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Digital Construction Adoption: Energy Conservation and Efficiency Readiness Model in Green Building Projects

Maranatha Wijayaningtyas[1*], Bayu Teguh Ujianto[1], Lies Kurniawati Wulandari[2], Lila Ayu Ratna Winanda[2], Mohd Syafiq Syazwan Mustafa[3]

[1] Architecture Department, Faculty of Civil Engineering and Planning, Institut Teknologi Nasional Malang, 65152 Malang, Indonesia
[2] Civil Engineering Department, Faculty of Civil Engineering and Planning, Institut Teknologi Nasional Malang, 65152 Malang, Indonesia
[3] Civil Engineering Technology Department, Faculty of Engineering Technology, University Tun Hussein Onn Malaysia (UTHM), 84600 Panchor, Malaysia

[*] Correspondence: Maranatha Wijayaningtyas (maranatha@lecturer.itn.ac.id)

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Abstract: This research examines the preparedness of individuals in Indonesia's green building sector to utilise digital construction technologies, including Internet of Things (IoT), building information modelling (BIM), and artificial intelligence (AI). The objective is to enhance energy conservation and efficiency. The research integrates Unified Theory of Acceptance and Use of Technology (UTAUT2) and Task-Technology Fit (TTF) to develop a model that assesses the readiness of green construction teams to implement digital tools to enhance energy performance. The Partial Least Squares Structural Equation Modelling (PLS-SEM) approach is employed to determine reliability, validity, and structural correlations. The final model accounts for 93.0% of the variance in behavioural intention (BI), 34.4% in use behaviour (UB), and 44.2% in performance expectancy (PE). BI is a robust predictor of actual usage (β = 0.586, $p < 0.001$). Social influence (SI) (β = 1.037, $p < 0.001$), perceived value (PV) (β = 1.300, $p < 0.001$), PE (β = 0.181, p = 0.0049), and habit (HB) (β = 0.283, p = 0.047) all positively affect BI. Conversely, facilitating situations exert a significant negative impact (β = -1.584, $p < 0.001$). When individuals excessively rely on organisational assistance, they diminish their intrinsic motivation. TTF is a significant predictor of PE (β = 0.665, $p < 0.001$); however, it does not directly influence BI. The integration of technology into tasks is primarily driven by individuals' perceptions of its performance advantages rather than by direct adoption. This study focuses on the unique requirements of green-construction processes, in which digital technologies contribute to reducing energy consumption, an approach notably different from prior UTAUT2 + TTF studies. The research presents a model illustrating how task alignment, performance perceptions, and the evaluation of costs against benefits influence individuals' readiness to adopt digital technology in green building project initiatives.

Keywords: Conservation; Digital construction project; Energy efference; Green building; Adoption model; Readiness

1 Introduction

Digitalisation has become an important driver of energy efficiency and resource optimisation in green building projects [1–3]. Technologies such as the Internet of Things (IoT), Building Information Modelling (BIM), and artificial intelligence (AI) enable real-time monitoring of energy consumption, automation of building systems, and improved operational performance in sustainable construction [4–7]. Previous studies indicate that these digital technologies can significantly enhance environmental performance and reduce energy waste through data-driven decision-making [8–10].

Despite these technological advances, the successful implementation of digital systems in construction projects remains strongly dependent on the readiness of the construction workforce [11–14]. The adoption of IoT-based monitoring systems, BIM-supported planning, and AI-driven analysis requires workers to understand digital processes and integrate them into daily construction activities. However, many construction organisations continue to face challenges related to limited digital literacy, resistance to technological change, and insufficient training. These challenges are particularly evident in developing countries, where the integration of digital construction technologies is still evolving.

In Indonesia, the government has introduced national initiatives, such as the ASTACITA programme, to strengthen workforce capacity to respond to the Industry 4.0 transformation [15]. Within the construction sector, this transformation includes the increasing integration of digital technologies in green building projects to improve energy conservation and environmental performance. Nevertheless, empirical evidence regarding the behavioural readiness of construction professionals to adopt these technologies remains limited.

Existing research on digital technology adoption frequently applies models such as the Unified Theory of Acceptance and Use of Technology (UTAUT2) and Task–Technology Fit (TTF). UTAUT2 focuses on behavioural, social, and psychological factors influencing technology adoption, while TTF emphasises the alignment between technological capabilities and task requirements [16, 17]. Although these models have been widely used in technology adoption studies, their application in sustainability-oriented construction projects remains relatively limited. In particular, few studies have examined how integrating digital technologies supports energy efficiency and resource conservation in green building projects [18, 19].

Furthermore, previous studies tend to emphasise the technical capabilities of digital technologies rather than the behavioural and cognitive responses of construction workers who interact with these systems. In practice, technology adoption is not determined solely by technical competence but also by how individuals perceive the usefulness, risks, and compatibility of digital tools within their work processes [20, 21].

To address these gaps, this study develops an integrated framework combining UTAUT2, TTF, and perceived risk (PR) to analyse the behavioural readiness of construction professionals in adopting digital technologies in green building projects [20, 21]. The model is applied to examine how task–technology alignment, perceived performance benefits, social influences (SI), and risk perceptions shape individuals' intentions and actual behaviour in using digital construction systems such as IoT, BIM, and AI [22].

By focusing on the human dimension of digital transformation in green construction, this study contributes to the literature in three ways [23, 24]. First, it extends digital technology adoption research by integrating sustainability considerations within the UTAUT2–TTF framework. Second, it provides empirical evidence on the behavioural readiness of the Indonesian construction workforce in adopting digital technologies for energy-efficient building projects. Third, the study offers practical insights for policymakers and construction managers in designing strategies that enhance workforce readiness for digital transformation in green construction.

2 Literature Review

Project building stakeholders are beginning to recognise how digital technologies such as IoT, BIM, and AI may significantly enhance resource efficiency and conserve energy in sustainable building initiatives. Upon reviewing the existing research, three prominent themes emerge: first, the influence of digital tools on green-building performance; second, a significant readiness gap among individuals to utilise these tools; and third, prior studies employing UTAUT2–TTF models inadequately address the dynamics of sustainability-oriented construction. This study explores these three domains.

2.1 Digitalisation and Internet of Things Adoption for Energy Efficiency in Green Buildings

To enhance resource management and energy efficiency, green buildings increasingly rely on digital technologies such as AI, BIM, and the IoT [25]. While BIM facilitates more effective design planning and optimisation, IoT enables real-time monitoring and control of energy consumption [19, 26]. AI is also used to analyse energy data to forecast consumption trends and optimise heating, ventilation, and air conditioning (HVAC) systems [27, 28].

Prior studies have demonstrated that several obstacles remain to the adoption of digital technology in the construction industry, particularly regarding the preparedness of human resources [29, 30]. According to a study by Batool et al. [31] although IoT technology has been shown to increase energy efficiency by up to 30%, workforce skill shortages and resistance to technological change often hinder its adoption. Thus, prior studies indicated that digital technologies, such as IoT, BIM, and AI, can significantly enhance energy monitoring, automate processes, optimise HVAC systems, and improve the operational efficiency of green buildings [26, 32, 33]. The utilisation of IoT facilitates real-time data acquisition, hence enhancing energy efficiency and streamlining processes. BIM facilitates more intelligent design and improved material utilisation. AI intervenes to forecast the future performance of buildings.

However, most studies focused on the capabilities of these instruments rather than on construction workers' preparedness to utilise them, particularly in developing nations. Green buildings have distinct digital difficulties, including energy modelling, tracking low-carbon materials, and continuous monitoring of environmental performance. Studies such as UTAUT2 and TTF have not yet extensively explored these domains [34, 35]. Then, by assessing the Indonesian construction workforce's preparedness to adopt digital technology and evaluating the extent to which the

ASTACITA program accelerates digital transformation in the green construction industry, this study advances the state of the art.

2.2 Human-Resource Readiness and Barriers to Digital Adoption in the Construction Industry

The construction industry needs to adopt digital technologies because projects are becoming increasingly complex, costs and timelines must be minimised, and worker safety and environmental sustainability are becoming more critical [36, 37]. Digital tools, such as BIM, the IoT, AI, and mobile project management apps, can help people work together more effectively, make decisions faster, and reduce the risk of delays and technical problems [24, 26].

However, since human resource (HR) is the primary user, the extent to which digital technology is utilised depends on their attitudes toward it and their level of readiness. Despite technological advancements, individuals continue to encounter similar obstacles in using new digital tools: insufficient digital literacy, resistance to change, inadequate training, and a lack of leadership support [38–40]. Moreover, complexity increases in green building initiatives. Workers must manage additional sustainability responsibilities, such as monitoring energy consumption or documenting waste, which need enhanced digital competencies and increased cognitive effort [41].

Most studies fail to examine how the added complexity of sustainable construction influences individuals' adoption of new technology [42–45]. They typically regard all building projects as equivalent, overlooking that green initiatives depend heavily on extensive, data-driven digital efforts. Consequently, ensuring individuals are adequately informed is of paramount importance. It is prudent to examine digital adoption explicitly within the realm of energy-efficient green construction, rather than conflating it with conventional construction practices.

2.3 Utilising Task-Technology Fit and Unified Theory of Acceptance and Use of Technology Theories to Assess Human Resources Perceptions and Preparedness for Digital Technology Adoption in Construction Projects

The TTF and UTAUT2 theories provide practical frameworks for understanding how people accept, evaluate, and utilise digital technology in construction projects. Venkatesh et al. [46] developed UTAUT2 as an enhancement to the original UTAUT model. This theory emphasises the behavioural, social, and psychological determinants that shape both intended and actual technology use. UTAUT2 was applied to determine how employees perceive the benefits, ease of use, peer pressure, and other factors that influence their willingness to use digital technology on construction projects. The most critical UTAUT2 variables within construction projects are:

1. Performance expectancy (PE) shows how much construction workers expect that using digital technology will help them do their jobs better. BIM, for instance, is thought to reduce rework by facilitating the identification of design issues. If HR believes that technology will increase productivity, they are more likely to adopt it.

