SASBE 2025 aims to encourage the international exchange of innovative ideas between researchers from academia and industry. In addition to knowledge dissemination, the conference offers a valuable platform for professional networking, particularly benefiting university professors, graduate students, and postdoctoral researchers.

Research Article

Evaluating AI Adoption and Readiness Among Architecture and Built Environment Students

Moein Latifinowsoud[1], Bolanle Noruwa[1]

University of West London, London W5 5RF, United Kingdom
Correspondence: Moein.latifinowsoud@uwl.ac.uk

Abstract

The construction industry is known as a slow adopter of technological change, yet Artificial Intelligence (AI) is increasingly challenging this trend by becoming a major catalyst for innovation. However, the readiness of the construction industry's future workforce to adopt AI remains unclear. The purpose of this study is to evaluate the readiness and intention of students (i.e., the future workforce) to adopt AI in their future professional practice. This study employs quantitative research design using a structured questionnaire based on the UTAUT 2 framework. The survey was distributed to undergraduate and postgraduate students in civil engineering, architecture, building surveying, quantity surveying, and construction project management programs. The questionnaire includes items measuring key UTAUT-2 constructs such as performance expectancy and effort expectancy, all contextualized to AI technologies. The study identifies some UTAUT 2 constructs that influence students' readiness and intention to adopt AI in their future careers. Findings also reveal the levels of AI use, exposure, and awareness among students. This study relies on self-reported data, which may be influenced by social desirability bias or limited understanding of AI technologies among students. This study aligns with SASBE 2025 themes on data science and artificial intelligence for optimization of the built environment, The study offers valuable implications for curriculum development, industry-academia collaboration, and students' preparation for future job demands. This research is among the first to apply the UTAUT 2 framework to assess AI adoption specifically within the context of construction students. While existing studies have explored technology adoption in the construction industry, limited work has focused on perceptions and preparedness of students regarding AI integration.

Keywords: Artificial Intelligence, Construction Students, UTAUT 2, Technology Adoption

Highlights

This study:

- Identifies which UTAUT2 constructs most influence students' AI adoption intentions.
- Offers insight for integrating AI into curricula and training.
- Identifies perceived obstacles in the way of adoption such as cost and lack of support.

1. Introduction

The construction industry has long been characterized by its resistance to technological change (Elkhayat, Adel, & Marzouk, 2024; Ogunmakinde, Aghajani, & Memari, 2025). Despite being one of the largest and most influential sectors that contributes significantly to GDP and employment in many economies, it has traditionally lagged behind other industries in embracing digital transformation (Alibakhshi, Saffarian, & Hassannayebi, 2024; Elbashbishy & El-Adaway, 2024; Hampson, Kraatz, & Sanchez, 2014; Ogunmakinde et al., 2025; Regona, Yigitcanlar, Xia, & Li, 2022). This sluggishness is evident in the slow integration of automation, digital tools, and innovative management practices into mainstream construction processes (Nnaji, Okpala, Awolusi, & Gambatese, 2023). While sectors such as manufacturing, healthcare, and finance have made strides in embedding technologies like Artificial Intelligence (AI) into their operational frameworks, construction has been more tentative, cautious, and fragmented in its approach to such innovations (Alibakhshi & Hassannayebi, 2025; Cao, 2022; Kim, Kong, Lee, & Lee, 2022; Okanlawon et al., 2025; Park et al., 2020; Regona, Yigitcanlar, Hon, & Teo, 2024; Sajjadi, Dinmohammadi, & Shafiee, 2025).

In recent years, however, there has been a discernible shift in this paradigm. AI is emerging as a transformative force within the construction industry, offering new possibilities in design optimization, project scheduling, risk analysis, safety management, cost estimation, and facility maintenance (Ali, Burhan, Kassim, & Al-Khafaji, 2022; Bahroun, Tanash, Ad, & Alnajar, 2023; Okanlawon et al., 2025; Saad, Haris, Ammad, & Rasheed, 2024; Usama, Ullah, Muhammad, Islam, & saba Hashmi, 2024). These capabilities are increasingly being recognized not just as enhancements to existing workflows, but as enablers of entirely new business models and construction paradigms (Regona et al., 2022). For instance, predictive analytics can anticipate delays or cost overruns (Afzal, Yunfei, Nazir, & Bhatti, 2021; Khodabakhshian, Malsagov, & Re Cecconi, 2024; Lhee, Flood, & Issa, 2014; Tripathi & Mittal, 2024), computer vision can be used for progress and safety monitoring on-site (Hsieh, Chen, Chen, & Wu, 2024; Irizarry & Karan, 2012; Perera et al., 2025; Rabbi & Jeelani, 2024), and generative design algorithms can assist architects and engineers in producing more efficient and sustainable structures (Chew, Wong, Tang, Yip, & Maul, 2024). As such, the role of AI is no longer peripheral, and it is becoming central to the future trajectory of construction practice.

