effective AI-enabled BIM adoption in Malaysia.

Therefore, the objective of this study is to apply the Unified Theory of Acceptance and Use of Technology (UTAUT) model to the context of AI-enabled BIM among Malaysian construction professionals and to test the relationships specified in the established theoretical framework. To achieve this goal, we conducted a nationwide online survey to assess the attitudes of construction professionals working in CIDB's G7 construction firms towards AI-enabled BIM. Based on the UTAUT model, we extended the framework by incorporating two additional variables: personal innovativeness and initial trust to better capture the unique dynamics of AI adoption in the construction sector. Specifically, we analyzed the impact of performance expectancy, effort expectancy, social influence, personal innovativeness, and initial trust on construction professionals' intention to use AI-enabled BIM.

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This study validated the core UTAUT pathways and elucidated the pivotal roles of drivers and barriers influencing AI-enabled BIM adoption among Malaysian construction professionals. The findings provide actionable insights for policymakers, construction firms, and technology developers to formulate targeted strategies that promote AI integration with BIM.

This report is structured as follows. Next, in Section 2, we present a review of the extant literature on technology acceptance models, constructs, and the hypothesis for this study. Section 3 describes research methodology and data collection. Section 4 presents statistical analysis, and Section 5 discusses the major findings. In Section 6, we reflect on the theoretical contributions and practical implications. Section 7 presents limitations and suggestions for future research. Section 8 presents the overall conclusions of the study.

LITERATURE REVIEW AND HYPOTHESES

Since its inception, the UTAUT framework has gained widespread use for understanding technology acceptance in various fields (Wang et al., 2021). Recent bibliometric analyses confirm that the UTAUT model and its variants are widely used to study intentions to adopt new technologies across organizational settings, including consumer health tech, E-health, higher education, and mobile learning (Wang et al., 2021). However, since 2021, there has been limited empirical research on technology adoption in the construction industry using UTAUT or its extensions. Instead, models like TAM (Lu & Deng, 2022; Mei et al., 2023 on 3D Digital Technology; Obidallah et al. on Blockchain technology, 2024), TAM combined with Task Technology Fit (Cai et al., 2023 on off-site construction technology), and TAM with TOE (Wang et al., 2022 on Blockchain technology) are more prevalent. Although TAM-based models are popular among researchers, they may not fully capture the complex and autonomous nature of phenomena such as AI-enabled BIM adoption (Min & Qu, 2008; Venkatesh et al., 2003). Additionally, UTAUT2 (Venkatesh et al., 2012) and its extension (Farooq et al., 2017) were designed to address post-adoption and voluntary consumer usage scenarios, making them less appropriate for studying construction professionals' adoption of AI-enabled BIM, as their technology use is typically driven by professional duties rather than personal enjoyment or cost factors. Consequently, this study employs the original UTAUT model to investigate the main factors influencing construction professionals' adoption of AI-enabled BIM.

For construction professionals, performance expectancy indicates how much they believe that using AI-powered BIM will improve their efficiency and skills. Effort expectancy relates to how easy they perceive learning and using AI-enabled BIM tools to be. Social influence refers to the effect of peers, supervisors, and others on individuals' intention to adopt AI. Facilitating conditions refer to the availability of technical support, training, and resources needed for AI implementation and usage. Research from other fields shows these factors generally boost individuals' willingness to adopt new technologies. This study excluded facilitating conditions and the four moderators because the goal is to identify factors affecting behavioral intention. According to Venkatesh et al. (2003), facilitating conditions predict actual usage behavior, and the four moderators indicate demographic differences rather than psychological or contextual influences. This study does not aim to analyze how the effects of these constructs vary across demographic groups.

Empirical findings supporting the influence of performance expectancy on behavioral intention, include, Abbad (2021) on e-Learning, Alvi (2021) on a social network tool, Handa and Kaur (2025) on online insurance, Heo and Na (2025) on construction AI technology, Lee et al. (2024) on ChatGPT, Rana et al. (2024) on AI, Rahim, Bakri et al. (2023) on Islamic fintech, Tai et al. (2025) on smart city technology, Tuyen and Nguyen (2025) on microlearning, and Wu et al. (2022) on AI-assisted learning. Therefore, the study hypothesizes that:

H1: Performance expectancy positively influences construction professionals' behavioral intention to adopt AI-enabled BIM.

Empirical findings supporting the influence of effort expectancy on behavioral intention, include, Arfi et al. (2021) on IoT in e-Health, Handa and Kaur (2025) on online insurance, Heo and Na (2025) on construction AI technology, Kim et al. (2024) on generative AI, Lee et al. (2024) on ChatGPT, Rana et al. (2024) on AI, Tai et al. (2025) on smart city technology, Tuyen and Nguyen (2025) on microlearning, Wu et al. (2022) AI-assisted

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learning, Wu et al. (2025) on AI in the construction industry, and Yizing et al. (2025) on BIM. Therefore, the study hypothesizes that:

H2: Effort expectancy positively influences construction professionals' behavioral intention to adopt AI-enabled BIM.

Empirical findings supporting the influence of social influence on behavioral intention, include, Alvi (2021) on social networking tool, Arfi et al. (2021) on IoT in e-Health, Handa and Kaur (2025) on online insurance, Heo and Na (2025) on construction AI technology, Kim et al. (2024) on generative AI, Lee et al. (2024) on ChatGPT, Rana et al. (2024) on AI, Tai et al. (2025) on smart city technology, Wu et al. (2022) AI-assisted learning, Wu et al. (2025) on AI in the construction industry, and Yizing et al. (2025) on BIM. Therefore, the study hypothesizes that:

H3: Social influence positively impacts construction professionals' behavioral intention to adopt AI-enabled BIM.

However, even though UTAUT overcomes the limitations of eight prominent theories and models, Venkatesh (2022) acknowledges the need to extend UTAUT to include AI-related factors, as the three predictors of behavioral intention do not capture all factors influencing the decision to adopt and use AI technologies. In addition, Nnaji et al. (2023) proposed that acceptance models for studying the adoption and use of integrated technologies, such as AI-enabled BIM, must be extended to include domain-specific factors. Wang et al. (2021) noted that numerous empirical studies have extended the UTAUT model by incorporating additional predictive factors.

The adoption of AI and AI-enabled BIM tools is still in its early stages (Pan & Zhang, 2023). It faces challenges arising from a complex mix of technological, organizational, social, and human factors, particularly from the perspective of construction professionals (Adebayo et al., 2025). While UTAUT can effectively assess how technological, organizational, and social factors influence traditional technologies, it needs to be expanded to address the human element when studying AI or AI-enabled tools. Human factors include personal innovativeness—defined as an individual's willingness to adopt and evaluate new information technologies (Agarwal & Prasad, 1998; Rogers, 2003)—and trust, which is the confidence that information technologies are reliable, capable, and acting in the user's best interest (Rousseau et al., 1998; McKnight et al., 2011).