2. Effort expectancy (EE) shows how many people think that using and understanding digital technology is easy. For instance, project management apps for mobile devices need a simple interface so field workers don't get overwhelmed. The rate at which people in different construction settings adopt it is directly related to its ease of use.

3. SI illustrates how coworkers, bosses, and other individuals with a stake in the decision can influence a person's decision to use technology. Construction project managers and upper management can accelerate the adoption of technology in construction projects by promoting its use and providing real-world examples.

4. Facilitating conditions (FC), which occur, refer to the support, training, and infrastructure that an organisation has in place to help people use technology. People won't be able to use cloud-based apps if the project site doesn't have a reliable internet connection, for example. Being ready also means seeking help from management, such as HR training programs.

5. Hedonic motivation (HM) is how much pleasure or satisfaction you get from using technology. Although this isn't a crucial aspect of building projects, apps with a nice, responsive interface design can enhance the experience and encourage people to get more involved.

6. Perceived value (PV) shows how HR weighs the pros and cons of using technology. HR will still consider BIM software worth the investment, despite the high licensing costs. This is because they believe it will reduce the cost of design errors.

7. Habit (HB) shows how often people use technology in their daily lives. HR will become accustomed to utilising digital systems on projects and will be prepared for emerging technologies.

With these factors in mind, UTAUT2 helps determine how HR perceives the benefits and drawbacks of using digital technology, the ease of use, the pressure to do so from others, and the level of support from the company.

Goodhue [47] developed the TTF theory, which focuses on how well technology aligns with the task at hand, whereas UTAUT2 emphasises social and psychological factors. For digital technologies to be effective on construction projects, they must meet the project's technical and managerial requirements. The following are some of the most critical TTF variables within construction projects:

1. The task's features talk about how hard, dependent, and unpredictable it is. For example, architects, contractors, and consultants need to collaborate by combining complex design and scheduling data. If technology can handle

these task characteristics, it will be easier for people to use.

2. Technology's features show what it can do, how dependable it is, and how easy it is to access. For instance, BIM technology provides high-quality 3D views for identifying issues during the design phase, and mobile apps enable real-time field reporting.

3. How well the technology fits the task. This is a measure of how well the technology performs its intended task. People find technological features useful and are more likely to use them when they directly help with work tasks.

The TTF model emphasises the importance of objective HR readiness, which is the technology's ability to meet operational needs in the field. Combining UTAUT2 and TTF in the context of building, a comprehensive understanding of how people perceive and prepare for building projects is achieved. UTAUT2 examines personal factors in HR management, including individuals' goals, beliefs, and reasons for using technology. The TTF examines objective elements to determine whether technology is suitable for specific tasks on a construction project. When the two are combined, the mapping becomes more accurate: if the technology fails to meet the task requirements (TTF), people won't use it, even if they like it (UTAUT2). On the other hand, TTF technology may be ineffective if users are reluctant to use it because they perceive it negatively (UTAUT2).

Researchers have employed UTAUT2 and TTF to examine a range of digital tools, including e-government systems, IoT devices, online education, and conventional construction projects [25, 34, 48]. However, upon further examination of the evidence, three significant holes become evident:

(1) It scarcely addresses sustainability-oriented construction practices

Much of the UTAUT2–TTF research broadly addresses digital adoption, such as the use of IoT devices or BIM software, without examining the alignment of task–technology fit with energy-efficiency initiatives. This is a significant oversight, as these positions are essential to green building initiatives. Previous TTF research focused on overall performance across general tasks but neglected finer details: Do the instruments support energy management, environmental monitoring, or tracking of sustainable materials? These are the genuine catalysts for sustainable construction, yet they remain largely unaddressed in discourse.

(2) It disregards the actual behaviour of construction workers

UTAUT2 often emphasises PE, EE, SI, and FCs as primary determinants of individuals' decisions to adopt new technology. However, few individuals examine the on-site dynamics, such as organisational culture, employee weariness, entrenched practices, or rigid hierarchies, that influence the genuine adoption of these techniques, particularly in environmentally sustainable initiatives. Much more is occurring than the models acknowledge.

(3) Perceived danger is overly simplified in the context of construction digitisation

Most research on the risk aspect focuses on privacy and data security. However, if they enquire with workers on a green building site, their primary fear is markedly different: Will this technology jeopardise my employment? Will it increase the workload? Will I be held accountable if an issue arises? The standard models fail to adequately address the problem.

A model that effectively integrates UTAUT2, TTF, and PR, tailored to the context of energy efficiency and conservation efforts, is currently lacking.

Therefore, this study presents three key contributions. Initially, it integrates digital-adoption models into sustainable construction, illustrating how digital tools are directly linked to energy efficiency and improved environmental performance. Secondly, it directly integrates the TTF framework with sustainability initiatives, such as energy monitoring and waste reduction, rather than focusing solely on conventional productivity measures. Third, it examines the reasons behind workers' preparedness for these technologies, considering how daily routines, organisational hierarchies, and sustainability requirements influence their intentions and actual behaviours. This study integrates themes of digital technology adoption in construction with project management, emphasising sustainability. This study integrates HR competency techniques with IoT technology in Green Construction Management, emphasising HR readiness and methods for improving construction workforce skills as crucial components of digitalisation, in contrast to previous research that focused on IoT's technical benefits for energy efficiency.

Indonesia's construction industry requires a unique HR technology deployment strategy, which this research will build. This model uses PR, TTF, and UTAUT2. This study provides data-based recommendations to the government and key industries to improve green building human resources. Using the ASTACITA program, this study will evaluate the policy's effectiveness in promoting the use of digital technologies in Green Building projects. This study encourages resource conservation and energy efficiency in Green Building projects while assessing workforce preparedness for adopting IoT.

2.4 Conceptual Model and Hypotheses

The conceptual model is shown in Figure 1. The integrated UTAUT2 + TTF conceptual framework for the adoption of digital technology in Green Building construction projects encompasses the subsequent narrative and rationale for each hypothesis:

H1: TTF $\rightarrow$ PE (positive)

When TTF is high, as when BIM/IoT significantly enhances clash detection, material tracking, or safety monitoring, users rate PE higher. This is because the features, reliability, and access of technology seem to “fit” with field and managerial work. Recent research integrating TTF into UTAUT2 indicates that TTF enhances perceived utility and amplifies the influence of benefits on usage intentions [16].

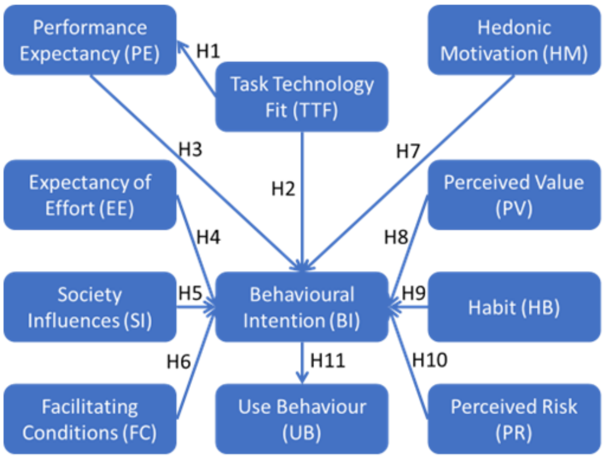

Figure 1. The conceptual model

H2: TTF → behavioural intention (BI) (positive)

When technology aligns with the task, cognitive and operational barriers are reduced, and utility is immediately recognised, thereby increasing BI. Recent PLS-SEM data indicate that TTF has a significant impact on BI across various digital learning and work environments. Some studies report a stronger association between TTF and BI (mixed results consistent with H2) [17, 25]. Still, integrative research using TTF + UTAUT2 also shows that adoption intentions are better explained than in separate models.

H3: PE → BI (positive)

The stronger someone believes that technology makes things faster, more accurate, or more productive, the more they plan to use it. Recent meta-analyses and BIM reviews indicate that PE is a significant factor in determining whether people in the construction industry will adopt new technologies [17, 34]. Research on AI adoption in construction design supports this.

H4: EE to BI (positive)

Field workers are more likely to adopt technology when they are under time pressure, know how to use it, have clear training, and have a simple user interface. Recent data indicate that EE enhances BI for several digital services [17, 46]. Task/individual fit is another way that EE is increased in the UTAUT2 extension with TTF.

H5: SI → BI (positive)

SI (such as supervisors, foremen, consultants, and project owners) can lead to the formation of injunctive or descriptive norms to “follow suit,” especially when adoption is built into project SOPs. In the AEC/IoT context, SI continues to raise BI. A recent BIM review backs up SI’s role as a key driver [25].

H6: FC → BI (positive)

FCs, such as the site network, devices, help desk, and organisational policies, reduce the likelihood that people will fail to adopt something. Evidence from digital services suggests that FC is important and can be influenced by PR; in the context of innovative construction, FC plays a significant role in the adoption of IoT [34].

H7: HM → BI (positive)

HM strengthens its intention by encouraging exploration and engagement through enjoyable and engaging user experiences. In an IoT model for construction that combined UTAUT2 and TTF, HM was a primary driver of adoption [34, 48].

H8: PV→ BI (positive)

If employees or managers value benefits (such as reducing rework costs, improving time efficiency, and enhancing safety) more than costs (such as training and licensing), BI increases. Recent BIM meta-analyses and reviews have identified PV and PV as significant predictors of BI; cross-domain research further indicates that PV positively affects intention [17, 48].

H9: HB → BI (positive)

HB speeds up the change from “intentional” to “automatic” use. If employees regularly use mobile/BIM viewer reports, they are more likely to stick with their plan. Recent research that utilises UTAUT2 to examine digital and sustainable technologies has found that HB are strong predictors of intention and behaviour [34, 48].

