www.itcon.org - Journal of Information Technology in Construction - ISSN 1874-4753

TRANSFORMATIVE TRAJECTORIES: PLS-SEM ANALYSIS OF FACTORS INFLUENCING EMERGING TECHNOLOGIES IN CONSTRUCTION ADOPTION IN MALAYSIA

SUBMITTED: September 2023
REVISED: January 2025
PUBLISHED: January 2025
EDITOR: Robert Amor
DOI: 10.36680/j.itcon.2025.003

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SUMMARY: *The rapid development and integration of emerging technologies in construction (ETC) have revolutionized traditional processes, workflows, and management systems. Despite these advancements, the adoption of these technologies varies widely across organizations and projects, posing challenges to the industry. This study aims to identify the key factors influencing ETC adoption and develop a structural equation model to analyze their relationships, using Malaysia as a case study. Through a systematic literature review, relevant factors were identified, followed by a survey with 147 industry professionals to evaluate the importance of the factors. Data were analyzed using agreement analysis, mean score ranking, exploratory factor analysis (EFA), and partial least squares structural equation modeling (PLS-SEM). The analyses identified 14 key factors, which can be further classified into three underlying constructs: organizational resources, organizational goals, and organizational strategy. Notably, the findings suggest that only organizational strategy plays a significant role in ETC adoption decisions. Consequently, strategic alignment should be a primary consideration for organizations planning to adopt ETC. This study contributes to the literature by providing a comprehensive analysis of the factors influencing ETC adoption. Researchers and industry professionals can leverage these insights to develop effective strategies that enhance ETC adoption rates, driving innovation and efficiency in the construction industry.*

KEYWORDS: *Emerging technologies, Technologies adoption, Construction industry, PLS-SEM.*

REFERENCE: *Fakhira Khudzari, Ahmad Tarmizi Haron, Steven K. Ayer, Rahimi A. Rahman (2025). Transformative trajectories: PLS-SEM analysis of factors influencing emerging technologies in construction adoption in Malaysia. Journal of Information Technology in Construction (ITcon), Vol. 30, pg. 45-64, DOI: 10.36680/j.itcon.2025.003*

1. INTRODUCTION

In today's fast-paced world, the architecture, engineering, and construction (AEC) industry must continuously adapt to emerging technologies in construction (ETC) to stay competitive and efficient (Darko et al., 2017). Embracing ETC is crucial for maintaining competitiveness, reducing project costs, meeting environmental and safety standards, and ensuring a sustainable built environment (Pu et al., 2021; Shamsuddin et al., 2013; Li & Liu, 2018). With rapid urbanization, population growth, and climate change intensifying existing challenges, the need to future-proof the AEC industry has never been more critical (Butsch et al., 2017). Addressing these challenges proactively can prevent setbacks for AEC organizations and enhance their ability to innovate and respond to new urban development demands. Understanding the factors influencing ETC adoption is essential for navigating the complexities and shaping a resilient future for the AEC industry.

Regrettably, the AEC industry faces challenges in ETC adoption, primarily due to conservative attitudes, resource constraints, and limited awareness of ETC benefits (Wuni & Shen, 2019; Smith & Tardif, 2009). These challenges can slow the ETC adoption progress. Enhanced collaboration among stakeholders, increased investment in research and development, and the establishment of clear policy frameworks are crucial to overcoming these challenges (Ganeshu et al., 2023). The industry's fragmented structure and the intricate landscape of regulations and standards can make it difficult for decision-makers to drive innovation (World Economic Forum, 2016). Additionally, the competitive nature of the industry often prioritizes short-term financial gains and immediate project outcomes over long-term strategic planning, which can deter ETC adoption (Abioye et al., 2021).

Despite these challenges, the future of the AEC industry looks promising. Understanding the factors that influence ETC adoption decisions can pave the way for transformative change. By encouraging collaboration among stakeholders, investing in education and training, and developing supportive regulatory frameworks, a more receptive environment for ETC adoption can be created (Hanna, 2018). Moreover, promoting a culture of innovation within the industry is crucial for stimulating the necessary shift in mindset to facilitate widespread ETC adoption. Integrating digital technologies, such as Building Information Modelling (BIM), artificial intelligence, and 3D printing, can revolutionize construction processes and significantly improve efficiency, sustainability, and safety (Pan & Zhang, 2021). Furthermore, embracing sustainable construction practices and materials, such as green building certifications and using renewable resources, can contribute to a more resilient and environmentally responsible built environment (Liu et al., 2022; Opoku et al., 2019). The concerted efforts in these areas can undoubtedly drive the construction industry towards a brighter and more sustainable future.

In light of the aforementioned concerns and opportunities, this study aims to identify the key factors influencing ETC adoption and to develop a comprehensive structural equation model (SEM) to analyse their relationships. To achieve that aim, the study objectives are to identify (1) key factors influencing ETC adoption; (2) compare the key factors; (3) develop underlying constructs for the key factors; and (4) model the relationship between the underlying constructs and ETC adoption decisions. Developing an SEM model that accounts for the different factors influencing this critical process supports the creation of targeted strategies for overcoming existing challenges in ETC adoption. Furthermore, examining the interplay between these factors can provide valuable insights into the complex dynamics shaping the decision-making processes of AEC industry stakeholders. Armed with this knowledge, AEC industry leaders and policymakers can make informed decisions and implement meaningful changes, ensuring that the industry continues to lead in technological innovation for generations to come.

2. LITERATURE REVIEW

2.1 Factors influencing ETC adoption

Understanding the factors influencing ETC adoption decisions is crucial for advancing the AEC industry (Sepasgozar & Bernold, 2012). Despite being perceived as a risk-averse, the construction industry shows great potential for embracing ETC when provided with compelling evidence of its benefits. Typically, organizations adopt ETC following successful adoption by competitors. AEC stakeholders often seek empirical proof from vendors demonstrating increased productivity, enhanced safety, and reduced waste before committing to ETC (Sepasgozar & Bernold, 2012). Factors influencing ETC adoption include education and training, software availability, and a supportive environment with informed clients keen in using the technology (Abubakar et al., 2014). Finally, ETC adoption is also influenced by organizational-, environmental-, and project-specific factors

(Fernandes, 2006). Embracing these insights can pave the way for more confident and widespread adoption of ETC in the industry, driving innovation and efficiency.