The Diffusion of Innovation (DOI) framework suggests that individuals vary in their response to adopting innovations (Rogers, 2003). Those with high IT innovativeness are generally better at managing new technology and tend to view it as less complex and less difficult (Eren et al., 2025; Fan et al., 2020). Personal innovativeness, as a key factor, helps focus on potential users' willingness to adopt (Senali et al., 2023). Numerous empirical studies on AI and related technologies recognize personal innovativeness as a predictor of behavioral intention. For example, Lee et al. (2021) found that it influences how users evaluate and adopt AI-enabled voice assistants. Research by Ramos Salazar and Peeples (2025) on ChatGPT in higher education shows that more innovative teachers are more likely to use ChatGPT in their teaching. Similarly, Bhadauria and Chennamaneni (2022), studying IoT adoption in the USA, identified a positive link between personal innovativeness and IoT device use. Gokcearslan et al. (2024) observed that more innovative pre-service teachers tend to use IoT technologies more frequently in education. Innovative construction professionals, naturally inclined to experiment with new tools, also strongly predict the intention to adopt technology. Based on this analysis, we propose the following hypothesis:

H4: Personal innovativeness positively impacts construction professionals' behavioral intention to adopt AI-enabled BIM.

Venkatesh et al. (2003) define effort expectancy as the perceived difficulty or complexity felt when using a technology. Numerous studies suggest that users with high IT innovativeness are more likely to view new technologies as less complex and easier to use (Eren et al., 2025; Fan et al., 2020). Empirical evidence linking personal innovativeness to effort expectancy includes Fan et al. (2020), who examined an AI-enabled medical diagnosis support system (AIMDSS), and Wu et al. (2011), who studied healthcare professionals' adoption of

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mobile healthcare. Additionally, Basak et al. (2015), in their research on PDA use physicians, and Vitente et al. (2024), in their study on BIM adoption, both found that personal innovativeness positively affects perceived ease of use.

Mata et al. (2024) suggested that personal innovativeness boosts an individual's perception of usefulness and effort, as it reflects their ability to adopt and adapt to new technologies. Their research on BIM adoption confirmed the links between personal innovativeness and both perceived usefulness (performance expectancy) and perceived ease of use (effort expectancy). Alkawsi et al. (2021) studied smart meter technology acceptance and found that the influence of performance expectancy and effort expectancy on behavioral intention is stronger among innovative individuals. Similarly, Senali et al. (2023) noted that the usefulness and ease of use of e-wallets have less impact on adoption decisions among highly innovative individuals than among those with lower innovativeness. Based on this analysis, we propose the following hypothesis:

H5: Personal innovativeness (PI) is positively correlated with performance expectancy (PE).

H6: Personal innovativeness (PI) is positively correlated with effort expectancy (EE).

In situations where outcomes are unpredictable or could go wrong, trust becomes especially important (McKnight et al. 2011). In AI-enabled BIM, trust represents construction professionals' confidence that the technology will improve project quality without causing harm. Currently, there is limited empirical evidence on how trust influences the adoption of BIM and other digital construction tools. Therefore, insights from other fields are used to highlight the significance of trust in the adoption of AI-enabled BIM.

Fan et al. (2020) highlight that initial trust (IT) is crucial for adopting new technology. They identify three key factors influencing initial trust: personal traits, perceptions of the technology, and the organizational context. These factors represent the trustor's views from personal, technical, and managerial perspectives. They also suggest that higher trust in a technology increases the likelihood of adoption or of considering adoption. Prakash and Das (2021) recognized trust as essential for the intention to use intelligent clinical diagnostic decision-support systems. Shahzad et al. (2025) showed that trust significantly influences Pakistani university students' actual use of ChatGPT. Furthermore, studies by Al-Haraizah et al. (2025) on smart city technology acceptance, Arfi et al. (2021) on IoT adoption in e-Health, and Chan and Lee (2021) on autonomous vehicle acceptance all found that trust affects behavioral intentions. Based on these findings, the following hypotheses are proposed.

H7: Initial trust positively impacts construction professionals' behavioral intention to adopt AI-enabled BIM.

There are apparent connections between trust, performance expectancy, and effort expectancy. In the context of UTAUT, Guo and Barnes (2007) suggested that trust could influence both performance and effort expectations. Similarly, McLeod et al. (2008) found that trust in software logic and performance expectancy loaded onto the same factor. Regarding TAM, studies have indicated that trust positively impacts perceived usefulness (Pavlou, 2003; Thiesse, 2007) and perceived ease of use (Pavlou, 2003).

Additional empirical evidence indicates that trust significantly influences performance expectancy, effort expectancy, and intention to use various technologies, including the adoption of a new technology service by Lee & Song (2013), the use of internet websites by Al-Gahtani (2011), the adoption of AI-health assistants for mobile payments by Su et al. (2025), the adoption of mobile internet by Alalwan et al. (2018), information systems by Söllner et al. (2016), and e-commerce by Al-Gahtani (2011). Thus, the following hypotheses are formulated:

H8: Initial Trust is positively correlated with performance expectancy.

H9: Initial Trust is positively correlated with effort expectancy.

The empirical evidence in the existing literature indicates that personal innovativeness and initial trust individually correlate with performance expectancy and effort expectancy, respectively. Consequently, both performance expectancy and effort expectancy act as mediators between personal innovativeness and behavioral intention and between initial trust and behavioral intention. Chen and Aklikokou (2020), in examining the

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determinants of E-government adoption, found that this proposition was supported for initial trust. Chong and Go (2024) explored the actual adoption of mobile wallets and found that this proposition was not supported for personal innovativeness. Thus, the following hypotheses are formulated:

H10: Performance expectancy mediates the relationship between personal innovativeness and behavioral intention.

H11: Performance expectancy mediates the relationship between Initial trust and behavioral intention.

H12: Effort expectancy mediates the relationship between personal innovativeness and behavioral intention.

H13: Effort expectancy mediates the relationship between Initial trust and behavioral intention.

RESEARCH METHODOLOGY AND DATA COLLECTION

Measurements

In the present study, we adopted the measurement items from previous studies that used UTAUT as the founding theory and research framework. Four constructs in the UTAUT model were adopted from Venkatesh et al. (2003), including Performance Expectancy (5 items), Effort Expectancy (5 items), Social Influence (5 items), and Behavioral Intention (5 items). In addition, the Personal Innovativeness construct has seven items and was adapted from Argawal and Prasad (1998) and Hurt et al. (1997). The Initial Trust construct has six items and was adapted from Choi et al. (2023) and Fan et al. (2020).

Sample and Data Collection

A self-administered online survey was conducted targeting construction professionals at CIDB's G7 firms across Malaysia. The total number of registered G7 construction firms under CIDB was known, and a sample of 385 was selected using Yamane's (1967) formula. The survey was sent via WhatsApp and email to the 385 randomly selected CIDB G7 companies, with a link to the questionnaire. Responses were recorded on a 5-point Likert scale. The response rate is detailed in Table 1.

Table 1: Response Rate

Response	Frequency
No. of distributed questionnaires	385
Returned questionnaires	269
Rejected questionnaires	None
Retained questionnaires	269
Response rate	69.87%

According to Lindner and Wingenbach (2002) and Lund (2023), a minimum response rate of 50% is adequate for the survey. Therefore, this study's response rate of 69.87% is acceptable for preliminary data analysis.