H10: PR → BI (positive)

Numerous UTAUT2 studies examining PR show that higher PR generally reduces BI (a harmful effect). If the construct is defined as a decrease in PR (e.g., "I feel safe/protected") or as confidence in the organisation's risk management, the positive correlation in hypothesis H10 can be explained: a higher PR score indicates a more manageable risk, thereby enhancing BI. Recent data underscores the significant influence of risk and trust on intention; in specific contexts, risk can even diminish the effects of PE, SI, and FC [48].

H11: BI → use behaviour (UB) (positive)

BI is the closest thing to UB; when people intend to use something and think they are getting enough support from the organisation, they actually use it, such as regularly uploading progress photos, conducting clash checks, or filling out app-based OHS checklists. Recent UTAUT2 studies and AI/BIM evidence substantiate a robust relationship between BI and UB [46].

3 Research Method

The research method is broadly described as follows:

• This research is a quantitative study to analyse HR readiness in adopting IoT and digitalisation in Green Building and Green Construction Management projects.

• A quantitative approach is used to measure the level of workforce readiness through surveys and statistical analysis. The data used are primary.

• Primary data collection, with quantitative respondent selection using a purposive sampling method, to explore construction project stakeholders' perceptions of the determinants of the UTAUT2, TTF, and PR models.

• A survey method was used by distributing questionnaires to 200 Green Building construction project stakeholders in Indonesia.

• The method of analysing the relationship and influence of internal factor determinants and the modified model (UTAUT2, TTF, and PR) on conservation and efficiency intentions and behaviours in Green Building projects was used using the SEM-PLS method with the initial measurement model as presented in Figure 2.

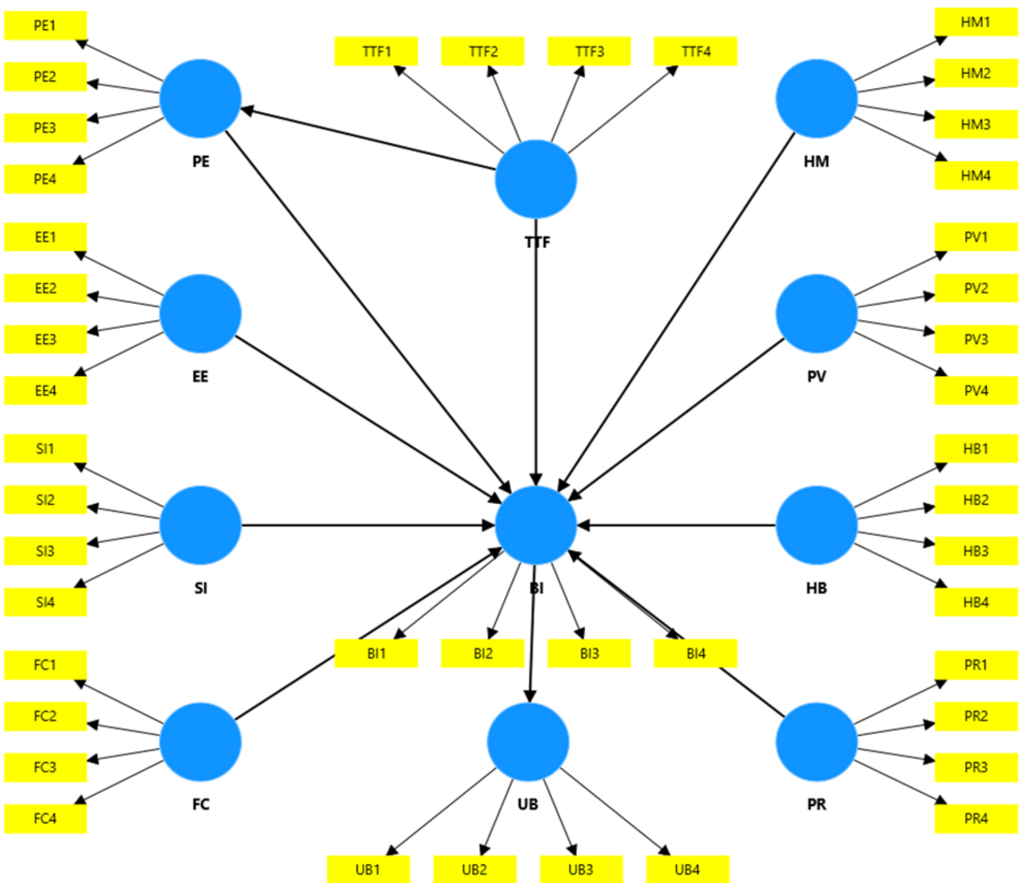

Figure 2. The initial measurement model

Note: PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

A "Likert Scale" is used to measure the variables related to the model. This scale measures an individual's or group's views, opinions, and beliefs regarding social phenomena. The researcher identified the social phenomena in this study as research variables. Indicator variables are the variables that will be measured. The components of the instrument are then assembled into statements or questions, using these indicators as benchmarks. Responses were scored for quantitative analysis as follows: 5 points were awarded for strongly agreeing, 4 points for agreeing, 3 points for affirmative, 2 points for disagreeing, and 1 point for strongly disagreeing.

A pilot study was conducted to assess the validity and reliability of the research tools used. This was done to enable the researchers to use the instruments. Thirty respondents who had worked on a Green Building construction project participated in the pilot study's validity and reliability testing. As indicated in Table 1, the Corrected Item-Total Correlation is used to test the validity of this research tool. The Cronbach's Alpha values can be used to evaluate the test's reliability.

Table 1. Reliability (Cronbach's Alpha) test

Variables	Indicators	Cronbach's Alpha
PE	PE1, PE2, PE3, PE4	0.970
EE	EE1, EE2, EE3, EE4	0.951
SI	SI1, SI2, SI3, SI4	0.952
FC	FC1, FC2, FC3, FC4	0.961
HM	HM1, HM2, HM3, HM4	0.954
PV	PV1, PV2, PV3, PV4	0.972
HB	HB1, HB2, HB3, HB4	0.893
TTF	TTF1, TTF2, TTF3, TTF4	0.989
PR	PR1, PR2, PR3, PR4	0.920
BI	BI1, BI2, BI3, BI4	0.980
UB	UB1, UB2, UB3, UB4	0.957

Note: PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

All constructs had Cronbach's Alpha > 0.89, indicating high internal consistency (the minimum requirement of 0.7 was met). According to the validity test results, the corrected item-total correlation for each indicator exceeded 0.3. This shows that each question item consistently and validly measures the intended construct. Consequently, primary research on the application of digital technology in construction projects can benefit from this research tool.

Before commencing data analysis, a rigorous data-cleaning procedure was implemented to ensure the integrity and reliability of the dataset. Two hundred questionnaires were distributed, and all were returned. The responses were subsequently screened to evaluate completeness and quality. The screening process involved checking for missing values, detecting straight-lining patterns (i.e., respondents selecting the same option throughout), identifying excessively short completion times that may indicate inattentive responding, and assessing inconsistencies in answers to reversed or conceptually similar items. After applying these criteria, 200 valid and usable responses remained, each meeting the minimum standards required for structural equation modelling.

To address potential common method bias (CMB), both procedural and statistical safeguards were incorporated into the research design. Procedurally, the anonymity of responses was ensured; participants were informed that there were no right or wrong answers, and questionnaire items were arranged across different constructs to minimise pattern recognition.

Statistically, two diagnostic tests were conducted. Harman's single-factor test showed that the most significant extracted factor accounted for less than 40% of the total variance, remaining well below the commonly accepted threshold. In addition, full collinearity variance inflation factors (VIFs) were examined, and all constructs exhibited VIFs below 3.3 [49, 50]. These results collectively indicate that CMB is unlikely to threaten the validity of the findings.

PLS-SEM was employed for data analysis given the complexity of our study model, which comprises multiple latent constructs (e.g., UTAUT2, TTF, and PR), each with distinct indicators. The configuration for forecasting individuals' readiness to adopt digital technologies is complex. PLS-SEM is particularly suitable when the emphasis is on prediction, which aligns with our objectives. Furthermore, our data did not follow a normal distribution, which is common in behavioural investigations, and our initial assessments corroborated this finding. This research does not merely evaluate an existing theory; instead, it enhances UTAUT2 by modifying and augmenting it. PLS-SEM effectively accommodates that versatility. It effectively addresses multicollinearity and outperforms CB-SEM in small to medium-sized samples. This is significant for us. According to Sarstedt et al. [50], PLS-SEM is an appropriate instrument for examining mediation effects, delineating intricate pathways, and assessing the proportion of variance explained (R^2 and Q^2). It is logically coherent with our objectives.

4 Results Analysis

4.1 Respondents Profile

Two hundred participants were recruited for this study, representing a diverse cohort of individuals engaged in green building and digital construction initiatives across Indonesia, as presented in Table 2. An examination of their backgrounds reveals that they are predominantly involved in digital technologies within the sector, including IoT, BIM, and AI. The majority of respondents were aged 31–40, with approximately 100 individuals. The predominant group comprises mid-career professionals, typically those in supervisory or managerial roles on construction sites. Subsequently, 40 individuals from both the 41–50 and 51–60 age brackets contribute significant experience and a profound comprehension of project management. Among the younger demographic, 20 individuals were aged 20–30, indicating the presence of emerging talent that is likely more receptive to experimenting with new technology.