However, the successful integration of AI in construction hinges not only on technological development and investment but also on the human capital that will operate, manage, and innovate with these tools (Hewavitharana, Nanayakkara, Perera, & Perera, 2021). In particular, the readiness of the future construction workforce, students currently enrolled in construction-related disciplines, will be a critical determinant of how smoothly and effectively AI can be adopted in the coming decades (Vázquez-Parra, Henao-Rodríguez, Lis-Gutiérrez, & Palomino-Gámez, 2024). The workforce's preparedness will shape how rapidly the industry adapts to technological advancements and how effectively it leverages them for performance improvement and competitive advantage (ElZomor, Pradhananga, Santi, & Vassigh, 2020; Sakib, 2022) . Despite this growing importance, there remains a conspicuous gap in the academic and practical understanding of how future professionals in the construction sector perceive AI, and how willing and prepared they are to adopt these technologies in their careers (Na, Heo, Choi, Kim, & Whang, 2023). While several studies have examined technology acceptance among construction professionals, project managers, and contractors (Wu, Yan, Zhu, & Yang, 2004), only few have explored these issues from the perspective of students—those who will soon transition into these professional roles (Wen, Adhikari, & Latifinowsoud, 2024).

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a model developed to explain user intentions to adopt technology and subsequent usage behaviour (Venkatesh, Morris, Davis, & Davis, 2003). It integrates elements from eight previous technology acceptance models, focusing on four core constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. UTAUT2 extends the original model by incorporating three additional factors, hedonic motivation, price value, and habit, making it more suitable for consumer and individual contexts (Venkatesh, Thong, & Xu, 2012). This study seeks to address the gap by evaluating the readiness and intention of students in construction-related disciplines to adopt AI technologies in their future professional practice. Figure 1 illustrates the key factors influencing user acceptance and use of technology, including performance expectancy, effort expectancy, social influence, and facilitating conditions. It extends the original UTAUT by adding hedonic motivation, price value, and habit as new determinants.

Figure 1: UTAUT 2 framework (Chang et al., 2019)