2.1.1 Organizational Goals

The influence of cost on ETC in the AEC industry is substantial, serving as both a catalyst and a challenge. Organizations often grapple with the financial implications of adopting ETC, weighing potential innovation and efficiency gains against immediate financial burdens. Khudzari et al. (2023) and Qi et al. (2021) highlight the pivotal role of costs in driving technological adoption, emphasizing their paramount importance in strategic decision-making processes. For instance, robotics and automated systems promise significant advantages to the AEC industry, yet their adoption remains hindered by substantial upfront investments (Delgado et al., 2019). Similarly, Qi et al. (2020) underscore the increased costs associated with ETC adoption, including equipment purchase, software development, staff training, and operational maintenance. Cost considerations are critical in shaping organizational goals for successful ETC integration.

2.1.2 Organizational Resources

Governmental policies and support mechanisms are crucial in shaping the landscape for ETC adoption. The intersection of technology and policy underscores the importance of a supportive regulatory environment that encourages innovation while addressing risks and uncertainties. The World Economic Forum (2016) advocates for governmental initiatives such as research and development (R&D) funding, tax incentives, and regulatory standards to catalyze technological adoption in construction. Initiatives supporting construction robots, for instance, set precedents for broader industry acceptance (Qi et al., 2020). Conversely, the absence of government support, as highlighted by Darko et al. (2017), can hinder technological adoption efforts, complicating cost management and scalability for stakeholders. Effective government involvement thus becomes a critical organizational resource for fostering innovation and overcoming financial barriers to ETC adoption.

2.1.3 Organizational Strategy

Resistance to change is a fundamental challenge in ETC adoption, rooted in human psychology and organizational culture within the AEC industry. The industry's reliance on traditional processes exacerbates this resistance, making stakeholders hesitant to adopt new technologies (Richter & Sinha, 2020). Employee reluctance, as identified by Darko et al. (2017), underscores the need for strategic approaches that address cultural barriers and facilitate smooth transitions to new technologies. Moreover, stakeholder involvement emerges as another crucial aspect influencing ETC adoption strategies. Zakaria et al. (2017) emphasize the importance of stakeholder participation in decision-making processes, citing its influence on project outcomes such as ROI, project margins, and market share. Organizational strategies incorporating stakeholder perspectives can effectively align ETC initiatives with project goals and market demands, driving innovation and progress in the AEC sector.

2.2 Modeling ETC adoption decisions

Integrating advanced modeling in decision-making processes has become a prominent topic in the literature, providing valuable insights into ETC adoption. A substantial body of research has employed different methodologies to model ETC adoption decisions. Prior works have explored numerous areas, including BIM, prefabricated construction, blockchain, digitalization, and green construction methods. For instance, Xu et al. (2023) examined the interdependencies among eleven factors influencing blockchain adoption in the AEC industry, using the integrated interpretive structural modelling (ISM) and decision-making trial and evaluation laboratory (DEMATEL) methods. Similarly, Dou et al. (2019) identified factors influencing the diffusion of Prefabricated Construction Technology Innovation (PCTI) within AEC organizations, employing a conceptual model and SEM to facilitate decision-making.

Researchers have also delved into specific factors influencing the adoption of digitalization and other technologies in construction. Bajpai and Misra (2022) analyzed key factors of digitalization using qualitative research methods, including multiple interviews and a multi-criteria decision-making (MCDM) approach. Singh et al. (2023) used a novel combination of fuzzy DEMATEL and fuzzy DEMATEL social network analysis (FDSNA) to uncover causal relationships among factors influencing blockchain adoption. Additionally, Arabshahi et al. (2022) developed a governance framework to facilitate sensor adoption in construction, using a mixed methods design and Partial Least Squares Structural Equation Modelling (PLS-SEM).

Moreover, prior works have examined factors influencing ETC adoption with an emphasis on sustainability. Gan et al. (2022) sought to identify factors for green building technology adoption in rural housing construction and visualized their cause-and-effect relationships through the grey decision-making trial and evaluation laboratory technique. Bastan et al. (2022) proposed a systemic and holistic model to analyze the dynamics of BIM adoption using grounded theory and system dynamics. Lastly, Hammond et al. (2020) introduced a theoretical model to address the limited adoption of green construction practices, despite the critical need to reduce the AEC industry's environmental impact and the presence of numerous policies aimed at motivating stakeholders.

This comprehensive body of research underscores the multifaceted nature of ETC adoption and highlights the importance of using advanced modeling techniques to inform decision-making and promote sustainable practices in construction project management.

2.3 Research gap and study positioning

Although prior works have provided valuable insights into the adoption of different ETC, an overview of the decision-making process in ETC adoption remains lacking. This limitation highlights the need for a study that captures the multifaceted nature of ETC adoption across different technologies and contexts. In response to this gap, this study aims to provide an analysis of the key factors influencing ETC adoption. Unlike prior works that focus on specific technologies, this study distinguishes itself by not focusing on a specific technology when incorporating insights from AEC professionals. This approach aims to transcend the specificity of prior works, offering insights that are broadly applicable across various technological domains and organisational contexts. The methodological framework, combining agreement analysis, mean score ranking, exploratory factor analysis (EFA), and PLS-SEM provides a thorough examination of the complex relationships among factors. Thus, this study is positioned to contribute to the filed, extending and complementing existing works on ETC adoption.

3. METHODOLOGY

To understand the factors influencing ETC adoption, this study was organized into a series of structured phases. The study began with survey development, drawing on existing academic findings and practical insights from AEC professionals. This dual approach ensured the survey's theoretical soundness and its relevance to industry practices. After developing the survey, it was then distributed to AEC professionals from small and medium enterprises (SMEs) and large enterprises (LEs), capturing a broad spectrum of perspectives. The collected data formed the foundation for the study's analyses. The upcoming subsections delve into each of these steps in more greater detail.