Statistical Analysis

Descriptive Statistics

The 269 responses were examined in IBM SPSS version 29 for outliers using Mahalanobis Distance. Eight outliers, respondents 13, 20, 184, 185, 197, 216, 220, and 249, were identified and removed from the dataset. The remaining 261 responses were then assessed for normality using skewness and kurtosis tests [Hair et al. (2021) criterion of between +1 and -1 as normal] and for multicollinearity using the variance inflation factor (VIF: >0.2 and <5.0). The normality test and multicollinearity (VIF) scores are both within the thresholds; hence, there are no normality or multicollinearity issues.

Given the risk of common method bias (CMB) in single-source self-reported data (Kock et al., 2021), we conducted Harman's single-factor test (Fuller et al., 2016; Podsakoff et al., 2003) and a full multicollinearity test

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(VIF) (Kock, 2015; Kock & Lynn, 2012) for statistical evaluation before computing descriptive statistics. The test results did not reveal common method bias in either Harman's single-factor test or the common method bias test.

Table 2 presents descriptive statistics computed in IBM SPSS V29 to summarize participants' basic characteristics and provide an overview of the sample composition.

Table 2: Demographic Profiles of Respondents

	Frequency	Percent (%)
1. Year of experience in industry:		
- Less than 2 years	10	3.80%
- 2-5 years	69	26.40%
- 6-10 years	116	44.40%
- 11-15 years	48	18.40%
- More than 15 years	18	6.90%
Total	261	
2. Level of experience with construction digital tools:		
- No experience and no knowledge of it	4	1.50%
- Beginner (Theoretical knowledge only or Limited practical use)	30	11.50%
- Intermediate (Regular user for specific tasks)	120	46.00%
- Advanced (Proficient user, capable of managing BIM projects)	93	35.60%
- Expert (Can develop and implement BIM protocols)	14	5.40%
Total	261	
3. Using AI for:		
- Curious explorer (General enquiries like travel ideas and health matters)	19	7.30%
- Convenience users (Also use for translation, letters, and general report writing)	138	52.90%
- Task optimizers (Use to generate spreadsheet formulas, meeting notes, and professional report outlines)	74	28.40%
- Workflow integrators (Use for analysis, drafting, testing, and ideation)	25	9.60%
- Strategic power users (Use to design systems and products, decision making, and training)	5	1.90%
Total	261	
4. Your Gender:		
- Male	194	74.30%
- Female	67	25.70%
Total	261	
5. Your Age Group: *		
- Under 25 years	1	0.40%
- 26 - 35 years	109	41.80%
- 36 - 45 years	114	43.70%
- 46 - 55 years	32	12.30%
- Over 55 years	5	1.90%
Total	261	
6. Your Highest Academic Qualification:		
- Diploma	9	3.40%
- Bachelor's Degree	12	4.60%
- Master's Degree	184	70.50%
- Doctorate's Degree	55	21.10%
- Other	1	0.40%
Total	261	
7. Your Current Position/Role:		

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- Project Manager	55	21.10%
- BIM Manager/Coordinator	42	16.10%
- Architect	22	8.40%
- Engineer (Civil, Structural, MEP)	109	41.80%
- Quantity Surveyor	20	7.70%
- Site Supervisor/Foreman	9	3.40%
- Other	4	1.50%
Total	261	

The respondents were predominantly mid-career and experienced construction professionals, with most having 6–10 years of industry experience (44.4%), followed by 2–5 years (26.4%) and 11–15 years (18.4%). The sample was largely male (74.3%) and concentrated within the 26–45 age range, indicating a professionally active group. Respondents were also highly educated, with the majority holding master's degrees (70.5%) or doctorates (21.1%). In terms of roles, engineers formed the largest group (41.8%), followed by project managers (21.1%) and BIM managers/coordinators (16.1%), suggesting strong representation from technical and managerial professionals directly involved in construction project delivery and digital implementation.

The respondents also demonstrated substantial familiarity with construction digital tools, with 46.0% identifying as intermediate users and 35.6% as advanced users, while only 1.5% reported no experience. AI usage was evident but mostly remained at a basic-to-intermediate level: 52.9% were convenience users who used AI for translation, writing, and routine documentation, while 28.4% were task optimizers using AI for more structured professional tasks. Only a small proportion were workflow integrators (9.6%) or strategic power users (1.9%). Overall, the demographic profile indicates that the sample comprises experienced, highly educated, and digitally aware construction professionals, making them well-positioned to provide informed views on AI-enabled BIM adoption, although the strategic use of AI within construction workflows remains limited.

Structural Equation Modeling (SEM)

Structural equation modeling (SEM) was used to examine relationships among latent and observed variables (Anderson & Gerbing, 1988). Confirmatory factor analysis (CFA) was conducted in SmartPLS 4 to assess the fit of the data to the specified measurement model. The specified model registered three indicators, EE2 (0.680), IT2 (0.675), and SI (0.673), with loadings below the 0.70 threshold. Hence, they are deleted. After deleting all three, SI2 fell below 0.70 and was also deleted. The validity and reliability of the re-specified measurement model were rigorously evaluated using analyses of construct reliability, convergent validity, and discriminant validity (Hair et al., 2021). The results are summarized in Tables 3 (construct reliability and convergent validity), 4 (Cross-Loadings), 5 (Fornell-Larcker Criterion), and 6 (Heterotrait-Monotrait Ratio).

Table 3 shows that all constructs exhibited robust internal consistency, with composite reliability and Cronbach's alpha ranging from 0.744 to 0.859, exceeding the recommended threshold of 0.70 and thereby confirming the reliability of the measurement scales. Convergent validity was assessed through factor loadings (FL) and average variance extracted (AVE). The FLs for all items ranged from 0.704 to 0.872, surpassing the minimum acceptable value of 0.70, indicating that each item effectively captured the essence of its corresponding latent construct. The AVE values for all constructs ranged from 0.541 to 0.707, consistently exceeding the critical threshold of 0.50, demonstrating that the latent variables accounted for a sufficient proportion of the variance in their respective indicators.

Table 3: Construct Reliability and Convergent Validity

Construct	Item	Factor Loading	Cronbach's alpha	Composite reliability	AVE
Performance Expectation:			0.819	0.823	0.581
	PE1	0.791			
	PE2	0.716			
	PE3	0.752			

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	PE4	0.731			
	PE5	0.818			
Effort Expectancy:			0.744	0.744	0.565
	EE1	0.741			
	EE3	0.765			
	EE4	0.742			
	EE5	0.759			
Social Influence:			0.793	0.797	0.707
	SI3	0.872			
	SI4	0.809			
	SI5	0.841			
Personal Innovativeness			0.859	0.859	0.541
	PI1	0.726			
	PI2	0.728			
	PI3	0.729			
	PI4	0.773			
	PI5	0.704			
	PI6	0.722			
	PI7	0.767			
Initial Trust			0.808	0.811	0.565
	IT1	0.778			
	IT3	0.769			
	IT4	0.729			
	IT5	0.755			
	IT6	0.724			
Behavioral Intention:			0.843	0.848	0.615
	BI1	0.832			
	BI2	0.707			
	BI3	0.798			
	BI4	0.769			
	BI5	0.808			

Discriminant validity was assessed using cross-loadings (Radomir & Moisescu, 2020). The results in Table 4 indicate that all indicators load higher on their respective constructs than on other constructs. This confirms that each construct is distinct and measures a unique concept. Although some constructs, particularly initial trust and self-efficacy, exhibit relatively higher cross-loadings, all indicators still load highest on their intended constructs. Therefore, discriminant validity is established.