Table 2. Respondents profile

Category	Description	Total
Age	20–30 Years	20
	31–40 Years	100
	41–50 Years	40
	51–60 Years	40
Education	Diploma	30
	Bachelor	115
	Master	55
Experience working on projects	<6 Years	20
	6–10 Years	40
	11–15 Years	60
	>15 Years	80
Position	Contractor/Owner	28
	Project Management staff	30
	Project Manager	33
	Project Supervisor	23
	Project Management Office (PMO)	24
	Senior Mechanical Engineer	20
	Site Manager	25
	Team Leader	20
Project type	Commercial Building	85
	Housing Development	70
	Public/Government	45

Most individuals possessed strong educational qualifications. Among the individuals, 115 held a Bachelor's degree, 55 a Master's degree, and 30 a Diploma. The group comprises hands-on operators, highly trained professionals, and management. The majority (80 individuals) have fewer than 6 years of experience in their roles. This signifies that numerous new professionals are now engaging in environmental initiatives. Forty individuals have 6–10 years of experience, whilst sixty have 11–15 years of experience in the field. The remaining 20 individuals, with over 15 years of expertise, constituted the most experienced group. These warriors have experienced the transition to digital tools firsthand. Individuals occupied various positions. There were 33 Project Managers, 30 from the Project Management staff, 28 representing contractors or owners, and 25 Site Managers—numerous decision-makers and coordinators. The team comprised 23 Project Supervisors, 24 Project Management Office (PMO) personnel, 20 Senior Mechanical Engineers, and 20 Team Leaders, all of whom are actively engaged with digital systems for design, reporting, and quality assurance.

Their efforts encompassed three primary categories: There were 85 commercial structures, 70 housing complexes, and 45 public or government projects. These digital solutions for energy conservation and efficiency are not confined to a single sector; they are implemented across a range of building types. This group is not biased toward any particular experience level or level of expertise. The group comprises leaders, mid-level employees, and newcomers, each with distinct educational backgrounds and responsibilities. This diversity indicates that the study assesses the readiness of various teams for digital transformation. It offers a clearer understanding of how professionals in the sector engage with emerging technologies in sustainable construction.

4.2 Outer Model

Based on the results of the outer loadings test, all indicators exceeded the 0.7 threshold, thereby meeting the requirements for convergent validity. The Cronbach's Alpha and Ccomposite reliability (CR) values for all constructs were above 0.70, indicating good internal reliability (see Table 1). Furthermore, the average variance extracted (AVE) values were greater than 0.50 for all constructs, concluding that each construct explained more than 50% of the variance in its indicators, as presented in Table 3.

Table 3. Validity (corrected item-total correlation) test

Variables	Indicators	Corrected Item-Total Correlation
PE	PE1	0.949
	PE2	0.920
	PE3	0.921
	PE4	0.904
EE	EE1	0.834
	EE2	0.906
	EE3	0.882
	EE4	0.905
SI	SI1	0.909
	SI2	0.954
	SI3	0.895
	SI4	0.784
FC	FC1	0.876
	FC2	0.953
	FC3	0.828
	FC4	0.976
HM	HM1	0.830
	HM2	0.841
	HM3	0.940
	HM4	0.946
PV	PV1	0.874
	PV2	0.957
	PV3	0.933
	PV4	0.967
HB	HB1	0.854
	HB2	0.512
	HB3	0.876
	HB4	0.905
TTF	TTF1	0.980
	TTF2	0.952
	TTF3	0.977
	TTF4	0.980
PR	PR1	0.642
	PR2	0.903
	PR3	0.877
	PR4	0.878
BI	BI1	0.945
	BI2	0.958
	BI3	0.963
	BI4	0.929
UB	UB1	0.852
	UB2	0.827
	UB3	0.953
	UB4	0.953

Note: PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

The results of the discriminant validity tests (Fornell-Larcker and Cross-Loading) indicated that the correlations between each construct and its indicators were higher than those between each construct and the other constructs. Therefore, there was no multicollinearity among the constructs, and each could be clearly distinguished.

All standardised loadings on their intended constructs are high (e.g., BI1–BI4: 0.869–0.930; PV1–PV4: 0.932–0.966; TTF1–TTF4: 0.856–0.929; UB1–UB4: 0.783–0.882), supporting indicator reliability. Cronbach's α ranges from 0.660 (PE) to 0.964 (PV); CR ranges from 0.853 to 0.969; AVE $\geq$ 0.715 for all constructs, supporting convergent validity. ($\alpha \approx 0.66$ for PE is tolerable in exploratory work when CR and AVE are strong).

Table 4. Outer loadings

Path	First Run	Second Run
BI1 ← BI	0.881	0.878
BI2 ← BI	0.927	0.930
BI3 ← BI	0.924	0.927
BI4 ← BI	0.872	0.869
EE1 ← EE	0.964	0.990
EE2 ← EE	0.805	0.900
EE3 ← EE	0.305	–
EE4 ← EE	0.379	–
FC1← FC	0.873	0.858
FC2 ← FC	0.930	0.937
FC3 ← FC	0.776	0.801
FC4 ← FC	0.392	–
HB1 ← HB	0.837	0.849
HB2 ← HB	0.441	–
HB3 ← HB	0.919	0.948
HB4 ← HB	0.908	0.899
HM1 ← HM	0.692	–
HM2 ← HM	0.653	–
HM3 ← HM	0.832	0.956
HM4 ← HM	0.783	0.873
PE1 ← PE	0.873	0.896
PE2 ← PE	0.780	0.828
PE3 ← PE	0.652	–
PE4 ← PE	0.400	–
PR1 ← PR	0.383	–
PR2 ← PR	0.984	0.990
PR3 ← PR	0.939	0.956
PR4 ← PR	0.792	0.822
PV1 ← PV	0.933	0.932
PV2 ← PV	0.931	0.932
PV3 ← PV	0.936	0.937
PV4 ← PV	0.965	0.966
SI1 ← SI	0.846	0.846
SI2 ← SI	0.969	0.962
SI3 ← SI	0.887	0.914
SI4 ←SI	0.677	–
TTF1←TTF	0.918	0.919
TTF2 ← TTF	0.857	0.856
TTF3 ← TTF	0.929	0.929
TTF4 ←TTF	0.918	0.919
UB1 ← UB	0.729	0.783
UB2← UB	0.528	–
UB3 ← UB	0.838	0.882
UB4 ← UB	0.840	0.869

Note: PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

In PLS-SEM, outer loadings are used to measure constructs (latent variables). These latent variables are constructs that cannot be observed directly but are measured through multiple indicators or items. The outer loading value indicates how well an item represents its construct. A high loading value (>0.7) indicates that the item is strongly correlated with the latent variable and is a valid measure [41]. A low loading value (below a predetermined threshold) indicates that the item does not correlate strongly with its construct and should be considered for removal or revision.

During the initial measurement run, several indicators—EE3, EE4, HB2, HM1, HM2, PE3, PE4, PR1, SI4, and UB2—did not meet the suggested 0.70 threshold for outer loadings (refer to Table 4 in the first run column). Indicators with low loadings contribute little to the explanation of their constructs and may introduce extraneous variability. Subsequently, these items were eliminated to enhance reliability and validity and to improve the quality and accuracy of the research results [41]. The elimination of weak items statistically enhanced CR, AVE, and indicator reliability, as demonstrated in Table 5. Following the cleanup, the AVE for each construct exceeded 0.50, indicating robust convergent validity. Discriminant validity was also enhanced by both the Fornell–Larcker criteria and cross-loadings, resulting in each construct being more distinctly differentiated from the others.

Table 5. Composite reliability (CR) and average variance extracted (AVE) second run results

Variables	CR (rho_a)	CR (rho_c)	AVE
BI	0.926	0.945	0.812
EE	1.885	0.944	0.895
FC	0.912	0.901	0.752
HB	0.892	0.927	0.809
HM	0.970	0.911	0.838
PE	0.684	0.853	0.744
PR	1.069	0.947	0.857
PV	0.790	0.969	0.887
SI	0.902	0.934	0.825
TTF	0.930	0.948	0.821
UB	0.827	0.883	0.715

Note: PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

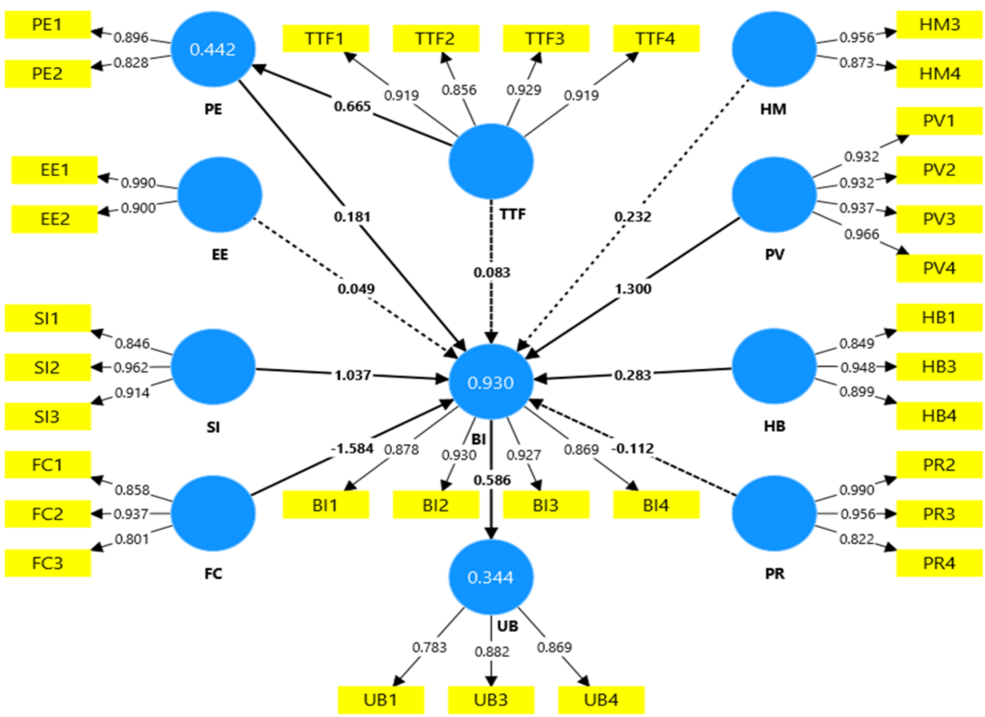

Figure 3. The second run/final structural model

Note: PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

After removal, the PLS-SEM analysis was repeated to determine whether there was an improvement in the outer loadings of the other indicators, CR, and AVE, as shown in Table 4 (second run outer loadings) and Table 5. Thus, the structural model was changed as presented in Figure 3.