3.1 Survey development

The survey development process follows a two-step approach designed to ensure its appropriateness and rationale. First, a systematic literature review (SLR) is conducted to thoroughly identify potential factors influencing ETC adoption. An SLR facilitates scoping, planning, identifying, screening, and assessing the current body of knowledge on a subject matter (Chung et al., 2022; Shafei et al., 2022; Malomane et al., 2022; Zabidin et al., 2020). The process begins with a search using the 'title/abstract/keyword' feature in Scopus. The Scopus database is selected due to its extensive range of literature surpassing other databases like Web of Science, Google Scholar, and PubMed (Owusu et al., 2020). The keywords employed are "decision" AND "technology," AND "construction industry," OR "construction project." To ensure the relevance and currency of the review, the review is limited to prior works from 2010 onward (Chen et al., 2021). Two criteria are applied to identify the articles: first, the journal should have published at least two papers on the subject matter; second, only peer-reviewed journal publications are considered. The complete search string is as follows: *TITLE-ABS-KEY (decision AND technology AND "construction industry" OR "construction projects" OR "construction project") AND PUBYEAR > 2009 AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT-TO (SUBJAREA, "ENGI") OR LIMIT-TO (SUBJAREA, "BUSI") OR LIMIT-TO (SUBJAREA, "SOCI") OR LIMIT-TO (SUBJAREA, "DECI") OR LIMIT-TO (SUBJAREA, "ECON")) AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "re"))*. The search yields 211 publications from over 60 journals.

Second, semi-structured interviews are conducted with AEC experts to identify additional factors influencing ETC adoption. This approach is chosen to capture insights not fully explored in existing literature. Semi-structured interviews are widely employed in qualitative and mixed-method research due to their flexibility and ability to delve deeply into emerging themes (Perera et al., 2023; McIntosh & Morse, 2015). The approach allows interviewers to probe and adapt questions in response to participants' responses, ensuring a focused yet exploratory approach (Magaldi & Berler, 2020). The target population is project managers from Grade 7 (G7) licensed AEC organizations with the local Construction Industry Development Board (CIDB). Project managers are targeted for their pivotal role in the decision-making processes of construction projects. G7 organizations are targeted as these organizations have the capability to undertake construction projects without value restrictions, unlike lower CIDB license levels which are restricted to projects up to MYR 10 million (approximately USD 2.5 million). Sixteen experts were interviewed, a number deemed sufficient as data saturation is achieved, indicating no new insights are emerging from further interviews (Glaser and Strauss, 2017). This sample size is consistent with similar works involving five to twelve experts (Aziz and Zainon, 2022; Pidgeon and Dawood, 2021).

The SLR and interview data are then used to develop the survey. The survey incorporated 35 factors identified from the SRL and interview findings. The survey is designed with three sections. The first section provides a concise overview of the research and confidentiality information to safeguard sensitive information and respect respondents' privacy (Albeaino and Gheisari, 2021). The second section collects respondents' background information crucial for ensuring all respondents are within the study's target population. The third section presents factors influencing ETC adoption, rated on a 5-point Likert scale from "not at all influential," "slightly influential," "somewhat influential," "influential," to "extremely influential." Additionally, respondents are invited to list and rate other factors based on their experiences, thereby enriching the study's comprehensiveness.

Within the second section of the survey, two specific questions are added to gain deeper insights into ETC adoption decisions. One such question, labeled "D01," inquires whether respondents have previously adopted ETC in their past construction projects. This variable holds significant importance as it directly infleunces the perceived ease of use - a key factor in technology acceptance according to the Technology Acceptance Model (TAM) (Davis, 1989). TAM suggests that an individual's acceptance of technology is primarily influenced by their perception of its ease of use and usefulness, with prior experience playing a pivotal role in shaping these perceptions. This viewpoint is supported further by the Theory of Planned Behaviour (TPB) by Ajzen (1991), which suggests that past experience strongly predicts future actions through behavioral, normative, and control beliefs. Another question, "D02," focuses on respondents' intentions to adopt ETC in future construction projects. This question serves as a direct indicator of actual use, aligning closely with both TAM and TPB frameworks. It gauges individuals' attitudes toward ETC adoption, influenced by factors such as perceived usefulness, ease of use, subjective norms, and perceived behavioral control.

Finally, a pilot test was conducted to validate the drafted survey. This step is a crucial part of the survey development. The pilot test allows the authors to identify and address potential issues that might otherwise have gone unnoticed by observing how respondents interpreted and responded to the survey (Jahanger et al., 2021; Adabre & Chan, 2019). The pilot test involved six respondents, three academics and three AEC professionals, each possessing over ten years of experience. Experts with extensive experience are recognized for their profound knowledge and expertise in the field (Perera et al., 2023; Lee et al., 2020b). The participants were tasked with evaluating the adequacy of the factors included in the survey and suggesting any additions or removals. Based on the feedback, the survey underwent refinements to enhance its structure and clarity. Importantly, to ensure unbiased and impartial feedback, the six individuals involved in the pilot test are independent of the sixteen semi-structured interview respondents. Following the pilot test, the survey's relevance and completeness are confirmed, leading to the finalization of factors, which are detailed in Table 1.

3.2 Data collection

To obtain a balanced perspective on the topic, the target population for the survey consists of AEC professionals representing key project stakeholders, including clients, contractors, and consultants from small and medium enterprises (SMEs) and large enterprises (LEs). According to the local government's definition, SMEs are defined locally as organizations with 5 to 50 full-time employees or annual sales turnover between MYR 200,000 and MYR 5 million (approximately USD 50,000 and USD 1.25 million); and LEs are organizations with more than 50 full-time employees or annual sales turnover greater than MYR 5 million (approximately USD 1.25 million). Employing a purposive sampling approach, the survey methodologically selected individuals exhibiting relevant characteristics from the sample frame of local AEC professionals. Initial contacts were followed up two weeks later to enhance the response rate. 147 valid responses were obtained (see Figure 1 for respondent profile). Rather than presenting a comprehensive assessment of the population's overall assessment of the variables, this study focuses on delineating the relative significance of the factors. This objective is consistent with other published work, such as identifying the underlying constructs and strategies related to organizational BIM capabilities and developing an SEM to establish their relationships (Munianday et al., 2022), identifying a list of key decision criteria for the construction readiness of highway projects (Radzi et al., 2022) and key design features that support office building occupants from the adverse effects on health, well-being, and productivity (Tan & Rahman, 2023). Hence, the sample size is sufficient for achieving the study's aim and objectives.