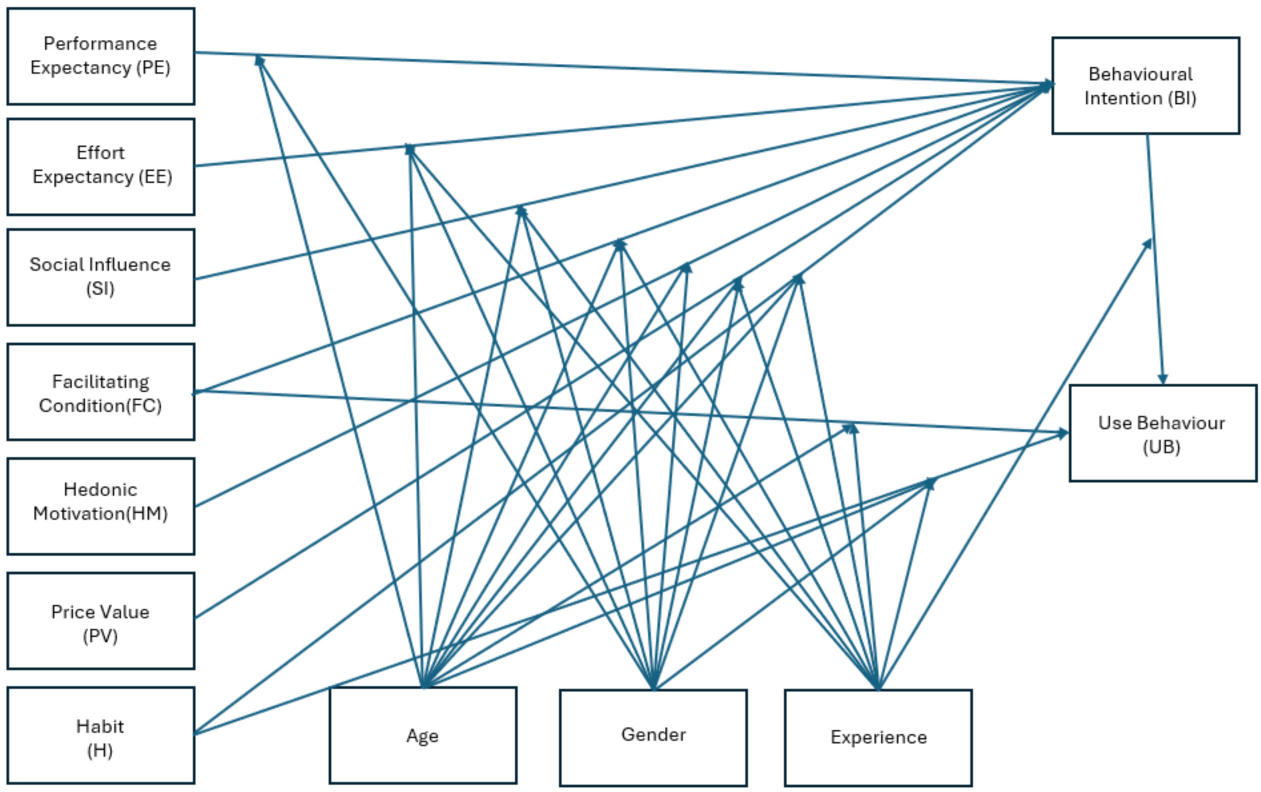

Table 1 outlines the key constructs of the UTAUT2 model along with their definitions. These include core factors, as well as extended variables. Together, these constructs form the theoretical basis for analysing users' behavioural intention and actual technology use.

Table 1: Summary of UTAUT 2 Constructs and Definitions (Venkatesh et al., 2012)

Construct	Definition
Performance Expectancy (PE)	The degree to which using a technology will provide benefits to consumers in performing certain activities.
Effort Expectancy (EE)	The degree of ease associated with consumers' use of technology.

Social Influence (SI)	The extent to which consumers perceive that important others believe they should use a particular technology.
Facilitating Conditions (FC)	Consumers' perceptions of the resources and support available to perform a behaviour.
Hedonic Motivation (HM)	The fun or pleasure derived from using a technology.
Price Value (PV)	Consumers' cognitive trade-off between the perceived benefits of the technology and the monetary cost.
Habit (H)	The extent to which people tend to perform behaviours automatically because of learning.
Behavioural Intention (BI)	The degree to which a person has formulated conscious plans to use or continue using the technology.
Use Behaviour (UB)	The actual usage of the technology by the consumer.

This study evaluates AI adoption and readiness among architecture and built environment students using UTAUT2. While existing literature on AI in the built environment primarily focuses on its application in professional practice, project optimization, or technological development, there is limited research addressing how future professionals, particularly students, are being prepared for this digital transformation. This study offers a novel contribution by evaluating AI adoption and readiness among architecture and built environment students, providing one of the first data-driven assessments of student perspectives, confidence, and institutional support regarding AI integration. This research directly aligns with the SASBE 2025's key theme of "Data Science, Artificial Intelligence... for Optimization of Built Environment," providing crucial insights into preparing future professionals. More broadly, the study supports additional SASBE 2025 themes, including people-centred design systems, smart and sustainable design, and sustainable urban development, by addressing the role of digital competency in shaping resilient, inclusive, and technologically advanced built environments.

The next section presents a detailed literature review on the application technology adoption studies. The methodology section follows, describing the research design, survey development, data collection process, and the analytical approach employed. Subsequently, the results section presents the key findings related to students' readiness, intention, and influencing factors for AI adoption. The discussion section then interprets these findings in light of existing literature, highlighting their implications for academia and industry. Finally, the paper concludes by summarizing the main contributions, discussing limitations, and suggesting directions for future research.

2. Literature Review

The construction industry is frequently described as conservative, fragmented, and slow to adopt emerging technologies (Oesterreich & Teuteberg, 2016; Olanrewaju, Chileshe, Babarinde, & Sandanayake, 2020). Unlike other sectors such as manufacturing, healthcare, and finance, where digital transformation has significantly reshaped business processes, the construction sector continues to rely heavily on manual labour, traditional project management techniques, and long-established practices (Oke, Aliu, Farhana, Jesudaju, & Lee, 2024; Shaheen, 2021).

Research on technology acceptance has been dominated by the Technology Acceptance Model (TAM), originally developed by Davis (Davis, 1989a). TAM posits that perceived usefulness and perceived ease of use directly influence users' Attitude and behavioural intention, which in turn affect actual use (Davies & Harty, 2013). Extensions such as TAM2 (Venkatesh & Davis, 2000) and TAM3 (Venkatesh & Bala, 2008), incorporate determinants like subjective norms, experience, output quality, and computer self-efficacy, enhancing its explanatory power. Building on these earlier models, UTAUT unified eight major theories, including TAM and TPB, into a comprehensive framework with four core constructs: Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, moderated by age, gender, experience, and voluntariness. UTAUT has been validated across diverse domains (e-government, m-learning, mobile banking, and found to explain up to ~70 % of the variance in Behavioural Intention and ~50 % in technology use (Yu, 2012; Zeebaree, Agoyi, & Aqel, 2022).

Despite the proven effectiveness of UTAUT, some critics note its employee-centric origins, limited direct effects, and potential contextual constraints (Shachak, Kuziemsky, & Petersen, 2019; Williams, Rana, Dwivedi, & Lal, 2011). A systematic review of over 650 UTAUT2 studies confirms its robustness and predictive improvements (74 % for intention, 52 % for use), though researchers often augment it with context-specific variables (Tamilmani, Rana, & Dwivedi, 2017). Table 2 provides a comparative summary of key technology acceptance models, including TAM, TAM2, TAM3, UTAUT, and UTAUT2. It highlights the core constructs, key extensions, strengths, and limitations of each model, offering a clear overview of their evolution and relevance to technology adoption research.