Table 4: Discriminant Validity – Cross-loading

	BI	EE	IT	PE	PI	SI
BI1	0.832	0.485	0.467	0.542	0.552	0.547
BI2	0.707	0.374	0.414	0.455	0.487	0.426
BI3	0.798	0.500	0.465	0.469	0.557	0.527
BI4	0.769	0.461	0.446	0.463	0.540	0.485
BI5	0.808	0.505	0.526	0.530	0.582	0.533
EE1	0.470	0.741	0.349	0.297	0.398	0.399
EE3	0.431	0.765	0.413	0.372	0.506	0.358
EE4	0.431	0.742	0.351	0.338	0.456	0.354
EE5	0.461	0.759	0.469	0.345	0.461	0.351
IT1	0.499	0.437	0.778	0.494	0.481	0.469
IT3	0.447	0.392	0.769	0.581	0.565	0.526
IT4	0.450	0.394	0.729	0.425	0.518	0.464

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IT5	0.435	0.409	0.755	0.528	0.523	0.469
IT6	0.390	0.342	0.724	0.403	0.498	0.456
PE1	0.487	0.378	0.518	0.791	0.565	0.517
PE2	0.473	0.357	0.444	0.716	0.504	0.454
PE3	0.495	0.342	0.527	0.752	0.553	0.525
PE4	0.408	0.328	0.485	0.731	0.495	0.488
PE5	0.524	0.314	0.513	0.818	0.580	0.534
PI1	0.507	0.478	0.527	0.481	0.726	0.522
PI2	0.502	0.416	0.520	0.508	0.728	0.533
PI3	0.489	0.433	0.501	0.484	0.729	0.461
PI4	0.526	0.465	0.515	0.540	0.773	0.518
PI5	0.525	0.463	0.546	0.583	0.704	0.484
PI6	0.506	0.452	0.466	0.512	0.722	0.555
PI7	0.517	0.413	0.465	0.535	0.767	0.542
SI3	0.580	0.390	0.545	0.597	0.557	0.872
SI4	0.517	0.410	0.538	0.504	0.619	0.809
SI5	0.527	0.428	0.521	0.565	0.601	0.841

Discriminant validity was further assessed using the Fornell–Larcker criterion (Henseler et al., 2015). A construct should share more variance with its own indicators than with other constructs. The results in Table 5 show that all constructs meet the required threshold, with the square root of the AVE exceeding the inter-construct correlations. Discriminant validity is established.

Table 5: Discriminant Validity – Fornell-Larcker Criterion

	BI	EE	IT	PE	PI	SI
BI	0.784					
EE	0.596	0.752				
IT	0.593	0.528	0.751			
PE	0.628	0.450	0.652	0.763		
PI	0.694	0.607	0.688	0.709	0.736	
SI	0.645	0.486	0.635	0.661	0.702	0.841

Heterotrait–Monotrait (HTMT) ratio is another discriminant validity test (Henseler et al., 2015; Roemer et al., 2021). For the constructs to meet the discriminant validity criteria, the HTMT ratio, according to Franke and Sarstedt (2019) and Kline (2023), should not exceed 0.85; according to Gold et al. (2001), it should not exceed 0.90. The results in Table 6 indicate that all HTMT values are below the recommended threshold of 0.90, confirming acceptable discriminant validity. Most values are below the stricter threshold of 0.85, indicating strong discriminant validity.

Table 6: Discriminant Validity – Heterorait-Monotrait Ratio (HTMT)

	BI	EE	IT	PE	PI	SI
BI						
EE	0.750					
IT	0.715	0.676				
PE	0.754	0.577	0.795			
PI	0.815	0.757	0.825	0.842		
SI	0.786	0.635	0.794	0.819	0.854	

In summary, the reliability and validity parameters of our study met the recommended standards, providing a solid foundation for structural model analysis.

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The structural model after bootstrapping is presented in Figure 1.