4.3 Structural Model

The R^2 values for the endogenous variables indicate the model's predictive power for the central construct (e.g., BI/UB), which was in the moderate-to-substantial range (>0.50) [50, 51], as presented in Table 6. This suggests that the model can account for a significant portion of the variation in the dependent variable. The results of the blindfolding Q^2 test were all positive (greater than 0), indicating that the model is predictive. In other words, the model not only explains the sample data but also predicts new observations, as shown in Table 7.

Table 6. The R^2 value

Variables	R^2	R^2 Adjusted
BI	0.930	0.927
PE	0.442	0.439
UB	0.344	0.341

Note: PE, performance expectancy; BI, behavioural intention; UB, use behaviour.

Table 7. The blindfolding Q^2 test results

Variables	SSO	SSE	$Q^2 (= 1 - SSE/SSO)$
BI	800.000	264.305	0.670
EE	400.000	189.349	0.527
FC	600.000	304.653	0.492
HB	600.000	247.106	0.588
HM	400.000	224.358	0.439
PE	400.000	303.691	0.241
PR	600.000	217.193	0.638
PV	800.000	205.149	0.744
SI	600.000	230.157	0.616
TTF	800.000	255.825	0.680
UB	600.000	358.217	0.403

Note: SSE, sum of squared errors; SSO, sum of squared observations; PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

4.4 Significance Test of Relationships Between Constructs (Bootstrapping)

The bootstrapping test results indicate that most path coefficients are significant, with t-statistics $>$ 1.96 (α = 0.05) and p-values $<$ 0.05, as shown in Table 8. The relationships between the primary constructs (e.g., PV $\rightarrow$ BI, SI $\rightarrow$ BI, and BI $\rightarrow$ UB) are all significant. There are several insignificant paths (if any), indicating that these variables do not play a direct role but may function as mediators or moderators. The path coefficients ranged from 0.20 to 0.60, indicating a positive influence of low to moderate strength. The path with the highest coefficient can be interpreted as the dominant factor influencing respondents' behaviour.

Table 8. The hypotheses testing results

Hypotheses	Path	Path Coefficients	p-Values	Results
H1	TTF $\rightarrow$ PE	0.665	0.000	Significant
H2	TTF $\rightarrow$ BI	0.083	0.787	Not Significant
H3	PE $\rightarrow$ BI	0.181	0.005	Significant
H4	EE $\rightarrow$ BI	0.049	0.804	Not Significant
H5	SI $\rightarrow$ BI	1.037	0.000	Significant
H6	FC $\rightarrow$ BI	-1.584	0.000	Significant but negative
H7	HM $\rightarrow$ BI	0.232	0.186	Not Significant
H8	PV $\rightarrow$ BI	1.300	0.000	Significant
H9	HB $\rightarrow$ BI	0.283	0.047	Significant
H10	PR $\rightarrow$ BI	-0.112	0.202	Not Significant
H11	BI $\rightarrow$ UB	0.586	0.000	Significant

Note: PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

5 Discussion

The results demonstrate that TTF has a significant positive effect on PE. This finding indicates that when digital technologies are perceived as compatible with the operational tasks of construction projects, users are more likely to recognise their performance benefits. In the context of green construction, digital tools such as BIM-based clash detection or IoT-based energy monitoring are considered useful when they directly support project coordination and environmental performance management [52]. This result is consistent with previous studies that emphasise the importance of task–technology alignment in enhancing perceived usefulness and technology acceptance in construction projects.

TTF was not found to be related to BI based on the results. This suggests that whereas the perceived usefulness is essential in persuading users to use a system that would enable them to do the job (more) effectively, the system must also be judged to be useful enough for the particular task for which it is intended for them to plan to use it [52]. A similar observation was reported by Dash et al. [53], who found that TTF had a greater impact on intention via PE. During the project in Surabaya, an energy monitoring application was installed; however, usage rates were very low because users did not see any utility in it.

However, TTF was not found to have a direct effect on BI. This suggests that technological compatibility alone is insufficient to stimulate adoption intentions unless users clearly perceive performance benefits. In other words, the influence of TTF appears to operate indirectly through PE. Similar findings have been reported in recent studies integrating TTF and UTAUT2, which indicate that perceived usefulness often mediates the relationship between technological suitability and BI. In green construction projects, workers may recognise that a system fits their tasks, but adoption intentions emerge only when tangible improvements in productivity or efficiency become evident.

PE significantly influences BI, indicating that perceived performance benefits remain a central driver of technology adoption. When construction professionals believe that digital tools can improve productivity, reduce rework, or enhance project coordination, they are more likely to adopt these technologies. This finding aligns with the broader technology acceptance literature, which consistently identifies perceived usefulness as one of the strongest predictors of BI [25]. In the context of green building projects, technologies such as BIM and IoT improve resource management and energy monitoring, thereby strengthening perceptions of their practical value.

In contrast, EE did not significantly influence BI. This finding suggests that ease of use is no longer a primary determinant of digital technology adoption among construction professionals. As digital applications become increasingly integrated into construction workflows, workers may already possess sufficient familiarity with basic digital tools [52]. Consequently, usability concerns become less relevant compared to performance-related benefits. This observation is consistent with recent studies indicating that the role of EE tends to diminish as users gain experience with digital systems.

A particularly notable result is the negative relationship between FC and BI. Contrary to the original UTAUT2 framework's assumptions, stronger organisational support appears to reduce individuals' willingness to adopt digital tools. One possible explanation is that highly formalised support systems may be perceived as bureaucratic or restrictive in dynamic project environments such as construction sites. Excessive procedural control or monitoring may create a perception of additional administrative burden rather than practical assistance. Similar patterns have been observed in project-based industries where rigid organisational structures can hinder adaptive work practices.

This phenomenon is not unique; it also manifests in other areas, particularly in industries characterised by constant change or spontaneous decision-making. Excessively structured support networks can make individuals feel constrained. It undermines their sense of agency and proficiency, prompting resistance to the imposition of new technology [54]. In construction, FC often indicates increased procedures, excessive documentation, or supervisors closely monitoring your activities. Most employees perceive that as more labour rather than genuine assistance.

Recent studies corroborate this finding. When official support fails to align with on-site realities, individuals respond adversely. Construction activities are chaotic and frequently ad hoc; established procedures fail to adapt [10, 13, 55]. Consequently, employees increasingly rely on informal methods to accomplish tasks, rendering formal help even less effective. The previous study frequently resists technology perceived as imposed by higher authorities [22, 56]. The adverse relationship between FC and BI in this study ultimately hinges on context. Excessively rigid support systems inhibit adaptability and discourage workers in green construction projects from adopting new digital technologies.

HM did not significantly affect BI. This suggests that the convenience or pleasure factor of technology is not particularly relevant in the construction industry. Darvazeh et al. [57] found that HM remained present but was much less prevalent in more digitally integrated construction fields. For example, workers in a green building construction project in Indonesia prioritised the functionality of the energy monitoring app over its fancy design.

PV was identified as one of the strongest predictors of BI. This finding indicates that construction professionals evaluate digital technologies based on the balance between perceived benefits and associated costs. When digital systems are perceived as reducing project costs, minimising design errors, or improving efficiency, individuals are more likely to adopt them. In green building projects, the ability of BIM systems to reduce material waste and optimise design coordination enhances the perceived economic value of adopting digital technology. This is similar to a meta-analysis of BIM adoption conducted by Prabarani et al. [58]. For example, employees on a green building project in Indonesia greatly appreciated adopting BIM, as it reduced material waste and design error costs.

HB also significantly influenced BI. The results suggest that repeated exposure to digital systems gradually transforms intentional use into routine behaviour. As construction professionals become accustomed to digital reporting systems or mobile project management tools, their reliance on these technologies increases. Previous studies on digital transformation similarly emphasise the role of habitual behaviour in stabilising technology adoption within organisational environments [59, 60]. Among employees engaged in the Indonesian green building project, the concept of a new system was quickly accepted, particularly when using a mobile application to report daily for a specified period.

PR, however, did not significantly influence BI. Although digital technologies often raise concerns about system reliability and data security, these risks appear to have limited influence on adoption decisions in green construction projects. One possible explanation is that the perceived operational benefits of digital technologies outweigh potential risks. When digital tools clearly improve task efficiency and project coordination, users may prioritise performance benefits over concerns regarding technological uncertainty. Interestingly, this does not align with Kim et al. [61], which argues that risk always accompanies AI adoption.

But in Indonesia's green building projects, what really drives workers is the promise of getting the job done better and faster. The benefits feel real, much more immediate than abstract worries about digital risks. This matches what we're starting to see in studies on AI and IoT in construction: when the technology clearly helps with everyday tasks, people barely notice the risk [62, 63]. Still, it's not always so simple. Other research indicates that in green construction, strict regulations necessitate reliability and traceability, which may further increase risk sensitivity [64].

The indirect effect analysis further indicates that PV influences actual technology use primarily through BI. The decision to adopt digital technologies is strongly influenced by users' evaluation of the benefits relative to the associated costs, as presented in Table 9. When the perceived economic and operational benefits outweigh implementation costs, adoption intentions increase. This finding is consistent with research on BIM adoption, which emphasises economic value as a critical driver of digital technology acceptance. For example, workers involved in green building projects in nIndonesia reported increased willingness to adopt BIM after observing reductions in material waste and design errors.