Table 2: Summary of Key Technology Adoption Models and Their Characteristics

Model	Core Constructs	Moderators / Extensions	Strengths	Limitations	References
TAM	PU, PEOU, Attitude, BI, Use	External variables (social influence, system quality)	Simple, widely validated	May overlook social/contextual factors	(Davis, 1989b)
TAM2 / TAM3	Adds social norms, experience, output quality, self-efficacy	Experience, result demonstrability, etc.	Better explanatory power	Increased complexity; still limited scope	(Venkatesh & Bala, 2008; Venkatesh & Davis, 2000)
UTAUT	PE, EE, SI, FC, BI, Use	Age, gender, experience, voluntariness	Integrative, strong predictors	May lack context-specific factors	(Venkatesh et al., 2003)
UTAUT2	PE, EE, SI, FC + Hedonic Motivation, Price Value, Habit, BI, Use	Removed voluntariness; retains other demographics	Tailored for consumers; robust	Complex; still expanded often	(Venkatesh et al., 2012)

The relevance of UTAUT 2 to the current study lies in its comprehensive consideration of both utilitarian and experiential factors that influence technology adoption. In the context of AI adoption among construction students, performance expectancy (the belief that AI will improve job performance) and effort expectancy (the perceived ease of use of AI technologies) are especially pertinent. Social influence (how peers, educators, and industry figures shape students' attitudes toward AI) is another critical factor in the construction education environment, where learning often occurs through collaborative, project-based activities.

Exposure to AI during formal education is a significant determinant of future adoption. Students who encounter AI tools and concepts as part of their academic programs are more likely to develop positive attitudes toward their use and to feel confident in applying them in professional settings (Bates, Cobo, Mariño, & Wheeler, 2020; Hinojo-Lucena, Aznar-Díaz, Cáceres-Reche, & Romero-Rodríguez, 2019). However, studies suggest that AI integration into construction curricula remains limited, often overshadowed by more established digital technologies such as BIM and CAD (Sawhney, Riley, Irizarry, & Riley, 2020).

3. Methodology

This study employed a quantitative research methodology to investigate the readiness and intention of construction students to adopt Artificial Intelligence (AI) technologies in their future professional practice. The UTAUT 2 model served as the theoretical framework for this research. The model has been extensively validated in technology adoption studies and includes key constructs such as performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioural intention. Each construct was carefully contextualized to the specific focus of AI adoption within the construction industry. A structured questionnaire was developed to collect quantitative data, with survey items adapted from validated UTAUT 2 measurement scales and modified to align with the construction and AI context. The questionnaire utilized a five-point Likert scale, where 1 indicated strong disagreement and 5 indicated strong agreement. The survey also included demographic information (age, gender, field of study, education level, and experience). The questionnaire comprised items that measured students' perceived usefulness of AI, anticipated ease of use, social and institutional support, personal enjoyment, and behavioural intentions toward AI adoption.

3.1. Participants and Data Collection

The data for this study were collected through an online survey administered via Google Forms, ensuring accessibility and ease of response. A QR code linking directly to the survey was generated and shared with the students during lectures and classes to encourage real-time participation. Additionally, the survey link was made available on the university's educational platform (Blackboard) to ensure broader accessibility and to allow students to complete it at their convenience. The survey was distributed to undergraduate and postgraduate students enrolled in construction-related programs, including civil engineering, architecture, building surveying, quantity surveying, and construction project management. A total of 43 responses were collected. Regarding the ethical considerations, participation in the study was voluntary, and respondents were assured of confidentiality and anonymity. The study adheres to ethical research standards, obtaining informed consent from all participants. Data is stored securely, and participants' identities are protected throughout the research process. Although the survey was spread comprehensively, not many participants filled out the survey.

3.2. Data Preparation and Cleaning

Following the data collection phase, the survey responses were subjected to a comprehensive data cleaning and preparation process to ensure the validity, reliability, and suitability of the dataset for subsequent statistical analysis. Initially, all responses were screened for completeness. Surveys that were less than 80% complete were excluded from the dataset, as they lacked sufficient information to provide meaningful input to the analysis. Responses in which straight-lining was obvious were also removed from the dataset. These were identified by a consistent selection of the same answer choice across all items within a section, suggesting a lack of attention or engagement. This step helped to maintain data quality and minimize potential biases that could arise from incomplete responses. Out of a total of 43 responses collected, 40 were selected for analysis.

3.3. Reliability Testing

Scale reliability was performed using Cronbach's alpha to verify the internal consistency of the multi-item constructs derived from the UTAUT 2 framework. This careful preparation ensured that the dataset was both clean and methodologically sound, providing a strong foundation for the subsequent statistical analyses and interpretation of the research findings. Table 3 shows the Cronbach's Alpha for different constructs and all constructs pass the 0.70 threshold.