Table 1: Potential factors influencing ETC adoption.

CODE	Factors influencing ETC adoption	Source
F01	Government involvement in the project	1,3.4, Interview
F02	Management's approach in making decisions	3,4
F03	Availability of industry standards	5,6,7,8
F04	Organization's strategic plan	Pilot study
F05	Project team's awareness	3,4,9
F06	Availability of related information	10,11
F07	Project team's competency	Pilot study
F08	Availability of external incentives (e.g., from government, project owner)	Interview
F09	Project team's confidence	Pilot study
F10	Adoption cost	1,5,6,9,12,13,14,15,16, Interview
F11	Project team's expectations	Pilot study
F12	Training cost	Interview
F13	Project team's preferences	Pilot study
F14	Procurement setup	3,4
F15	Project team's prior experience	3,4,17
F16	Communication process	3,4,17
F17	Project condition	4
F18	Project team's support	Pilot study
F19	Impact on project cost	1
F20	Readiness of technology	Pilot study
F21	Impact on the environment	5,11,13
F22	Impact on project resources	5
F23	Compatibility of technology	1,6,7,12,14
F24	Impact on legal (e.g., contract, liability)	10,15,16,17
F25	Availability of technology	1,17
F26	Impact on data security	17
F27	Technology's potential in developing new business services	Pilot study
F28	ROI of technology	Pilot study
F29	Impact on worker's competency	11, Interview
F30	Interoperability of technology	6,7,9,14
F31	Impact on project quality	6,12,13, Interview
F32	Mobility of technology	11
F33	Success rate of technology	Pilot study
F34	Impact on project duration	1,12, Interview
F35	User interface of technology	Pilot study

Note: 1. Pan et al., 2020; 2. Khudzari et al., 2021; 3. Akmam Syed Zakaria et al., 2017[a] . 4. Akmam Syed Zakaria et al. 2017[b]; 5. Correia et al. 2020; 6. Xu et al. 2014; 7. Chien et al. 2014; 8. Guven & Ergen, 2013; 9. Silverio-Fernandez et al. 2019; 10. Rose & Manley, 2014; 11. Häkkinen & Belloni, 2011; 12. Qi et al. 2020; 13. Darko et al. 2017; 14. Leite et al. 2016; 15. Khosrowshahi & Arayici, 2012; 16. Bohn & Teizer, 2010; 17. Gu & London, 2010.

4. ANALYSIS AND RESULTS

4.1 Reliability analysis

Before proceeding with further data analysis, reliability analysis was conducted to verify the consistency and reliability of the collected data (Tavakol & Dennick, 2011). Cronbach's alpha, a prominent approach for measuring the internal consistency of variables in surveys, was employed for this purpose (Salem et al., 2018). According to Santos (1999), Cronbach's alpha (α) values range from 0 to 1, with 0 indicating no reliability and 1 indicating perfect internal consistency across all variables measured on multipoint and/or dichotomous scales. Several reports on acceptable alpha values range from 0.70 to 0.95 (Tavakol & Dennick, 2011). However, according to Nunnally (1978), an alpha value not less than 0.70 is considered acceptable to ensure scale credibility. In this study, an overall Cronbach’s alpha value for the 35 factors is 0.950, indicating high reliability at a 95% significance level. The results confirm the adequacy of the collected data for further investigation.

Then, to assess the influence of respondent characteristics (such as organization type, organization size, and years of experience) on the criticality of the identified factors, a Chi-square analysis was conducted. In this analysis, a p-value below 0.05 indicates a statistically significant influence of these characteristics. The results revealed that only 2 out of 105 Chi-square values (approximately 1.9%) were below the threshold (refer to Table 2), specifically for communication process (F16) and project resources (F22), which had p-values of 0.008 and 0.028 for organization type and size. Given the overall influence was minimal (less than 5%), this analysis confirms that respondent characteristics had a negligible influence on the criticality of the factors. Consequently, no further comparison between different respondent groups was necessary, allowing this study to focus on the broader findings with confidence in their applicability across various respondent profiles.