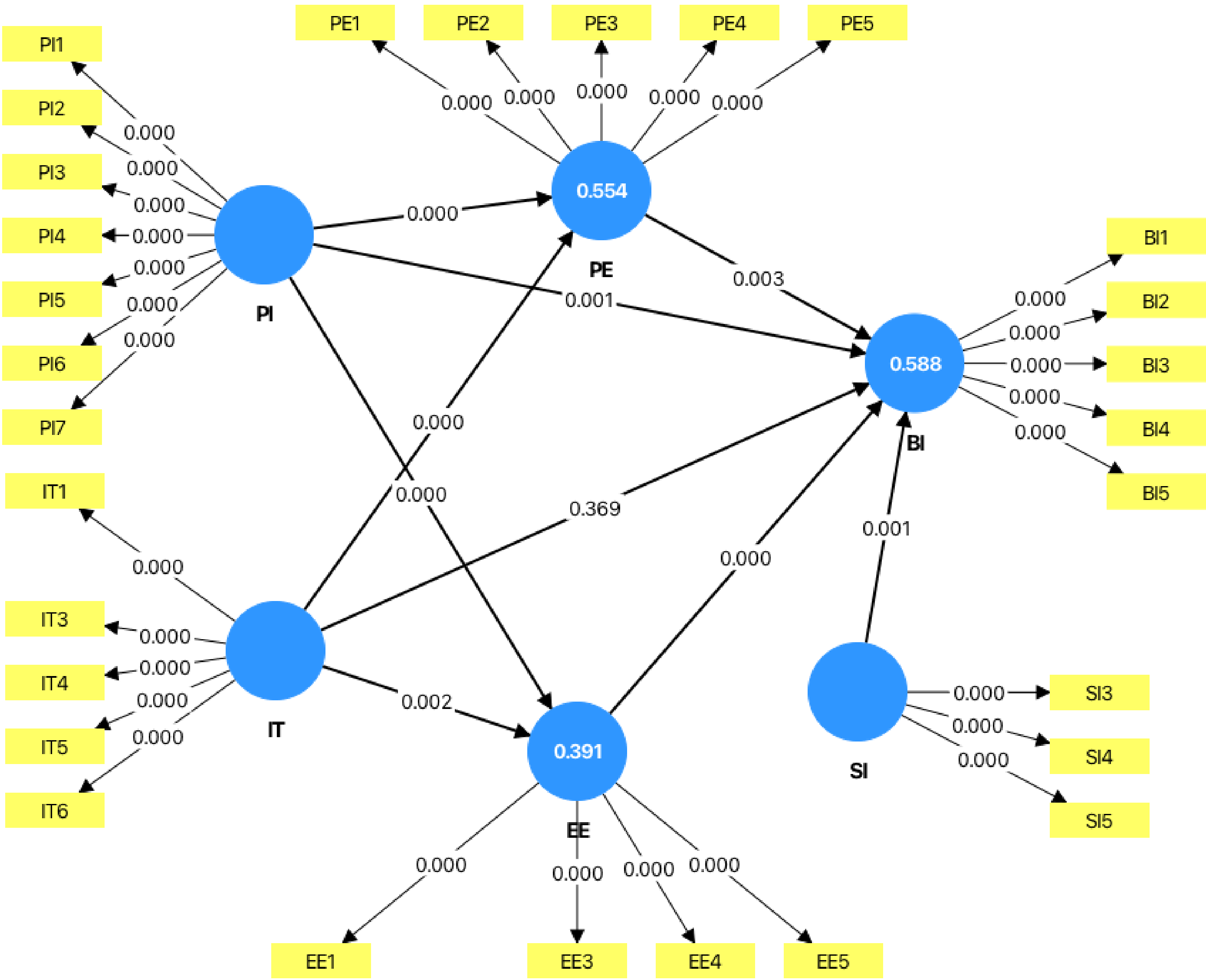

Figure 1: Structural Model

The results show that behavioral intention (BI) achieved an R^2 (coefficient of determination) of 0.588, indicating that approximately 58.8% of the variance in behavioral intention toward AI-enabled BIM systems is explained by the model's predictor constructs. This suggests a moderate to substantial explanatory power. Effort expectancy (EE) had an R^2 of 0.391, indicating that 39.1% of the variance in EE is explained by its antecedent variables, representing a moderate level of explanatory power. Similarly, performance expectancy (PE) demonstrated an R^2 of 0.554, indicating that the model explains 55.4% of the variance in PE, a substantial amount.

The study then computes the effect size (f^2) to evaluate the model's predictive accuracy (Henseler, 2020; Hair et al., 2019). Following Cohen's (1962) standards, f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively (Hair et al., 2019). Accordingly, the impact of exogenous constructs on their corresponding endogenous constructs was assessed individually for each effect size, as detailed in Table 7.

Table 7: f-Square (f^2)

	BI	EE	PE
EE	0.086		
IT	0.003	0.039	0.115
PE	0.032		
PI	0.045	0.184	0.289
SI	0.046		

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Based on Table 7, effort expectancy (EE) had a small effect on behavioral intention (BI) with an f^2 value of 0.086, while performance expectancy (PE), personal innovativeness (PI), and social influence (SI) also demonstrated small effects on BI, with f^2 values of 0.032, 0.045, and 0.046, respectively. Initial trust (IT) had a negligible effect on BI ($f^2 = 0.003$), indicating that it contributed minimally to the explanation of behavioral intention. Regarding the determinants of EE and PE, personal innovativeness (PI) exerted the strongest influence, showing a medium effect on EE ($f^2 = 0.184$) and a moderate-to-large effect on PE ($f^2 = 0.289$). In contrast, IT demonstrated only a small effect on EE ($f^2 = 0.039$) and PE ($f^2 = 0.115$). Overall, the findings suggest that personal innovativeness is the most influential predictor in the model, particularly in shaping respondents' perceptions of effort expectancy and performance expectancy toward AI-enabled BIM systems.

Next, the study assesses the Predictive Relevance (Q^2) and Power (RMSE) of the structural model. If the cross-validated redundancy measure (Q^2) for an endogenous construct exceeds zero ($Q^2>0$), it indicates that the latent constructs are predictive. The predictive power can be assessed by comparing the RMSE (root mean square error) values of the PLS-SEM and LM (multiple linear regression) models. The comparison is to determine whether this study model is better than a simple regression model. SmartPLS 4 has generated the Q^2predict values, PLS-SEM RMSE, and LM RMSE as shown in Table 8.

Table 8: Predictive Relevance and Predictive Power Level

	Q^2predict	PLS-SEM_RMSE	LM_RMSE	PLS-LM
EE1	0.158	0.930	0.950	-0.020
EE3	0.254	0.856	0.888	-0.032
EE4	0.197	0.866	0.894	-0.028
EE5	0.237	0.811	0.824	-0.013
PE1	0.345	0.746	0.749	-0.003
PE2	0.265	0.920	0.946	-0.026
PE3	0.338	0.847	0.845	0.002
PE4	0.275	0.839	0.825	0.014
PE5	0.351	0.851	0.858	-0.007
BI1	0.341	0.923	0.941	-0.018
BI2	0.247	0.878	0.882	-0.004
BI3	0.338	0.883	0.903	-0.020
BI4	0.308	0.928	0.958	-0.030
BI5	0.373	0.824	0.862	-0.038

As shown in Table 8, all indicators for effort expectancy (EE), performance expectancy (PE), and behavioral intention (BI) recorded positive Q^2predict values ranging from 0.158 to 0.373. This indicates that the model possesses adequate predictive relevance for all endogenous constructs. Among the indicators, BI5 (Q^2predict=0.373) and PE5 (Q^2predict=0.351) demonstrated the strongest predictive relevance, while EE1 (Q^2predict=0.158) showed the lowest but still acceptable predictive capability.

The table also compares the Root Mean Squared Error (RMSE) values from the PLS-SEM and linear (LM) models. Most indicators in Table 8 showed negative "PLS-LM" values, suggesting superior predictive performance of the PLS-SEM model. Although two indicators (PE3 and PE4) recorded very small positive differences, the values were minimal, indicating only marginally weaker performance compared to the linear model. Overall, the findings indicate that the model demonstrates medium predictive power and satisfactory out-of-sample predictive relevance for explaining behavioral intention, effort expectancy, and performance expectancy toward AI-enabled BIM systems.

Hair et al. (2021) proposed including the Cross-Validated Predictive Ability Test (CVPAT) as an additional test to evaluate the model's predictive performance. The results of the CVPAT generated using PLSpredict of SmartPLS 4 are presented in Table 9.

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Table 9: Cross-Validated Predictive Ability Test (CVPAT)

	PLS loss	LM loss	Average loss difference	t value	p value
EE	0.751	0.792	-0.041	3.153	0.002
PE	0.710	0.717	-0.007	0.439	0.661
BI	0.788	0.828	-0.040	2.756	0.006
Overall	0.750	0.778	-0.028	2.880	0.004

The findings show that for EE, the PLS-SEM loss value (0.751) was lower than the LM loss value (0.792), with a significant negative average loss difference of -0.041 (t = 3.153, p = 0.002). Similarly, for BI, the PLS-SEM loss value (0.788) was lower than the LM loss value (0.828), with a significant average loss difference of -0.040 (t = 2.756, p = 0.006). These results indicate that the PLS-SEM model predicts EE and BI more accurately than the benchmark linear model.

For performance expectancy (PE), although the PLS-SEM model yielded a slightly lower loss value (0.710) than the linear model (0.717), the difference was very small and not statistically significant (t = 0.439, p = 0.661). This suggests that the predictive performance of the PLS-SEM model for PE was comparable to that of the linear model rather than significantly better.

Overall, the model demonstrated a significantly lower overall prediction loss (0.750) than the linear model (0.778), with a statistically significant average loss difference of -0.028 (t = 2.880, p = 0.004). This indicates that the proposed PLS-SEM model possesses satisfactory out-of-sample predictive ability and performs better overall than the benchmark linear model in predicting the adoption-related constructs of AI-enabled BIM systems. The findings therefore support the predictive robustness and practical applicability of the proposed research model in the Malaysian construction industry.

Finally, an importance-performance map analysis (IPMA) was performed. Importance is assessed on a scale from 0 to 1, while performance is evaluated on a scale from 0 to 100. This study's IPMA statistics are presented in Table 10.