Table 3: Cronbach's Alpha for UTAUT 2 Constructs

Construct	Cronbach's Alpha
Performance Expectancy	0.88
Effort Expectancy	0.83
Social Influence	0.87
Facilitating Conditions	0.84
Hedonic Motivation	0.88
Price Value	0.90
Habit	0.86
Behavioural Intention	0.92

4. Results

The analysis of the collected data offers valuable insights into the readiness and intention of construction students to adopt AI in their future professional practices. The data were carefully cleaned and prepared to ensure the integrity and completeness of the dataset. Normality was assessed through visual inspection of histograms. The distributions of most items were approximately normal, supporting the validity of subsequent parametric analyses.

4.1. Descriptive statistics analysis

descriptive statistics were computed for each survey item, including the mean, minimum, maximum, median, and standard deviation. The results provide insight into which aspects of AI adoption students perceive most positively and where potential gaps or challenges may exist. Table 4 presents the descriptive statistics of the extracted values through the questionnaire.

No of questions	Survey Questions	N	Mean	Std. Deviation	Min	Median	Max
1.	I believe that learning about AI tools will benefit me.	42	4.03	1.07	1	4	5
2.	AI will help me make faster, more accurate decisions.	42	3.86	1.09	1	4	5
3.	Understanding AI will enable me to contribute to ... the construction industry.	41	3.93	1.06	1	4	5
4.	AI tools can help solve common problems in construction projects.	42	3.9	1.08	1	4	5
5.	I believe that AI tools in construction will improve performance.	41	3.51	1.14	1	3	5
6.	I will be able to use AI technology in construction projects.	40	3.6	1.08	1	3	5
7.	The use of AI-based systems will require minimal training.	41	3.24	1.24	1	3	5
8.	Interacting with AI tools will be useful in my work.	41	3.63	1.09	1	4	5
9.	My peers believe that learning about AI is important.	41	3.88	0.9	2	4	5
10.	I am motivated to learn about AI because my peers support it.	42	3.6	1.01	1	3	5
11.	I often hear that AI knowledge is becoming essential in construction.	42	3.67	1.07	1	4	5
12.	The construction industry is increasingly interested in AI solutions.	42	3.64	1.06	1	4	5
13.	My university provides adequate resources for AI learning.	42	3.29	1.2	1	3	5
14.	There are sufficient online platforms and courses for AI in construction.	42	3.43	1.11	1	3	5
15.	My faculty offers adequate support for AI integration.	42	3.21	1	1	3	5
16.	AI tools are integrated into my course curriculum.	42	2.98	1.21	1	3	5
17.	I find learning about AI in construction to be exciting and engaging.	41	3.9	0.97	1	4	5
18.	I enjoy the challenge of using AI to solve construction problems.	42	3.71	1.07	1	4	5
19.	Exploring AI concepts and tools is a rewarding experience.	42	3.6	0.86	2	3	5
20.	The benefits of learning AI in construction outweigh the costs.	41	3.37	0.97	1	3	5
21.	Understanding AI will provide me with a competitive advantage.	42	3.71	1.09	1	4	5
22.	AI tools in construction will likely save time and costs.	42	3.74	0.99	2	4	5
23.	I am already using or exploring AI-based tools.	42	3.29	1.17	1	3	5
24.	It has become second nature for me to look for AI-based solutions.	41	3.46	1.1	1	4	5
25.	I believe I will frequently use AI-based solutions in the future.	42	3.62	1.1	1	4	5
26.	I intend to actively seek out AI-based solutions in my career.	41	3.61	1.05	1	4	5
27.	I am likely to adopt AI tools once I enter the construction industry.	42	3.71	0.86	1	4	5
28.	I believe knowing AI will make me a more competitive professional.	42	3.76	1.03	2	4	5

5. Discussion

Across the survey items, almost all the mean scores ranged from 3.00 to 4.00 on a five-point Likert scale, indicating a generally positive orientation toward AI integration in construction. The highest-rated item was “I believe that learning about AI tools will improve my future performance in construction projects” (PE) with a mean score of 4.03, indicating strong agreement. This was followed by “Understanding AI will enable me to contribute to innovative solutions in the construction industry” (PE) (M = 3.95). These high-scoring items reflect a clear recognition among students of the value and future importance of AI in enhancing performance and promoting innovation in the construction sector. Similarly, items addressing social influence and hedonic motivation, including perceptions of peer support and enjoyment derived from AI use, also demonstrated favourable responses, highlighting the influence of social and personal factors on students' readiness to engage with AI technologies. Conversely, the lowest-rated item was “AI tools are integrated into my course curriculum” (FC) with a mean of 2.98, suggesting that students perceive limited exposure to AI through formal education. Other low-scoring items include “My faculty offers adequate support in terms of AI integration” (FC) (M = 3.21) and “The use of AI-based systems will require minimal training” (EE) (M = 3.24). These results imply that while students are generally optimistic about the benefits of AI, they feel underprepared or under supported in terms of institutional readiness, training, and curriculum integration.