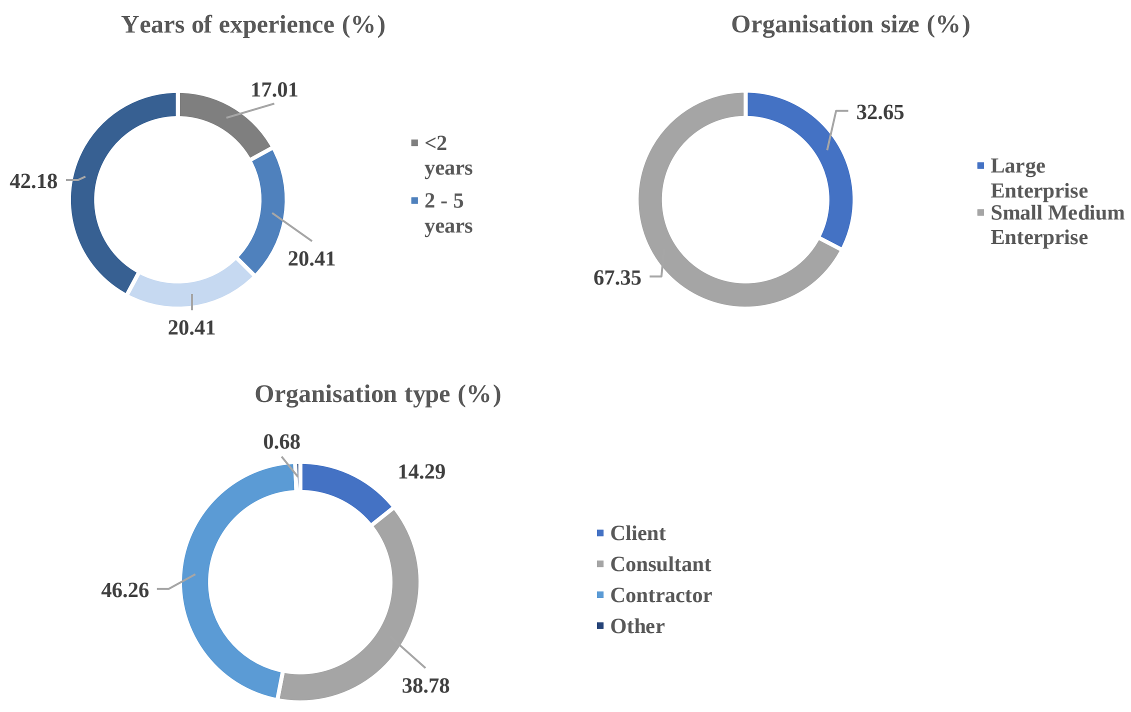

Figure 1: Respondent profile.

4.2 Mean score ranking and normalization analysis

The analysis commences by determining the ranking of the factors using mean score (MS) ranking analysis. A smaller standard deviation (SD) in MS indicates fewer disparities between responses and a more reliable mean (King et al., 2021). Consequently, when two or more factors exhibit identical means, those with the lowest SD are prioritized in ranking. Subsequently, normalized mean values are calculated to identify the key factors, defined as those with normalized mean scores of 0.50 or higher. The normalization analysis adjusts all data proportionately relative to the mean, providing a standardized measure across organizational characteristics.

Table 2 presents the results of the mean score ranking and normalization analysis. The analysis reveals that 14 factors exhibit normalized mean values exceeding 0.50, designating them as key factors. These key factors encompass a range of variables, including impact on project cost, ROI of technology, compatibility of technology, impact on project duration, availability of technology, readiness of technology, adoption cost, success rate of technology, management's approach in making decisions, impact on project resources, impact on project quality, technology's potential in developing new business services, organization's strategic plan and impact on worker's competency.

Table 2: Results for mean score ranking with normalization and chi-squared analysis.

Code	Mean	Standard deviation	Normalized values	Rank	Chi-squared (p-value)		
					Organization type	Organization size	Years of experience
F19	4.401	0.737	1.000 [a]	1	0.237	0.200	0.126
F28	4.211	0.830	0.711[a]	2	0.623	0.385	0.164
F23	4.190	0.770	0.680 [a]	3	0.968	0.608	0.648
F34	4.190	0.953	0.680 [a]	4	0.126	0.244	0.231
F25	4.177	0.897	0.660 [a]	5	0.732	0.419	0.583
F20	4.156	0.825	0.629 [a]	6	0.813	0.056	0.864
F10	4.143	0.965	0.608 [a]	7	0.461	0.895	0.432
F33	4.136	0.857	0.598 [a]	8	0.596	0.456	0.688
F02	4.129	0.901	0.588 [a]	9	0.313	0.665	0.419
F22	4.102	0.792	0.546 [a]	10	0.817	0.028[b]	0.718
F31	4.102	0.792	0.546 [a]	11	0.193	0.081	0.647
F27	4.082	0.790	0.515 [a]	12	0.416	0.881	0.824
F04	4.082	0.856	0.515 [a]	13	0.265	0.930	0.650
F29	4.075	0.845	0.505 [a]	14	0.707	0.614	0.711
F06	4.054	0.897	0.474	15	0.301	0.572	0.112
F18	4.041	0.883	0.454	16	0.095	0.511	0.307
F32	4.034	0.797	0.443	17	0.080	0.293	0.261
F17	4.027	0.875	0.433	18	0.322	0.636	0.414
F35	4.027	0.883	0.433	19	0.575	0.166	0.128
F05	4.007	0.925	0.402	20	0.338	0.950	0.206
F07	3.993	0.903	0.381	21	0.154	0.529	0.643
F03	3.973	0.844	0.351	22	0.817	0.716	0.986
F30	3.973	0.844	0.351	23	0.449	0.064	0.637
F11	3.952	0.909	0.320	24	0.469	0.801	0.207
F16	3.918	0.933	0.268	25	0.008[b]	0.573	0.283
F09	3.912	0.906	0.258	26	0.582	0.788	0.452
F15	3.837	0.965	0.144	27	0.466	0.794	0.075
F13	3.803	0.873	0.093	28	0.474	0.425	0.614
F08	3.803	1.089	0.093	29	0.310	0.867	0.464
F12	3.796	1.079	0.082	30	0.510	0.953	0.120
F21	3.789	1.055	0.072	31	0.544	0.159	0.347
F26	3.769	1.060	0.041	32	0.636	0.311	0.824
F24	3.755	1.102	0.021	33	0.121	0.119	0.850
F14	3.748	0.905	0.010	34	0.301	0.887	0.670
F01	3.741	1.171	0.000	35	0.616	0.537	0.055

Note: SD = Standard deviation.
NV = Normalized value = (mean – minimum mean)/ (maximum mean – minimum mean).
[a] the normalized value indicates that the factor is key (normalized ≥ 0.50).
[b] significant different criticality between subgroups (p-value < 0.05)

4.3 Agreement analysis

In this study, an effort was made to determine the key factors influencing ETC adoption. However, potential variations in perceptions among stakeholders such as clients, consultants, and co6ntractors exist. To uncover these differences, the study uses analysis of variance (ANOVA) to assess any significant differences in the mean scores across respondent groups (Boadu et al., 2020; Senouci et al., 2016). The analysis aims to determine whether organizational size, organizational type, and project specialization influence these perceptions (Dolla et al., 2023; Perera et al., 2023).

The results reveal the factors exhibit p-values greater than 0.50 for organizational type and project specialization, indicating no significant differences. However, significant differences are observed for organizational size. LEs demonstrated statistically higher mean scores than SMEs in three factors: readiness of technology, impact on project resources, and impact on legal. These findings underscore distinct perceptions and priorities in ETC adoption between LEs and SMEs.