Table 9. The path indirect results

Path Indirect	Path Indirect Coefficient	p-Value	Results
PV → BI → UB	0.762	0.000	Significant
SI → BI → UB	0.608	0.000	Significant
TTF → BI → UB	0.048	0.780	Not Significant
TTF → PE → BI	0.120	0.004	Significant
TTF → PE → BI → UB	0.070	0.004	Significant
EE → BI → UB	0.028	0.791	Not Significant
FC → BI → UB	-0.929	0.000	Significant
HB → BI → UB	0.166	0.036	Significant
HM → BI → UB	0.136	0.169	Not Significant
PE → BI → UB	0.106	0.004	Significant
PR → BI → UB	-0.066	0.196	Not Significant

Note: PE, performance expectancy; EE, effort expectancy; SI, social influences; FC, facilitating conditions; HM, hedonic motivation; PV, perceived value; HB, habit; TTF, Task-Technology Fit; PR, perceived risk; BI, behavioural intention; UB, use behaviour.

In contrast, the indirect pathway from TTF to use behaviour through BI was not statistically significant. This finding indicates that technological compatibility alone does not necessarily lead to technology use unless users clearly perceive the technology's performance benefits. The result reinforces the mediating role of PE in the relationship between TTF and BI. For example, an energy-monitoring application may align well with the responsibilities of a project technician; however, the system may not be used consistently unless workers recognise its practical benefits in improving efficiency or decision-making.

EE was also found to have no significant indirect effect on technology use behaviour. One possible explanation is that construction professionals have become increasingly familiar with digital technologies in their daily work activities [14, 65]. As a result, usability concerns become less important compared to performance-related benefits. In the context of green construction projects, workers appear to prioritise technologies that directly support efficiency, coordination, and productivity. FC, however, demonstrated a significant negative effect on BI. This finding suggests that excessive organisational support may unintentionally reduce users' intrinsic motivation to adopt technology. When digital systems are perceived as being imposed through rigid organisational structures or excessive monitoring, workers may interpret such support as an additional administrative burden rather than practical assistance [30]. Consequently, overly structured support mechanisms may discourage voluntary technology adoption.

HB also significantly influenced use behaviour through BI. As workers become increasingly familiar with digital applications, they are more likely to continue using them in their daily activities. These findings are consistent with previous research highlighting habit as a strong determinant of digital technology adoption [66]. Workers who routinely used mobile applications for progress reporting in green construction projects were more likely to maintain consistent usage behaviour.

HM did not significantly influence use behaviour through BI. This result suggests that enjoyment or entertainment value is not a critical determinant of technology adoption in construction environments. Construction professionals appear to prioritise functionality and efficiency over user experience design. For example, a visually appealing energy monitoring application may not increase adoption if it does not provide clear operational benefits [67, 68].

PE, however, demonstrated a significant indirect influence on use behaviour through BI. When workers perceive that digital technologies improve productivity and project performance, they are more likely to use these technologies consistently. This finding is consistent with previous meta-analyses on BIM adoption, which identify perceived usefulness as a key driver of sustained technology usage [19].

In terms of intentionality, the PR has no significant effect on the use behaviour. This demonstrates that concerns about hazards or data safety do not influence an employee's decision to use technology [25]. That means, as long as you are building things, the benefits will always outweigh any risk involved. This is because, since their chief objective was to save both time and funds (in addition), on green-building sites, workers made extensive use of electronic tools.

Finally, PR did not demonstrate a significant effect on use behaviour through BI. This suggests that concerns about technological risk are less influential in determining technology-use decisions in green construction projects. In practice, construction professionals appear to prioritise operational benefits such as efficiency, cost reduction, and improved coordination over potential digital risks [69].

Overall, the findings highlight important gaps in workforce readiness for digital technology adoption in green construction projects. While some workers can interpret digital outputs, such as BIM clash detection or IoT energy dashboards, many still struggle to understand and utilise these systems effectively. These results indicate the need to strengthen digital competencies in data interpretation, problem-solving with digital tools, and decision-making supported by digital systems.

Another important issue concerns the overreliance on organisational support. Excessive reliance on institutional assistance may indicate limited confidence in using digital technologies independently. To support sustainable digital transformation, workers must develop the capability to manage digital systems independently, solve operational problems, and adapt to new technological environments.

Habitual interaction with digital technologies, therefore, becomes essential. Regular exposure to digital systems reduces user resistance and improves confidence in using these tools. Training programmes should therefore focus not only on technical instruction but also on integrating digital tools into daily project activities. Continuous practice and real project scenarios can help strengthen digital competence and support long-term adoption.

Based on the results of the SEM-PLS analysis and stakeholder validation discussions, several practical strategies can be proposed to support digital adoption in green construction projects. First, top management should clearly communicate the operational benefits of digital systems, particularly their ability to improve coordination, reduce design conflicts, and enhance project efficiency. Second, project managers should balance the provision of technological infrastructure with motivational mechanisms such as incentives for consistent digital reporting. Third, field supervisors and workers should receive structured guidance during the early stages of digital implementation to ensure that technology use becomes habitual. Finally, consultants and architects should emphasise BIM's broader capabilities beyond 3D modelling, particularly its role in energy analysis, material sustainability assessment, and life-cycle evaluation in green building projects.

6 Conclusion

This study examined the behavioural factors influencing the adoption of digital technologies in green construction projects by integrating the UTAUT2, the TTF framework, and the PR framework. The findings indicate that BI plays a central role in translating perceptions of digital technologies into actual use behaviour within green building projects.

Among the examined factors, PE, PV, SI, and HB were identified as key drivers shaping BI. Construction professionals are more likely to adopt digital tools when these technologies are perceived as improving project efficiency, reducing operational errors, and providing clear practical benefits. Habitual interaction with digital systems also plays an important role in stabilising technology adoption, as repeated use gradually transforms intentional behaviour into routine practice within project workflows.

The results further demonstrate that BI mediates the relationship between several antecedent variables and actual technology use. In particular, PV and SI indirectly influence technology usage through BI, highlighting the importance of organisational support and perceived economic benefits in encouraging digital adoption. Task–technology fit was also found to influence adoption behaviour indirectly through PE, suggesting that digital technologies are more likely to be adopted when they clearly support operational tasks and improve work performance.

In contrast, EE, HM, and PR were found to have limited influence on technology adoption in green construction projects. These findings suggest that construction professionals prioritise functional and performance-related benefits over usability or entertainment-related factors when evaluating digital technologies. Concerns about technological risk also appear secondary when the perceived operational advantages of digital tools are evident.

Overall, the findings highlight that successful digital transformation in green construction projects depends not only on technological availability but also on workforce readiness, perceived operational benefits, and the alignment between digital technologies and construction tasks. For practitioners, the results suggest that organisations should emphasise the practical value of digital technologies, strengthen digital competencies among construction professionals, and integrate digital tools into routine project workflows to encourage sustained adoption.

This study has the following limitations:

1. The research context is limited to green building projects, so it cannot represent all types of construction projects in Indonesia.

2. The cross-sectional design is unable to capture the dynamics of changes in intentions and behaviours regarding technology use over time.

3. Moderating variables such as age, work experience, contract type, and organisational culture have not been tested in depth.

Therefore, opportunities for further research include:

1. Expanding the sample and context: Testing the model on other construction projects (EPC, public infrastructure, mass housing) to determine the consistency of the findings.

2. Longitudinal approach: Tracking changes in perceptions, intentions, and behaviours regarding digital technology use from the initial project phase to completion.

3. Testing moderating variables: Including digital experience, organisational support, and work culture to examine interactions between variables.

4. Combining qualitative methods: Complementing the SEM-PLS analysis with in-depth interviews to capture worker perceptions and resistance.

5. Focusing on sustainability metrics: Integrating green building performance indicators (energy efficiency, water conservation, carbon emissions) to assess the broader impact of technology.

Therefore, this study concludes that digital transformation in construction is not simply about technology adoption, but rather about how tangible values, SI, work habits, and the suitability of technology to the task can create sustainable behavioural change.

Author Contributions

Conceptualization, M.W. and B.T.U.; methodology, M.W. and L.K.W.; software, B.T.U.; validation, M.W., B.T.U., and M.S.S.M.; formal analysis, M.W.; investigation, M.W., L.K.W., and L.A.R.W.; resources, L.K.W. and L.A.R.W.; data curation, M.W. and B.T.U.; writing—original draft preparation, M.W.; writing—review and editing, M.W., B.T.U., and M.S.S.M.; visualization, B.T.U.; supervision, M.W.; project administration, M.W. and L.K.W.; funding acquisition, M.W. All authors have read and agreed to the published version of the manuscript.