To evaluate the correlation between the UTAUT2 constructs and BI to adopt AI in construction, a Pearson correlation analysis was conducted. The results revealed consistently strong positive correlations between BI and all seven constructs, underscoring the multidimensional nature of technology acceptance. PE demonstrated the strongest linear relationship with behavioural intention (r = 0.87), suggesting that students who perceive AI as enhancing their academic performance are significantly more likely to adopt it. PV (r = 0.85), EE (r = 0.83), SI (r = 0.82), and H (r = 0.83) also exhibited robust correlations, indicating that perceptions of affordability, ease of use, peer dynamics, and established usage patterns are critical determinants of adoption intent. FC (r = 0.80) and HM (r = 0.81) were similarly influential, reflecting the role of institutional support and intrinsic enjoyment in driving adoption. These findings validate the theoretical assumptions of the UTAUT2 framework and reinforce its applicability in examining behavioural drivers of AI integration within construction contexts. Table 5 presents the Pearson correlation coefficients between key UTAUT2 constructs and behavioural intention to adopt AI in construction

Table 5: Pearson correlation coefficient between constructs and behavioural intention

Construct	Pearson’s *r* with BI
Performance Expectancy	0.87
Price Value	0.83
Effort Expectancy	0.82
Habit	0.80
Social Influence	0.81
Hedonic Motivation	0.85
Facilitating Condition	0.83

Potential limitations include self-selection bias, as individuals with strong opinions about AI may be more inclined to participate. Additionally, the reliance on self-reported data may introduce inaccuracies due to social desirability or recall bias. In addition, this survey was carried out with the built environment students in view, the

Overall, the results reveal that construction students are generally receptive to AI technologies and perceive them as beneficial for future professional performance. However, the relatively moderate levels of current AI use among built environment students suggest that greater emphasis on AI exposure and practical application within the academic curriculum may be necessary to fully prepare students for the technological demands of the construction industry. The positive influence of social factors, including peer encouragement and industry trends, points to the potential effectiveness of collaborative learning and industry-academia partnerships in promoting AI adoption. These findings provide critical insights for educational institutions and construction industry stakeholders aiming to support the next generation of construction professionals in embracing AI-driven innovations.

6. Conclusions

This study examined construction students' readiness and intention to adopt AI in their future careers using the UTAUT 2 model. While the construction industry is traditionally slow to adopt technology, students showed positive attitudes toward AI, especially valuing its potential to improve job performance and decision-making. Key factors influencing adoption intentions included performance expectancy and social influence. However, despite strong theoretical awareness, students had limited hands-on experience with AI tools, highlighting a need for more practical AI integration in construction education to break the stigma of slow adoption to technology. The findings of this study have significant practical implications for educators, academic institutions, and policymakers involved in shaping built environment curricula. By identifying current gaps in AI awareness, confidence, and training among architecture and construction students, the research provides insight for integrating AI into higher education programs. Enhancing digital readiness at the student level ensures that future professionals are better equipped to engage with emerging technologies. These insights can inform curriculum development, upskilling strategies, and institutional policies aimed at aligning education with the evolving demands of industry and sustainable urban development. This research directly contributes to SASBE 2025's core themes of artificial intelligence and data science, while also supporting broader goals related to people-centred design, smart construction, and sustainable urban development through the lens of education and digital readiness in the built environment. The study's survey was reliable, though limited by self-reported data and sample size. Future research should track AI adoption over time and explore educational interventions to better prepare students for AI-driven construction practices, ultimately supporting the industry's technological advancement.

Funding: This research received no funding.

Data Availability Statement: The authors cannot share the data with anyone because of the ethical considerations.

Conflicts of Interest: The authors declare no conflict of interest.

7. References

Afzal, F., Yunfei, S., Nazir, M., & Bhatti, S. M. (2021). A review of artificial intelligence based risk assessment methods for capturing complexity-risk interdependencies: Cost overrun in construction projects. *International journal of managing projects in business, 14*(2), 300–328.

Ali, Z. H., Burhan, A. M., Kassim, M., & Al-Khafaji, Z. (2022). Developing an integrative data intelligence model for construction cost estimation. *Complexity, 2022*(1), 4285328.

Alibakhshi, A., & Hassannayebi, E. (2025). Towards an enhanced next activity prediction using attention based neural networks. *Cluster Computing, 28*(1), 54.

Alibakhshi, A., Saffarian, A., & Hassannayebi, E. (2024). Socio-Economical Analysis of a Green Reverse Logistics Network under Uncertainty: A Case Study of Hospital Constructions. *Urban Science, 8*(4), 171.