Furthermore, many prior works in construction project management research have successfully used EFA for similar purposes. For instance, Kahvandi et al. (2019) used EFA to identify and categorize challenges in implementing Integrated Project Delivery (IPD). Similarly, Radzi et al. (2022) applied the same method to model the relationships between COVID-19 impacts and response strategies in the AEC industry. Both works highlight the value of EFA in uncovering latent constructs and providing insights into complex issues, whether understanding new project delivery methods or navigating the impacts of a global pandemic. These examples underscore the usage of EFA in this study.

To ensure the suitability of the data for EFA, the Kaiser-Meyer-Olkin (KMO) measure is employed to assess the sampling adequacy. The KMO value ranges between zero and one, and values closer to one indicate strong correlations between variables, making the sample appropriate for EFA (Qi et al., 2020). According to Kaiser (1970), a KMO value higher than 0.5 is suitable for EFA. In this study, the KMO value is 0.89, higher than the required minimum value, indicating that the data is suitable for EFA. Additionally, the Bartlett test of sphericity is used to determine if the variables are correlated by checking if the correlation matrix is an identity matrix. P-values below 0.05 indicate that the correlation matrix is not an identity matrix, meaning the variables are related and suitable for EFA. In this study, Bartlett's test of sphericity indicates a significance level of 0.00 and a test statistic of 1021.761, further confirming the data's suitability for EFA.

Table 3 summarizes the EFA results after the Varimax rotation. The analysis reveals three underlying constructs with eigenvalues greater than one, accounting for 55.946% of the total variance. Fourteen key factors are rotated using the varimax rotation approach. Of these, ten are successfully loaded into the three underlying constructs, and four key factors, adoption cost, technology's potential in developing new business services, success rate of technology, and impact on project duration, are excluded due to factor loadings lower than 0.50. Based on the key factors, the three underlying constructs are identified as organizational resources, goals, and strategy. This rigorous analysis demonstrates the efficacy of EFA in identifying and categorizing the key factors, offering a framework for future research and practical applications in the field.

Table 3: Results for the exploratory factor analysis.

Code	Key factors influencing ETC adoption	Construct		
		1	2	3
Construct 1: Organizational Resources				
F25	Availability of technology	0.714	-	-
F20	Readiness of technology	0.711	-	-
F23	Compatibility of technology	0.677	-	-
F19	Impact on project cost	0.694	-	-
F22	Impact on project resources	0.654	-	-
F28	ROI of technology	0.572	-	-
Construct 2: Organizational Goals				
F31	Impact on project quality	-	0.928	-
F29	Impact on worker's competency	-	0.549	-
Construct 3: Organizational Strategy				
F04	Organization's strategic plan	-	-	0.838
F02	Management's approach in making decision	-	-	0.647
Eigenvalue		3.708	2.220	1.905
Variance (%)		26.482	15.855	13.609
Cumulative variance (%)		26.482	42.337	55.946

Note: Extraction method: Principal Axis Factoring; Rotation: Varimax

4.4 Hypotheses for structural models

Based on the EFA results, the following hypotheses were developed to examine relationships between the 'ETC adoption decisions' and 'underlying constructs influencing ETC adoption':

- Hypothesis 1 (H1): ETC adoption decisions are affected by Organizational Resources
- Hypothesis 2 (H2): ETC adoption decisions are affected by Organizational Goals
- Hypothesis 3 (H3): ETC adoption decisions are affected by Organizational Strategy

4.5 Partial least square structural equation modelling (PLS-SEM)

Next, PLS-SEM, a method known for its effectiveness in demonstrating the relationships between latent and observable variables regardless of the data distribution, was employed to test the hypothesis. PLS-SEM stands out as a widely used and advanced multivariate data analysis technique, ideal for exploring complex relationships between these variables (Kineber et al., 2021). Its strength lies in its ability to investigate the relationship between multiple independent variables and a single dependent variable, providing valuable insights into the structural relationships within the data (Munianday et al., 2022).

4.6 Measurement model evaluation

The initial step in evaluating the reflective measurement model involves examining the factor loading of the variables aggregated from the EFA. For a factor to be considered valid, it must account for more than 50% of the variance in its indicator, with a minimum acceptable path coefficient or factor loading of 0.70 (Hair et al., 2019). As illustrated in Table 4 and Figure 2, all key factors exceed this 0.70 threshold, affirming their robustness.

Table 4: Summary of the reflective measurement model evaluation.

Constructs	Indicators	Loadings	AVE	CR (ρc)	CA (α)
Organizational Goals			0.797	0.887	0.760
	F29	0.945	-	-	-
	F31	0.837	-	-	-
Organizational Resources			0.644	0.900	0.864
	F20	0.850	-	-	-
	F22	0.755	-	-	-
	F23	0.813	-	-	-
	F25	0.852	-	-	-
Organizational Strategy			0.758	0.861	0.721
	F28	0.735	-	-	-
	F02	0.961	-	-	-
Decision-making			0.683	0.811	0.546
	D01	0.770	-	-	-
	D02	0.765	-	-	-

Note: AVE: Average variance extracted; CR: Composite reliability; CA: Cronbach alpha