Table 10: Importance-Performance Map Analysis (IPMA)

	Importance	Performance
EE	0.242	68.975
IT	0.159	69.732
PE	0.177	69.784
PI	0.439	69.044
SI	0.209	67.959

The results indicate that personal innovativeness (PI) had the highest importance value (0.439), making it the most influential predictor of behavioral intention toward AI-enabled BIM systems. However, its performance score (69.044) was only moderate compared to other constructs. This suggests that improving construction professionals' innovativeness, openness to new technologies, and willingness to experiment with AI-enabled BIM systems could substantially enhance adoption intentions. Effort expectancy (EE) also demonstrated relatively high importance (0.242) with a performance score of 68.975, indicating that ease of use and user-friendliness remain important drivers of behavioral intention and should continue to be enhanced through training, intuitive system design, and technical support. Social influence (SI) showed moderate importance (0.209) but the lowest performance score (67.959), suggesting that organizational encouragement, peer influence, and management support for AI-enabled BIM adoption remain relatively weak and warrant greater attention. Performance expectancy (PE) had moderate importance (0.177) and one of the highest performance scores (69.784), suggesting that respondents generally perceive AI-enabled BIM systems as useful for improving job performance. Similarly, initial trust (IT) demonstrated lower importance (0.159) but relatively high performance (69.732), indicating that respondents already possess a reasonable level of trust in AI-enabled BIM systems, although its influence on behavioral intention is comparatively weaker. Overall, the IPMA findings highlight personal innovativeness as the most critical area for strategic improvement due to its strong influence on

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behavioral intention and only moderate performance level. Enhancing users' readiness to embrace innovation, improving effort expectancy, and strengthening social influence could significantly increase the adoption and use of AI-enabled BIM systems in the Malaysian construction industry.

The final step involved testing the hypothesized relationships by running a bootstrapping algorithm in SmartPLS 4. Tables 11 and 12 present the results of the hypothesis testing for this study.

Table 11: Hypotheses Testing - Direct Effect

		Path Coefficient	T statistics	P values	Decision
H1	PE -> BI	0.177	3.001	0.003	Accepted
H2	EE -> BI	0.242	5.047	0.000	Accepted
H3	SI -> BI	0.209	3.480	0.001	Accepted
H4	PI -> BI	0.239	3.463	0.001	Accepted
H5	PI -> PE	0.495	8.322	0.000	Accepted
H6	PI -> EE	0.461	6.278	0.000	Accepted
H7	IT -> BI	0.052	0.899	0.369	Rejected
H8	IT -> PE	0.312	5.577	0.000	Accepted
H9	IT -> EE	0.211	3.117	0.002	Accepted

Table 12: Hypotheses Testing - Mediating Effect

		Path Coefficient	T statistics	P values	Decision
H10	PI -> PE -> BI	0.088	2.833	0.005	Accepted
H11	IT -> PE -> BI	0.055	2.411	0.016	Accepted
H12	PI -> EE -> BI	0.112	3.878	0.000	Accepted
H13	IT -> EE -> BI	0.051	2.610	0.009	Accepted

DISCUSSION OF MAJOR FINDINGS

The main purpose of this study was to investigate, using an extended UATAU framework, the impact of performance expectancy, effort expectancy, social influence, personal innovativeness, and initial trust on construction professionals' intention to use AI-enabled BIM, with performance expectancy and effort expectancy also acting as mediators. Tables 11 and 12 present the results for the direct and mediating effects of the proposed hypotheses on the adoption of AI-enabled BIM systems among Malaysian G7 construction firms. The findings provide important insights into the factors influencing construction professionals' behavioral intention (BI) to adopt AI-enabled BIM technologies.

The results of the direct effects analysis in Table 11 indicate that performance expectancy (PE), effort expectancy (EE), social influence (SI), and personal innovativeness (PI) significantly influence behavioral intention (BI). Specifically, PE had a significant positive effect on BI ($\beta = 0.177$, $p = 0.003$), supporting H1 as found by Abbad (2021) on e-Learning, Alvi (2021) on a social network tool, Handa and Kaur (2025) on online insurance, Heo and Na (2025) on construction AI technology, Lee et al. (2024) on ChatGPT, Rana et al. (2024) on AI, Rahim et al. (2023) on Islamic fintech, Tai et al. (2025) on smart city technology, Tuyen and Nguyen (2025) on microlearning, and Wu et al. (2022) on AI-assisted learning. This suggests that construction professionals are more likely to adopt AI-enabled BIM systems when they perceive that the technology can improve work performance, productivity, and project outcomes.

Effort expectancy (EE) also significantly influenced BI ($\beta = 0.242$, $p < 0.001$), supporting H2 that aligned with the empirical study by Arfi et al. (2021) on IoT in e-Health, Handa and Kaur (2025) on online insurance, Heo and Na (2025) on construction AI technology, Kim, Blaznez, and Oh (2024) on generative AI, Lee et al. (2024) on ChatGPT, Rana et al. (2024) on AI, Tai et al. (2025) on smart city technology, Tuyen and Nguyen (2025) on microlearning, Wu et al. (2022) AI-assisted learning, Wu et al. (2025) on AI in the construction industry, and

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Yizing et al. (2025) on BIM. This indicates that ease of use and perceived simplicity of AI-enabled BIM systems are important determinants of adoption intention. Among the UTAUT-related constructs, EE had the strongest direct influence on BI, indicating that user-friendliness is critical to encouraging adoption in the Malaysian construction context.

Similarly, social influence (SI) positively affected BI ($\beta = 0.209$, $p = 0.001$), supporting H3 that was consistent with the findings of Alvi (2021) on social networking tool, Arfi et al. (2021) on IoT in e-Health, Handa and Kaur (2025) on online insurance, Heo and Na (2025) on construction AI technology, Kim et al. (2024) on generative AI, Lee et al. (2024) on ChatGPT, Rana et al. (2024) on AI, Tai et al. (2025) on smart city technology, Wu et al. (2022) AI-assisted learning, Wu et al. (2025) on AI in the construction industry, and Yizing et al. (2025) on BIM. This finding implies that organizational encouragement, peer opinions, industry expectations, and management support significantly shape professionals' willingness to adopt AI-enabled BIM systems.

Personal innovativeness (PI) also significantly influenced BI ($\beta = 0.239$, $p = 0.001$), supporting H4, similar to the empirical results of Lee et al. (2021) on the adoption of AI-enabled voice assistants, Ramos Salazar and Peeples (2025) on ChatGPT in higher education, Bhadauria and Chennamaneni (2022) on IoT adoption in the USA, and Gokcearslan et al. (2024) on the use of IoT technologies more frequently in education. This suggests that individuals who are more open to experimenting with new technologies are more likely to embrace AI-enabled BIM. Furthermore, PI significantly influenced both PE ($\beta = 0.495$, $p < 0.001$) and EE ($\beta = 0.461$, $p < 0.001$), supporting H5 and H6. These findings indicate that innovative individuals tend to perceive AI-enabled BIM systems as both more useful and easier to use.