Bahroun, Z., Tanash, M., Ad, R. A., & Alnajar, M. (2023). Artificial intelligence applications in project scheduling: A systematic review, bibliometric analysis, and prospects for future research. *Management Systems in Production Engineering*.

Bates, T., Cobo, C., Mariño, O., & Wheeler, S. (2020). Can artificial intelligence transform higher education? In (Vol. 17, pp. 1–12): Springer.

Cao, L. (2022). Ai in finance: challenges, techniques, and opportunities. *ACM Computing Surveys (CSUR), 55*(3), 1–38.

Chew, Z. X., Wong, J. Y., Tang, Y. H., Yip, C. C., & Maul, T. (2024). Generative design in the built environment. *Automation in construction, 166*, 105638.

Davies, R., & Harty, C. (2013). Measurement and exploration of individual beliefs about the consequences of building information modelling use. *Construction management and economics, 31*(11), 1110–1127.

Davis, F. D. (1989a). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS quarterly*, 319–340.

Davis, F. D. (1989b). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption, 205*(219), 5.

Elbashbishy, T., & El-Adaway, I. H. (2024). System dynamics modeling for investigating the retention of skilled labor in the construction market. In *Computing in Civil Engineering 2023* (pp. 564–572).

Elkhayat, Y., Adel, K., & Marzouk, M. (2024). Technology adoption in the construction industry (1999–2023): Science mapping and visualization. *Automation in construction, 165*, 105491.

ElZomor, M., Pradhananga, P., Santi, G., & Vassigh, S. (2020). *Preparing the future workforce of architecture, engineering, and construction for robotic automation processes.* Paper presented at the 2020 ASEE Virtual Annual Conference Content Access.

Hampson, K. D., Kraatz, J. A., & Sanchez, A. X. (2014). The global construction industry and R&D. In *R&D investment and impact in the global construction industry* (pp. 4–23): Routledge.

Hewavitharana, T., Nanayakkara, S., Perera, A., & Perera, P. (2021). *Modifying the unified theory of acceptance and use of technology (UTAUT) model for the digital transformation of the construction industry from the user perspective.* Paper presented at the Informatics.

Hinojo-Lucena, F.-J., Aznar-Díaz, I., Cáceres-Reche, M.-P., & Romero-Rodríguez, J.-M. (2019). Artificial intelligence in higher education: A bibliometric study on its impact in the scientific literature. *Education Sciences, 9*(1), 51.

Hsieh, C.-C., Chen, H.-M., Chen, W.-Y., & Wu, T.-Y. (2024). *Integration of Construction Progress Monitoring Results using AI Image Recognition from Multiple Cameras onto A BIM.* Paper presented at the ISARC. Proceedings of the International Symposium on Automation and Robotics in Construction.

Irizarry, J., & Karan, E. P. (2012). Optimizing location of tower cranes on construction sites through GIS and BIM integration. *Journal of Information Technology in Construction (ITcon), 17*(23), 351–366.

Khodabakhshian, A., Malsagov, U., & Re Cecconi, F. (2024). *Machine Learning Application in Construction Delay and Cost Overrun Risks Assessment.* Paper presented at the Future of Information and Communication Conference.

Kim, S. W., Kong, J. H., Lee, S. W., & Lee, S. (2022). Recent advances of artificial intelligence in manufacturing industrial sectors: A review. *International Journal of Precision Engineering and Manufacturing*, 1–19.

Lhee, S. C., Flood, I., & Issa, R. R. (2014). Development of a two-step neural network-based model to predict construction cost contingency. *Journal of Information Technology in Construction (ITcon), 19*(24), 399–411.

Na, S., Heo, S., Choi, W., Kim, C., & Whang, S. W. (2023). Artificial intelligence (AI)-Based technology adoption in the construction industry: a cross national perspective using the technology acceptance model. *Buildings, 13*(10), 2518.

Nnaji, C., Okpala, I., Awolusi, I., & Gambatese, J. (2023). A systematic review of technology acceptance models and theories in construction research. *Journal of Information Technology in Construction, 28*.

Oesterreich, T. D., & Teuteberg, F. (2016). Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. *Computers in industry, 83*, 121–139.

Ogunmakinde, O. E., Aghajani, M., & Memari, A. (2025). Identifying risks in sustainable procurement for construction: a systematic literature review and text-mining approach. *Smart and Sustainable Built Environment*, 1–27.

Okanlawon, T. T., Oyewobi, L. O., Dauda, J. A., Ogunjimi, O. S., Bello, A. O., & Jimoh, R. A. (2025). Modelling the effect of integrating augmented reality on construction lifecycle using partial least squares structural equation modelling (PLS-SEM). *Smart and Sustainable Built Environment*, 1–30.