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Data Availability

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

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Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] M. M. Fakhabi, S. M. Hamidian, and M. Aliehyaei, "Exploring the role of the Internet of Things in green buildings," *Wiley Interdiscip. Rev. Energy Environ.*, vol. 12, no. 9, pp. 3779–3822, 2024. https://doi.org/10.1002/ese3.1840

[2] A. Herzanita, R. T. Lestari, and A. P. Dewi, "Assessing green building implementation and barriers in campus settings," *Int. J. Environ. Impacts*, vol. 7, no. 3, pp. 591–599, 2024. https://doi.org/10.18280/ijei.070320

[3] M. Wijayaningtyas, A. Lomi, E. Nursanti, N. Sebayang, and M. Istiqhoma, "Artificial intelligence and the Internet of Things in environmentally building water consumption model: Bibliometric analysis," *BIO Web Conf.*, vol. 155, p. 08004, 2024. https://doi.org/10.1051/bioconf/202515508004

[4] S. Nižetić, P. Šolić, D. López-de-Ipiña González-de Artaza, and L. Patrono, "Internet of Things (IoT): Opportunities, issues and challenges towards a smart and sustainable future," *J. Clean. Prod.*, vol. 274, p. 122877, 2020. https://doi.org/10.1016/j.jclepro.2020.122877

[5] L. Y. Rock, F. P. Tajudeen, and Y. W. Chung, "Usage and impact of the internet-of-things-based smart home technology: A quality-of-life perspective," *Univ. Access Inf. Soc.*, vol. 23, no. 1, pp. 345–364, 2024. https://doi.org/10.1007/s10209-022-00937-0

[6] A. Das and A. R. Chowdhury, "Empowering sustainable water management: The confluence of artificial intelligence and Internet of Things," in *Water Footprints and Sustainable Development*. Elsevier, 2024, pp. 275–291. https://doi.org/10.1016/B978-0-443-23631-0.00019-4

[7] R. Maqbool, M. R. Saiba, and S. Ashfaq, "Emerging industry 4.0 and Internet of Things (IoT) technologies in the Ghanaian construction industry: Sustainability, implementation challenges, and benefits," *Environ. Sci. Pollut. Res.*, vol. 30, no. 13, pp. 37 076–37 091, 2023. https://doi.org/10.1007/s11356-022-24764-1

[8] F. Elghaish, S. Matarneh, S. Talebi, M. Kagioglou, M. R. Hosseini, and S. Abrishami, "Toward digitalization in the construction industry with immersive and drones technologies: A critical literature review," *Smart Sustain. Built Environ.*, vol. 10, no. 3, pp. 345–363, 2021. https://doi.org/10.1108/SASBE-06-2020-0077/FULL/HTML

[9] S. Su, R. Zhong, and Y. J. Twin, "Digital twin and its applications in the construction industry: A state-of-art systematic review," *Digital Twin*, vol. 2, no. 1, p. 2501499, 2024. https://doi.org/10.12688/digitaltwin.17664.3

[10] O. C. Madubuike, C. Anumba, and R. Khallaf, "A review of digital twin applications in construction," *J. Inf. Technol. Constr.*, vol. 27, pp. 145–172, 2022. https://doi.org/10.36680/j.itcon.2022.008

[11] D. Hamid and W. Dhewanto, "Digital transformation strategy in construction industry: A case study on PT. Konstruksi Membangun Negeri Tbk," *Am. Int. J. Bus. Manage.*, vol. 6, no. 7, pp. 19–34, 2023.

[12] Y. Li, H. Sun, D. Li, J. Song, and R. Ding, "Effects of digital technology adoption on sustainability performance in construction projects: The mediating role of stakeholder collaboration," *J. Manage. Eng.*, vol. 38, no. 3, p. 04022016, 2022. https://doi.org/10.1061/(ASCE)ME.1943-5479.0001040

[13] A. Olanipekun and M. Sutrisna, "Facilitating digital transformation in construction—A systematic review of the current state of the art," *Front. Built Environ.*, vol. 7, p. 660758, 2021. https://doi.org/10.3389/fbuil.2021.660758

[14] R. Nyqvist, A. Peltokorpi, R. Lavikka, and A. Ainamo, "Building the digital age: Management of digital transformation in the construction industry," *Constr. Manage. Econ.*, vol. 43, no. 4, pp. 262–283, 2025. https://doi.org/10.1080/01446193.2024.2416033

[15] R. Mubarok, "Integrating the deep learning paradigm and Asta Cita values in the development of multicultural islamic religious education in Indonesia," *J-TELITE: J. Transform. Educ. Leadersh. Innov. Teach. Excell.*, vol. 2, pp. 56–72, 2026. https://doi.org/10.58586/zek9ws38

[16] E. K. Penney, J. Agyei, E. K. Boadi, E. Abrokwah, and R. Ofori-Boafo, "Understanding factors that influence consumer intention to use mobile money services: An application of UTAUT2 with perceived risk and trust," *Sage Open*, vol. 11, no. 3, p. 21582440211023188, 2021. https://doi.org/10.1177/21582440211023188

[17] M. N. Addy, E. T. Addo, T. E. Kwofie, and J. E. Yartey, "Predicting the adoption of e-procurement in construction project delivery in Sub-Saharan Africa: An application of UTAUT2," *Constr. Innov. Inf. Process Manage.*, vol. 23, no. 5, pp. 1038–1053, 2023. https://doi.org/10.1108/CI-09-2021-0174/FULL/HTML

[18] M. Oraee, M. Hosseini, D. Edwards, and E. Papadonikolaki, "Collaboration in BIM-based construction networks: A qualitative model of influential factors," *Eng. Constr. Archit. Manage.*, vol. 3, no. 29, pp. 1194–1217, 2022. https://doi.org/10.1108/ECAM-10-2020-0865

[19] N. Van Tam, N. Q. Toan, and V. Van Phong, "Impact of BIM-related factors affecting construction project performance," *Int. J. Build. Pathol. Adapt.*, vol. 41, no. 42, pp. 454–475, 2021. https://doi.org/10.1108/IJBPA-05-2021-0068

[20] C. J. Kibert, *Sustainable Construction: Green Building Design and Delivery*. Wiley, 2022.

[21] M. Wijayaningtyas, H. Sujatmiko, and N. Sebayang, "Sustainable construction: Optimization of road potholes repair with polymer mix aggregates," *Civ. Eng. Archit.*, vol. 11, no. 1, pp. 381–394, 2023. https://doi.org/10.13189/cea.2023.110130

[22] S. K. Alfaiz, S. B. A. Karim, and A. M. Alashwal, "Critical success factors of green building retrofitting ventures in Iraq," *Int. J. Sustain. Constr. Eng. Technol.*, vol. 12, no. 1, pp. 12–17, 2021. https://doi.org/10.30880/ijscet.2021.12.01.002

[23] S. Muench, E. Stoermer, K. Jensen, T. Asikainen, M. Salvi, and F. Scapolo, *Towards a Green & Digital Future*. Publications Office of the European Union, 2022.

[24] C. Wang, M. Zhu, S. A. S. Zakaria, and J. Chen, "Green building performance prediction and evaluation system under BIM-based digital construction technology," *J. Comb. Math. Comb. Comput.*, vol. 127, pp. 7549–7564, 2025. https://doi.org/10.61091/jcmcc127b-412

[25] K. Wang, F. Guo, C. Zhang, H. Jianli, and Z. Wang, "Unlocking determinants of smart construction: An integrated model of UTAUT2, TTF, and perceived risk for IoT acceptance in AEC industry," *Eng. Constr. Archit. Manage.*, vol. 32, no. 8, pp. 5394–5428, 2025. https://doi.org/10.1108/ECAM-05-2023-0482

[26] M. van den Berg, H. Voordijk, and A. Adriaanse, "BIM uses for deconstruction: An activity-theoretical perspective on reorganising end-of-life practices," *Constr. Manage. Econ.*, vol. 39, no. 4, pp. 323–339, 2021. https://doi.org/10.1080/01446193.2021.1876894

[27] Y. Wang and L. Liu, "Research on sustainable green building space design model integrating IoT technology," *PLoS One*, vol. 19, no. 4, p. e0298982, 2024. https://doi.org/10.1371/journal.pone.0298982

[28] M. Q. Raza and A. Khosravi, "A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings," *Renewable Sustainable Energy Rev.*, vol. 50, pp. 1352–1372, 2015. https://doi.org/10.1016/j.rser.2015.04.065

[29] O. Samuelson and L. Stehn, "Digital transformation in construction—A review," *J. Inf. Technol. Constr.*, vol. 28, pp. 385–404, 2023. https://doi.org/10.36680/j.itcon.2023.020

[30] Z. Alwashah, G. J. Sweis, H. Abu Hajar, W. Abu-Khader, and R. J. Sweis, "Challenges to adopt digital construction technologies in the Jordanian construction industry," *Constr. Innov. Inf. Process Manage.*, vol. 25, no. 5, pp. 1610–1630, 2024. https://doi.org/10.1108/CI-03-2023-0056

[31] K. Batool, G. Ali, K. Ullah Khan, M. Asif Kamran, and N. Yan, "Integrating role of green buildings in achieving carbon neutrality in an era of climate emergency," *Sustainable Dev.*, vol. 32, no. 4, pp. 4186–4201, 2024. https://doi.org/10.1002/sd.2883

[32] B. Singh, M. S. Khan, and M. Z. Khan, "Applications and challenges in IoT based smart homes," *Int. J. Mech. Eng.*, vol. 6, no. 3, pp. 1235–1243, 2021.

[33] C. Debrah, A. P. C. Chan, and A. Darko, "Artificial intelligence in green building," *Autom. Constr.*, vol. 137, p. 104192, 2022. https://doi.org/10.1016/J.AUTCON.2022.104192

[34] J. Sun and Y. Guo, "A new destination on the palm? The moderating effect of travel anxiety on digital tourism behavior in extended UTAUT2 and TTF models," *Front. Psychol.*, vol. 13, p. 965655, 2022. https://doi.org/10.3389/fpsyg.2022.965655

[35] F. Zheng, S. Wu, R. Liu, and Y. Bai, "What influences user continuous intention of digital museum: Integrating task-technology fit (TTF) and unified theory of acceptance and usage of technology (UTAUT) models," *Herit. Sci.*, vol. 12, no. 1, p. 253, 2024. https://doi.org/10.1186/S40494-024-01365-4

[36] D. Cao, X. Teng, Y. Chen, D. Tan, and G. Wang, "Digital transformation strategies of project-based firms: Case study of a large-scale construction company in China," *Asia Pac. J. Innovation Entrepreneurship*, vol. 17, no. 2, pp. 82–98, 2023. https://doi.org/10.1108/APJIE-02-2023-0027/FULL/PDF

[37] F. Y. Y. Ling, G. T. H. Heng, A. Chang-Richards, X. Chen, and T. W. Yiu, "Impact of digital technology adoption on the comparative advantage of architectural, engineering, and construction firms in Singapore," *J. Constr. Eng. Manage.*, vol. 149, no. 12, p. 04023125, 2023. https://doi.org/10.1061/JCEMD4.COENG-13743

[38] B. P. Surendro, S. Hidayat, and M. Wijayaningtyas, "The worker perception toward foreman leadership in construction project," *Int. J. Sci. Technol. Res.*, vol. 9, no. 6, pp. 1–4, 2020.