Interestingly, initial trust (IT) did not significantly influence BI directly ($\beta = 0.052$, $p = 0.369$), leading to the rejection of H7. This was contrary to the findings of Prakash and Das (2021) on the use of intelligent clinical diagnostic decision-support systems, Shahzad et al. (2025) on university students' actual use of ChatGPT, Al-Haraizah et al. (2025) on smart city technology acceptance, Arfi et al. (2021) on IoT adoption in e-Health, and Chan and Lee (2021) on autonomous vehicle acceptance. This suggests that although trust in AI-enabled BIM systems exists, it does not directly motivate Malaysian construction professionals to adopt them. One possible explanation is that users may prioritize practical benefits and ease of use over trust considerations when evaluating new digital technologies. Nevertheless, IT significantly influenced both PE ($\beta = 0.312$, $p < 0.001$) and EE ($\beta = 0.211$, $p = 0.002$), supporting H8 and H9. These findings are in line with the findings of Lee & Song (2013) on the adoption of a new technology service, Al-Gahtani (2011) on the use of internet websites, Su et al. (2025) on the adoption of AI-health assistants for mobile payments, Alalwan et al. (2018) on the adoption of mobile internet, Söllner et al. (2016) on the use of information systems, and Al-Gahtani (2011) on the use of e-commerce. This indicates that higher trust in AI-enabled BIM systems improves users' perceptions of usefulness and ease of use, even though trust alone is insufficient to directly drive behavioral intention.

The mediation analysis presented in Table 12 further clarifies the indirect mechanisms influencing AI-enabled BIM adoption. The results show that PE significantly mediated the relationship between PI and BI ($\beta = 0.088$, $p = 0.005$), supporting H10, and between IT and BI ($\beta = 0.055$, $p = 0.016$), supporting H11. These findings are consistent with those of Chen and Aklikokou (2020) on the determinants of E-government adoption. This implies that innovative individuals and users with higher initial trust are more likely to adopt AI-enabled BIM systems because they perceive the systems as beneficial and performance-enhancing. Similarly, EE significantly mediated the relationship between PI and BI ($\beta = 0.112$, $p < 0.001$), supporting H12, and between IT and BI ($\beta = 0.051$, $p = 0.009$), supporting H13. These findings also resonated with those of Chen and Aklikokou (2020) on the determinants of E-government adoption. This suggests that innovative and trusting users are more inclined to adopt AI-enabled BIM systems when they perceive the technology as easy to learn and operate.

Overall, the findings indicate that the adoption of AI-enabled BIM systems in Malaysia is primarily driven by perceived usefulness, ease of use, social influence, and personal innovativeness. Personal innovativeness emerged as one of the strongest predictors in the model, both directly and indirectly influencing adoption intention through PE and EE. Although initial trust did not directly predict behavioral intention, it played a significant indirect role by enhancing users' perceptions of system usefulness and ease of use. These findings highlight the importance of developing user-friendly AI-enabled BIM platforms, strengthening organizational support, and cultivating innovative mindsets among construction professionals to accelerate digital transformation in Malaysia's construction industry.

Theoretical Contribution and Practical Implications

This study contributes to the growing body of knowledge on digital transformation and technology adoption in the construction industry by extending the original Unified Theory of Acceptance and Use of Technology (UTAUT) framework to AI-enabled BIM systems. While previous studies have largely examined BIM and AI adoption separately, this research integrates these technologies into a single adoption framework, thereby addressing an important gap in construction technology literature. The study demonstrates that the convergence of AI and BIM introduces new behavioral and cognitive considerations beyond those traditionally associated with conventional BIM adoption. A major theoretical contribution of this study is the incorporation of personal innovativeness (PI) and initial trust (IT) into the UTAUT model. The findings reveal that PI is a strong predictor of behavioral intention both directly and indirectly through performance expectancy (PE) and effort expectancy (EE), highlighting the importance of individual innovativeness in the adoption of emerging intelligent construction technologies. Additionally, although IT did not directly influence behavioral intention, it significantly affected PE and EE, exerting indirect effects through these mediators. This finding contributes to the literature by demonstrating that trust in AI-enabled systems may operate indirectly through users' perceptions of usefulness and ease of use rather than directly influencing adoption intention. The study also contributes empirically by offering one of the earliest investigations into AI-enabled BIM adoption in the Malaysian construction industry, particularly among CIDB Grade 7 (G7) firms. Given the limited global empirical research on AI-enabled BIM systems and the near-absence of studies in Malaysia, the findings provide valuable evidence on the determinants of behavioral intention toward next-generation construction technologies in a developing-country context. Furthermore, the study validates the applicability of the extended UTAUT model in explaining AI-enabled BIM adoption, thereby strengthening the theoretical robustness of technology acceptance models in Construction 4.0 environments. Another important theoretical contribution lies in demonstrating the mediating roles of PE and EE. The findings show that users' perceptions of usefulness and ease of use are key psychological mechanisms through which personal innovativeness and initial trust shape behavioral intention. These advances in understanding how cognitive evaluations influence technology adoption in highly technical, AI-driven construction systems.

The findings suggest that construction firms should prioritize strategies that improve employees' perceptions of the usefulness and ease of use of AI-enabled BIM systems. Since effort expectancy emerged as one of the strongest predictors of behavioral intention, firms should invest in user-friendly platforms, structured training programs, technical support systems, and continuous professional development to reduce the perceived complexity of AI-enabled BIM technologies. The strong influence of personal innovativeness indicates that firms should cultivate a culture of innovation and digital experimentation within their organizations. Encouraging employees to explore new technologies, participate in pilot projects, and engage in digital innovation initiatives can significantly enhance AI-enabled BIM adoption. Firms may also benefit from recruiting digitally competent professionals and establishing internal champions or BIM innovation teams to accelerate organizational transformation. Furthermore, the significant role of social influence suggests that leadership support and organizational commitment are critical. Senior management should actively promote AI-enabled BIM adoption through clear strategic direction, incentives, awareness programs, and integration of digital technologies into standard operating procedures. This can help foster positive peer influence and strengthen organizational readiness for the implementation of Construction 4.0.

For policymakers, particularly the Construction Industry Development Board (CIDB) and related government agencies, the findings highlight the need for stronger institutional support to accelerate AI-enabled BIM adoption in Malaysia. Existing BIM policies and Construction 4.0 initiatives should be expanded to include AI integration frameworks, AI-enabled BIM implementation guidelines, and standardized best practices. The results also suggest that policymakers should focus on improving digital competencies within the construction workforce. This can be achieved through industry-wide certification programs, subsidized training, university-industry collaboration, and national digital upskilling initiatives related to AI, BIM, data analytics, and automation technologies. Additionally, financial incentives such as tax deductions, grants, technology adoption funds, and

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pilot project support could help reduce barriers to implementing AI-enabled BIM systems, particularly for firms facing high setup costs and infrastructure limitations. Policymakers may also consider establishing regulatory frameworks and ethical guidelines addressing AI reliability, data governance, cybersecurity, and interoperability to strengthen industry trust in AI-enabled construction technologies.