Oke, A. E., Aliu, J., Farhana, M. Z., Jesudaju, O. T., & Lee, H.-P. (2024). A capability assessment model for implementing digital technologies in Nigerian heavy construction firms. *Smart and Sustainable Built Environment*.

Olanrewaju, O. I., Chileshe, N., Babarinde, S. A., & Sandanayake, M. (2020). Investigating the barriers to building information modeling (BIM) implementation within the Nigerian construction industry. *Engineering, Construction and Architectural Management, 27*(10), 2931–2958.

Park, C.-W., Seo, S. W., Kang, N., Ko, B., Choi, B. W., Park, C. M., . . . Lee, H. (2020). Artificial intelligence in health care: current applications and issues. *Journal of Korean medical science, 35*(42).

Perera, P., Perera, S., Jin, X., Rashidi, M., Nanayakkara, S., Yazbek, G., & Yazbek, A. (2025). An Innovative Software Development Methodology for Deep Learning-Driven Visual Computing in Built Environment Applications. *Journal of Information Technology in Construction (ITcon), 30*(41), 1017–1040.

Rabbi, A. B. K., & Jeelani, I. (2024). AI integration in construction safety: Current state, challenges, and future opportunities in text, vision, and audio based applications. *Automation in construction, 164*, 105443.

Regona, M., Yigitcanlar, T., Hon, C., & Teo, M. (2024). Artificial intelligence and sustainable development goals: Systematic literature review of the construction industry. *Sustainable Cities and Society*, 105499.

Regona, M., Yigitcanlar, T., Xia, B., & Li, R. Y. M. (2022). Opportunities and adoption challenges of AI in the construction industry: A PRISMA review. *Journal of open innovation: technology, market, and complexity, 8*(1), 45.

Saad, S., Haris, M., Ammad, S., & Rasheed, K. (2024). AI-assisted building design. In *AI in material science* (pp. 143–168): CRC Press.

Sajjadi, P., Dinmohammadi, F., & Shafiee, M. (2025). Machine Learning in Prognostics and System Health Management of Cyber-Physical Systems: A Review. *IEEE Access*.

Sakib, M. N. (2022). *The Future Workforce: Exploring the Role of Artificial Intelligence and Technology in Workforce Skilling*.

Sawhney, A., Riley, M., Irizarry, J., & Riley, M. (2020). Construction 4.0. *Sawhney, A., Riley, M., Irizarry, J., Eds*.

Shachak, A., Kuziemsky, C., & Petersen, C. (2019). Beyond TAM and UTAUT: Future directions for HIT implementation research. *Journal of biomedical informatics, 100*, 103315.

Shaheen, M. Y. (2021). Applications of Artificial Intelligence (AI) in healthcare: A review. *ScienceOpen Preprints*.

Tamilmani, K., Rana, N. P., & Dwivedi, Y. K. (2017). *A systematic review of citations of UTAUT2 article and its usage trends*. Paper presented at the Digital Nations–Smart Cities, Innovation, and Sustainability: 16th IFIP WG 6.11 Conference on e-Business, e-Services, and e-Society, I3E 2017, Delhi, India, November 21–23, 2017, Proceedings 16.

Tripathi, P., & Mittal, Y. K. (2024). Risk assessment and ranking methodology for occupational hazards in construction: a case of Indian high-rise projects. *Smart and Sustainable Built Environment*.

Usama, M., Ullah, U., Muhammad, Z., Islam, T., & saba Hashmi, S. (2024). AI-Enabled Risk Assessment and Safety Management in Construction. In *Ethical Artificial Intelligence in Power Electronics* (pp. 105–132): CRC Press.

Vázquez-Parra, J. C., Henao-Rodríguez, C., Lis-Gutiérrez, J. P., & Palomino-Gámez, S. (2024). Importance of university students' perception of adoption and training in artificial intelligence tools. *Societies, 14*(8), 141.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences, 39*(2), 273–315.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science, 46*(2), 186–204.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425–478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157–178.

Wen, J., Adhikari, S., & Latifinowsoud, M. (2024). Understanding Students' perceptions of Construction Technology Utilizing UTAUT Framework. *Proceedings of 60th Annual Associated Schools, 5*, 321–329.

Williams, M., Rana, N., Dwivedi, Y., & Lal, B. (2011). Is UTAUT really used or just cited for the sake of it? A systematic review of citations of UTAUT's originating article.

Wu, X., Yan, Y., Zhu, W., & Yang, N. (2004). An extended UTAUT model study on the adoption behavior of artificial intelligence technology in construction industry. *Journal of Intelligent & Fuzzy Systems*, JIFS–240798.

Yu, C.-S. (2012). Factors affecting individuals to adopt mobile banking: Empirical evidence from the UTAUT model. *Journal of electronic commerce research, 13*(2), 104.

Zeebaree, M., Agoyi, M., & Aqel, M. (2022). Sustainable adoption of E-government from the UTAUT perspective. *Sustainability, 14*(9), 5370.