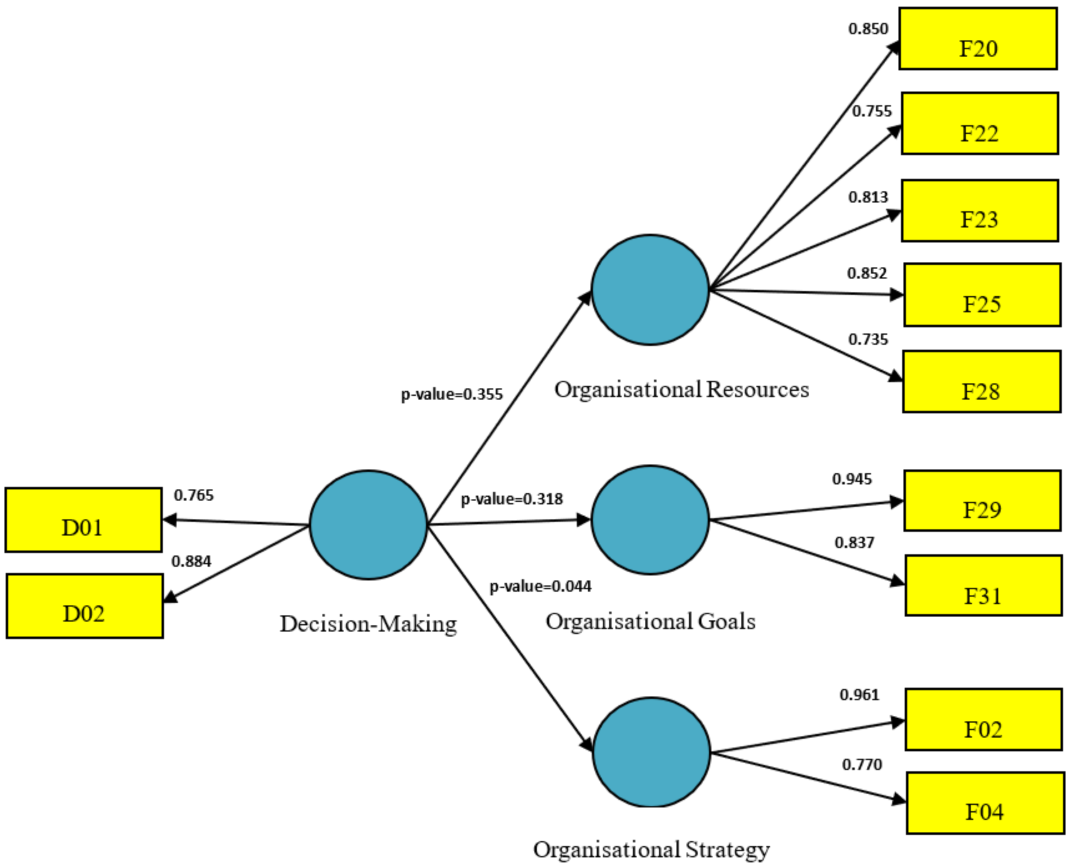

Figure 2: Measurement model.

To ensure the internal consistency of the constructs, Cronbach's alpha (α) and composite reliability (ρc) are used to examine adherence to the recommended lower limit of 0.70 (Hair et al., 2019; Henseler et al., 2016; Wong, 2013). Internal consistency is critical as it verifies that the variables accurately measure the intended constructs, ensuring reliable results. The analysis, presented in Table 4, indicates that the construct 'ETC adoption decisions' has the lowest α value. However, its ρc surpasses the acceptable threshold. These results suggest that despite lower internal consistency, 'ETC adoption decisions' still maintain a satisfactory level of reliability.

Then, the convergent validity is assessed using average variance extracted (AVE) to ensure that the measurement variables are free from systematic measurement errors. The ideal cut-off for AVE is 0.5, which is essential for establishing that the variables within a construct share a high proportion of variance, thus capturing the same underlying concept. (Fornell & Larcker, 1981; Hair et al., 2019). The analysis demonstrates that all variables satisfy this requirement, indicating a robust measurement model.

To test the discriminant validity, which ensures the empirical distinction between constructs, the heterotrait–monotrait (HTMT) ratio was employed, with a lower limit of < 0.85 (Hair et al., 2019; Henseler et al., 2016). According to Franke and Sarstedt (2019), clear discrimination between constructs requires an HTMT value of less than 1, ideally below 0.85. As illustrated in Table 5 shows, all constructs had HTMT values below 0.85, affirming that each construct is distinct and that the variables measuring them are unique.

For hypotheses testing and determining the significance of the path coefficients, this study employed the bootstrapping method, a non-parametric resampling technique that estimates the sampling distribution of a statistic by generating multiple samples from the original data. Five thousand bootstrap samples are used in this investigation (Hair et al., 2011). As shown in Table 6, the path coefficient for Hypothesis 3 is positive and significant at $p<0.01$, indicating a statistically significant relationship. In contrast, the path coefficients for Hypotheses 1 and 2 are low, suggesting that the data do not support the proposed relationships in these hypotheses.

Table 5: Heteroit-Monotrait (HTMT).

Constructs	ETC adoption decisions	Organizational Goals	Organizational Resources
Organizational Goals	0.133	-	-
Organizational Resources	0.144	0.761	-
Organizational Strategy	0.253	0.378	0.412

Table 6: Structural model evaluation.

Hypothesis	Path	Path coefficient	P-value	Decision
H1	ETC adoption decisions -> Organizational Resources	-0.111	0.355	Not Supported
H2	ETC adoption decisions-> Organizational Goals	-0.096	0.318	Not Supported
H3	ETC adoption decisions-> Organizational Strategy	-0.173	0.044	Supported[a]

Note: [a] when $p<0.05$

5. DISCUSSION

5.1 Relationship between 'ETC adoption decisions' and 'Organizational Strategy'

The PLS-SEM analysis has shown that 'organizational strategy' significantly influences decision-making related to ETC adoption. These results indicate the pivotal role organizational strategy plays in guiding emerging technology adoption decisions within construction organizations. It demonstrates that strategic orientations dictate how decision-makers approach and prioritize the integration of emerging technologies. For instance, a strategic focus on innovation and sustainability may lead to the proactive adoption of advanced construction methodologies and materials to enhance operational efficiency and environmental responsibility. Conversely, a strategy emphasizing cost minimization may result in a cautious approach to technology adoption, which only prioritises proven emerging technologies that offer clear cost benefits. Other than that, this finding also underscores the necessity for construction organizations to align their strategic planning with technological advancements to maintain competitiveness and meet evolving industry standards and expectations. Moreover, it suggests that strategic adjustments may be essential for organizations lagging in emerging technological adoption (Hendrawan et al., 2024), providing a clear directive for re-evaluating and possibly reshaping strategic frameworks to better support the advancements. This alignment facilitates the strategic adoption of technology, optimizes resource allocation, and enhances organizational agility in responding to dynamic market demands and technological opportunities.