The findings provide important guidance for AI-enabled BIM software developers and vendors. Since effort expectancy significantly influences adoption intention, developers should focus on designing intuitive, user-friendly, and accessible systems that minimize technical complexity. Simplified interfaces, conversational AI functions, automation tools, and seamless interoperability with existing BIM platforms can improve user acceptance. The importance of performance expectancy suggests that software vendors should clearly demonstrate the practical benefits of AI-enabled BIM systems, including improved project efficiency, automated clash detection, predictive analytics, real-time monitoring, and enhanced decision-making. Providing measurable evidence of productivity gains and cost savings can strengthen users' perceptions of usefulness. Moreover, because initial trust indirectly affects adoption, developers must emphasize system reliability, transparency, data security, and explainability of AI outputs. Features such as audit trails, error validation mechanisms, transparent AI recommendations, and cybersecurity safeguards can improve user confidence in AI-enabled BIM technologies. Finally, the significant role of personal innovativeness implies that software vendors should actively engage users through interactive demonstrations, pilot testing opportunities, hands-on workshops, and continuous customer support. Encouraging experimentation and providing practical exposure to AI-enabled BIM applications can help construction professionals become more comfortable and confident with these emerging technologies.

Limitations and Future Research

Despite providing valuable insights into the adoption of AI-enabled BIM systems among Malaysian construction firms, this study has several limitations that should be acknowledged. First, the study focused exclusively on CIDB Grade 7 (G7) construction firms in Malaysia. These firms generally possess greater financial resources, technological infrastructure, and organizational capabilities compared to small and medium-sized construction firms. Consequently, the findings may not fully reflect the perceptions and adoption behaviors of smaller firms facing distinct technological, financial, and operational constraints. The generalizability of the findings beyond large construction firms may therefore be limited. Second, this study employed a cross-sectional research design in which data were collected at a single point in time. As a result, the study captures respondents' perceptions and behavioral intentions only within a specific period and cannot fully explain changes in attitudes or technology adoption behavior over time. Since AI-enabled BIM technologies continue to evolve rapidly, users' perceptions and acceptance levels may also change as familiarity, organizational exposure, and technological maturity increase. Third, the study relied on self-reported data from a questionnaire administered to construction professionals. Although statistical procedures were conducted to minimize common method bias, self-reported responses may still be influenced by social desirability bias, subjective interpretation, and respondents' personal perceptions. Additionally, behavioral intention was measured rather than actual usage, which means the study examines adoption intention rather than the implementation and ongoing use of AI-enabled BIM systems. Fourth, the research adopted an extended UTAUT framework incorporating personal innovativeness and initial trust. While the model demonstrated satisfactory explanatory and predictive power, other potentially influential factors were not examined. Variables such as organizational readiness, facilitating conditions, top management support, perceived risk, technology anxiety, data security concerns, AI explainability, organizational culture, and regulatory support may also significantly influence AI-enabled BIM adoption, but were beyond the scope of this study. Fifth, the study was conducted in the Malaysian construction industry, which has unique institutional, cultural, economic, and technological characteristics. Therefore, the findings may not be directly transferable to construction industries in other countries with different levels of digital maturity, regulatory frameworks, or technological adoption environments.

Future research should expand the scope of investigation to include small- and medium-sized construction firms, consultants, developers, subcontractors, and public-sector organizations to provide a more comprehensive understanding of AI-enabled BIM adoption across the entire construction ecosystem. Comparative studies between large and small firms may also reveal differences in adoption barriers, technological readiness, and

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organizational capabilities. Longitudinal studies are recommended to examine how perceptions, trust, and adoption behaviors evolve over time as AI-enabled BIM technologies mature and become more widely implemented. Such studies could provide deeper insights into the transition from behavioral intention to actual use, continued use, and organizational integration. Future researchers may also extend the theoretical model by incorporating additional constructs, including facilitating conditions, organizational support, perceived risk, AI transparency, cybersecurity concerns, ethical considerations, technology anxiety, resistance to change, and data governance. Integrating theories such as the Technology–Organization–Environment (TOE) framework, Diffusion of Innovation (DOI) theory, or trust-based AI adoption models may further enrich understanding of AI-enabled BIM adoption behavior. In addition, future studies should investigate the actual implementation outcomes of AI-enabled BIM systems, including project performance, productivity improvements, cost reductions, sustainability improvements, safety management, and decision-making effectiveness. Examining how AI-enabled BIM contributes to circular economy practices and sustainable construction objectives would also provide valuable practical and theoretical contributions. Cross-country comparative research is another promising avenue for future investigation. Comparing AI-enabled BIM adoption across developed and developing countries could help identify how institutional support, digital infrastructure, national policies, and cultural factors influence adoption behavior. Finally, future research could employ mixed-method or qualitative approaches, such as interviews, case studies, and ethnographic investigations, to gain deeper insights into organizational experiences, implementation challenges, employee resistance, and strategic transformation processes associated with AI-enabled BIM adoption in real-world construction environments.

OVERALL CONCLUSION

This study examined the factors influencing the adoption of AI-enabled Building Information Modeling (AI-BIM) systems among CIDB Grade 7 (G7) construction firms in Malaysia, using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Specifically, the study investigated the direct and indirect effects of performance expectancy (PE), effort expectancy (EE), social influence (SI), personal innovativeness (PI), and initial trust (IT) on behavioral intention (BI) to use AI-enabled BIM systems. The findings revealed that performance expectancy, effort expectancy, social influence, and personal innovativeness significantly influenced behavioral intention to adopt AI-enabled BIM systems. Among these factors, effort expectancy and personal innovativeness emerged as particularly important determinants, indicating that construction professionals are more likely to adopt AI-enabled BIM systems when they perceive them as easy to use and when they possess a stronger inclination toward innovation and experimentation with new technologies. Social influence also played a significant role, demonstrating the importance of organizational encouragement, management support, and industry influence in shaping adoption behavior. The study further found that personal innovativeness and initial trust significantly enhanced both performance expectancy and effort expectancy. However, initial trust did not directly affect behavioral intention, suggesting that trust alone may not be sufficient to drive adoption unless users also perceive the technology as beneficial and user-friendly. The mediation analysis confirmed that performance expectancy and effort expectancy are important mechanisms by which personal innovativeness and initial trust indirectly shape behavioral intention toward AI-enabled BIM adoption.

Overall, the study demonstrates that the successful adoption of AI-enabled BIM systems in Malaysia depends not only on technological capabilities but also on human, organizational, and psychological factors. The findings contribute theoretically by extending the UTAUT framework to the emerging context of AI-enabled BIM systems and empirically by providing one of the earliest studies on AI-enabled BIM adoption in Malaysia. Practically, the study offers valuable insights for construction firms, policymakers, and software developers in designing strategies, policies, training initiatives, and user-centered systems that can accelerate digital transformation in the Malaysian construction industry. As the construction sector continues to transition toward Construction 4.0, the integration of AI and BIM technologies is expected to become increasingly important for enhancing productivity, sustainability, collaboration, and intelligent decision-making throughout the project lifecycle. Therefore, strengthening digital readiness, fostering innovative mindsets, and improving user acceptance of AI-enabled BIM systems will be essential for achieving a more competitive, efficient, and technologically advanced construction industry in Malaysia.

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Author contributions

Shiau-Yoon Choong conceptualized the whole research. Zahir Osman supervised and reviewed the research.

Ethical approval

Ethics approval has been obtained from the first author's institution.

Competing interests

The authors declare that they have no competing interests.

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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