[39] M. Wijayaningtyas and K. Lukiyanto, "Informal housing construction workers' perceptions toward the improvement of effective leadership and performance," *MATEC Web Conf.*, vol. 258, p. 02004, 2019. https://doi.org/10.1051/matecconf/201925802004

[40] K. Lukiyanto, "Leadership style that effective and capable to increase performance based on informal workers perception (case study on Indonesia construction project)," *Int. J. Civ. Eng. Technol.*, vol. 9, no. 6, pp. 850–860, 2018.

[41] Y. Fu, G. Ye, X. Tang, and Q. Liu, "Theoretical framework for informal groups of construction workers: A grounded theory study," *Sustainability*, vol. 11, no. 23, p. 6769, 2019. https://doi.org/10.3390/su11236769

[42] B. Liu, Q. Wang, G. Wu, J. Zheng, and L. Li, "How family-supportive supervisor affect Chinese construction workers' work-family conflict and turnover intention: Investigating the moderating role of work and family identity salience," *Constr. Manage. Econ.*, vol. 38, no. 9, pp. 807–823, 2020. https://doi.org/10.1080/01446193.2020.1748892

[43] P. Bowen, R. P. Zhang, and P. Edwards, "An investigation of work-related strain effects and coping mechanisms among South African construction professionals," *Constr. Manage. Econ.*, vol. 39, no. 4, pp. 298–322, 2021. https://doi.org/10.1080/01446193.2020.1870045

[44] S. Siregar, H. Sitompul, K. Wijaya, S. Z. Yuzni, and A. A. Solahuddin, "A work-based learning E DeAL model for building construction workers," *Int. J. Sci. Technol. Res.*, vol. 9, no. 12, pp. 59–63, 2020.

[45] R. Wirahadikusumah, M. Abduh, Y. Messah, and M. Aulia, "Introducing sustainability principles into the procurement of construction works—Case of Indonesian developers," *Int. J. Constr. Manage.*, vol. 21, no. 9, pp. 932–944, 2021. https://doi.org/10.1080/15623599.2019.1599559

[46] V. Venkatesh, "Adoption and use of AI tools: A research agenda grounded in UTAUT," *Ann. Oper. Res.*, vol. 308, no. 1–2, pp. 641–652, 2022. https://doi.org/10.1007/s10479-020-03918-9

[47] D. L. Goodhue, "Task-technology fit: A critical (but often missing!) construct in models of information systems and performance," in *Human-Computer Interaction and Management Information Systems: Foundations*. Armonk, New York: M.E. Sharpe, Inc, 2006, pp. 184–204. https://doi.org/10.4324/9781315703619-18

[48] A. M. Al-Rahmi, A. Shamsuddin, E. Wahab, W. M. Al-Rahmi, U. Alturki, A. Aldraiweesh, and S. Almutairy, "Integrating the role of UTAUT and TTF model to evaluate social media use for teaching and learning in higher education," *Front. Public Health*, vol. 10, p. 905968, 2022. https://doi.org/10.3389/fpubh.2022.905968

[49] M. H. Miraz, R. Sham, and S. Annamalah, "Advancing mixed-methods research through PLS-SEM and NVivo: A methodological integration in AI literacy studies," *Qual. Quant.*, 2025. https://doi.org/10.1007/S11135-025-02401-6

[50] M. Sarstedt, N. F. Richter, S. Hauff, and C. M. Ringle, "Combined importance–performance map analysis (cIPMA) in partial least squares structural equation modeling (PLS–SEM): A SmartPLS 4 tutorial," *J. Mark. Anal.*, vol. 12, no. 4, pp. 746–760, 2024. https://doi.org/10.1057/S41270-024-00325-Y

[51] K. K. K. Wong, "Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS," *Mark. Bull.*, vol. 24, pp. 1–32, 2013.

[52] S. Hafeez, M. N. Sabzwari, and M. Tariq, "Information technology self-efficacy and personal knowledge management in the current era of overloaded information: A study of generation 'Z' students," *J. Inf. Manage. Libr. Stud.*, vol. 7, no. 1, pp. 276–299, 2024.

[53] B. Dash, P. Sharma, and S. Swayamsiddha, "Organizational digital transformations and the importance of assessing theoretical frameworks such as TAM, TTF, and UTAUT: A review," *Int. J. Adv. Comput. Sci. Appl.*, vol. 14, no. 2, pp. 1–6, 2023. https://doi.org/10.14569/IJACSA.2023.0140201

[54] M. Galesic, D. Barkoczi, A. M. Berdahl, D. Biro, G. Carbone, I. Giannoccaro, R. L. Goldstone, C. Gonzalez, A. Kandler, A. B. Kao, and et al., "Beyond collective intelligence: collective adaptation," *J. R. Soc. Interface*, vol. 20, p. 20220736, 2023. https://doi.org/10.1098/RSIF.2022.0736

[55] M. Conner, S. F. L. Kirk, J. E. Cade, and J. H. Barrett, "Why do women use dietary supplements? The use of the theory of planned behaviour to explore beliefs about their use," *Soc. Sci. Med.*, vol. 52, no. 4, pp. 621–633, 2001. https://doi.org/10.1016/S0277-9536(00)00165-9

[56] H. O. Onubi, N. Yusof, and A. S. Hassan, "Adopting green construction practices: Health and safety implications," *J. Eng. Des. Technol.*, vol. 18, no. 3, pp. 635–652, 2020. https://doi.org/10.1108/JEDT-08-2019-0203

[57] S. S. Darvazeh, F. M. Mooseloo, S. Aeini, H. R. Vandchali, and E. B. Tirkolaee, "An integrated methodology for green human resource management in construction industry," *Environ. Sci. Pollut. Res.*, vol. 30, no. 60, pp. 124 619–124 637, 2023. https://doi.org/10.1007/S11356-022-20967-8

[58] I. R. Prabarani, D. Larasati, and H. E. Kusuma, "BIM's role in Indonesia's green buildings: Benefits, challenges, and stakeholder preferences," *Dimensi (J. Archit. Built Environ.)*, vol. 52, no. 1, pp. 1–13, 2025. https://doi.org/10.9744/DIMENSI.52.1.1-13

[59] W. L. Chen, T. W. Chan, L. H. Wong, C. K. Looi, C. C. Y. Liao, H. N. H. Cheng, S. L. Wong, J. Mason, H. J. So, S. Murthy, and et al., "IDC theory: Habit and the habit loop," *Res. Pract. Technol. Enhanc. Learn.*, vol. 15, no. 10, 2020. https://doi.org/10.1186/s41039-020-00127-7

[60] M. Aranyossy, "Technology adoption in the digital entertainment industry during the COVID-19 pandemic: An extended UTAUT2 model for online theater streaming," *Informatics*, vol. 9, no. 3, p. 71, 2022. https://doi.org/10.3390/INFORMATICS9030071

[61] J. Kim, J. Byun, and T. Im, "Motivational determinants of continuance usage intention for generative AI: An investment model approach for ChatGPT users in the United States," *Behav. Inf. Technol.*, vol. 44, no. 12, pp. 3080–3096, 2025. https://doi.org/10.1080/0144929X.2024.2429647

[62] H. Fitriani and S. Ajayi, "Investigation of requisite measures for enhancing sustainable construction practices in Indonesia," *Eng. Constr. Archit. Manage.*, vol. 30, no. 6, pp. 2602–2620, 2023. https://doi.org/10.1108/ECAM-11-2021-1051

[63] M. Agnes and R. H. Koestoer, "A review on sustainable construction regulations in Asian countries: Savvy insights for Indonesia," *J. Ilmu Lingkung.*, vol. 19, no. 2, pp. 459–464, 2021. https://doi.org/10.14710/jil.19.2.459-464

[64] H. A. Rani, M. S. Al-Mohammad, R. A. Rahman, and M. S. Aqsha, "Building information modeling implementation in the Indonesian construction industry: A systematic literature review," *Malays. Constr. Res. J.*, vol. 26, no. 3, pp. 98–108, 2025.

[65] J. Brozovsky, N. Labonnote, and O. Vigren, "Digital technologies in architecture, engineering, and construction,"

Autom. Constr., vol. 158, p. 105212, 2024. https://doi.org/10.1016/J.AUTCON.2023.105212

[66] A. T. Alqadami, N. A. W. A. Zawawi, Y. Rahmawati, W. Alaloul, and A. F. Alshalif, "Key success factors of implementing green procurement in public construction projects in Malaysia," *IOP Conf. Ser.: Earth Environ. Sci.*, vol. 498, no. 1, p. 012098, 2020. https://doi.org/10.1088/1755-1315/498/1/012098

[67] I. Atmika, P. Wahyuni, and I. N. Sinarta, "Implementation of construction management system based on information technology (IT) and integrated towards digital construction in industry 4.0," *AIP Conf. Proc.*, vol. 2599, p. 070033, 2023. https://doi.org/10.1063/5.0146372

[68] W. Lu, J. Lou, B. K. Ababio, R. Y. Zhong, Z. Bao, X. Li, and F. Xue, "Digital technologies for construction sustainability: Status quo, challenges, and future prospects," *Mater. Sustain.*, vol. 2, p. 10, 2024. https://doi.org/10.1038/s44296-024-00010-2

[69] N. Van Tam, "Mitigating digital transformation risks for circular construction in emerging economies: An empirical investigation in Vietnam," *Int. J. Constr. Manage.*, vol. 25, no. 10, pp. 1130–1140, 2025. https://doi.org/10.1080/15623599.2024.2397628