5.2 Relationship between ‘ETC adoption decisions’ and ‘Organizational Resources’

PLS-SEM analysis examining the influence of organizational resources on the decision-making process for adopting emerging technologies in the Malaysian construction industry presented an unexpected outcome: organizational resources, despite being critical underlying factors in exploratory factor analysis (EFA), did not significantly influence decision-making, as evidenced by a p-value greater than 0.05. This result challenges conventional assumptions about the direct role of resources in technological adoption (Khudzari et al., 2023; Zamani, 2022; Kristianto et al., 2012). EFA analysis identified several of the most influential factors under the umbrella of organizational resources. However, the PLS-SEM analysis results show that despite the critical nature of these factors, their presence alone did not predict or significantly influence the adoption decisions. This suggests that other non-resource-based factors may play more decisive roles in influencing emerging technology adoption decisions. Furthermore, this outcome prompts a need for a deeper evaluation of how resources are managed, suggesting that merely having access to technology and financial assets is insufficient.

5.3 Relationship between ‘ETC adoption decisions’ and ‘Organizational Goals’

The rejection of the hypothesis that organizational goals significantly influence decisions to adopt emerging technologies, as indicated by a p-value greater than 0.05 in a PLS-SEM analysis, suggests that the connection between these goals and technology adoption decisions might be weaker or less direct than initially assumed. This could indicate a need for re-evaluating and possibly redefining organizational goals to encapsulate the benefits of technological advancements better. It might also suggest that other factors, outside of stated goals, are currently more influential in guiding decision-making processes.

5.4 Study Implications

5.4.1 Practical Implications

The study findings have substantial implications for AEC organizations looking to adopt ETC. By identifying the key factors influencing ETC adoption, organizations can better assess their readiness and develop targeted strategies to overcome potential challenges. Although organizational resources and goals are essential considerations, this study highlights the role of organizational strategy in driving ETC adoption decisions. A clear and coherent strategy that aligns technology investments with broader objectives and addresses project-specific needs and challenges is critical for optimizing the ETC adoption process. This approach can enhance project performance, reduce costs, and bolster competitiveness within the industry. Furthermore, the study emphasizes the importance of cross-functional collaboration and communication in ETC adoption. A culture of openness and collaboration can facilitate knowledge sharing and learning across different departments and teams, building the necessary skills and expertise for successful ETC adoption. By embracing these implications, AEC organizations can effectively navigate the ETC adoption process, ensuring smooth and beneficial integration, ultimately leading to improved project outcomes and more substantial market positions.

5.4.2 Managerial Implications

The study findings also have implications for external stakeholders, such as policymakers and industry associations, in promoting ETC adoption. By understanding the key factors, stakeholders can design targeted initiatives to support organizations in overcoming adoption challenges. Policymakers, for example, can develop tax incentives, grants, or other financial support mechanisms to encourage AEC organizations to adopt ETC. Meanwhile, industry associations can facilitate knowledge sharing, training, and collaboration among AEC organizations to build the required skills and expertise. Moreover, external stakeholders can drive standardization and certification efforts to streamline ETC adoption. Developing standards and guidelines can create a shared understanding of ETC adoption processes, allowing organizations to navigate this complex landscape more effectively. These initiatives can also help to reduce uncertainties and risks associated with ETC adoption, fostering a more conducive environment for innovation and growth in the AEC industry.

5.4.3 Theoretical Implications

Finally, the study findings contribute to the existing literature on ETC adoption, offering insights into the interplay of different factors in the adoption process. The study findings lay a foundation for future research aiming at evaluating the effectiveness of different initiatives to increase ETC adoption rates. By enhancing the understanding of ETC adoption factors, researchers can develop more effective models and theories that inform decision-making processes for AEC organizations, policymakers, and industry associations. As ETC continues to transform the AEC industry, understanding the factors that drive the adoption is essential for ensuring long-term sustainability and success. This study enriches the understanding of these factors and offers a theoretical framework for analyzing ETC adoption decisions, paving the way for more informed and strategic advancements in the field.

5.5 Limitations and Future Directions

One limitation of this study is its reliance on a cross-sectional research design, which provides a snapshot of the factors influencing ETC adoption at a specific time. Although cross-sectional research designs offer valuable insights, they may not fully capture the dynamic nature of the subject matter, as data is collected at a single point in time (Wang & Cheng, 2020). Given the rapid changes in emerging technologies, market conditions, and industry practices, the factors identified in this study might evolve in future contexts (Wood, 2022). Additionally,, a cross-sectional design does not allow for examining causal relationships (Wang & Cheng, 2020). Consequently, it may be challenging to determine whether the identified factors directly influence changes in adoption rates or if other unmeasured factors are driving the observed relationships. Furthermore, the study findings might be limited to the Malaysian context as the data collection involves construction industry professionals from Malaysia only.

To address this limitation, future research can employ a longitudinal research design, which involves collecting data at multiple time points. This approach allows researchers to track changes in factors influencing ETC adoption over time and to establish causal relationships between these factors (Rindfleisch et al., 2008). Additionally, expanding the scope of the study to include professionals from different countries would provide a more comprehensive understanding of ETC adoption. Comparative research across different cultural and economic contexts can identify similarities and differences in the factors influencing ETC adoption between countries. Such an approach would provide a deeper understanding of ETC adoption decisions, offering valuable insights for AEC organizations as they navigate the complex landscape of ETC adoption.

6. CONCLUSION

In conclusion, this study identified the key factors influencing ETC adoption and developed an SEM to analyze their relationships, using Malaysia as a case study. The analysis identified 14 key factors influencing ETC adoption. These factors include project cost impact, ROI of technology, technology compatibility, project duration impact, technology availability, technology readiness, adoption cost, technology success rate, management's decision-making approach, project resources impact, project quality impact, technology's potential for developing new business services, organizational strategic plan, and impact on worker competency. While organizational type and project specialization showed no significant differences, significant differences were observed based on organizational size. LEs reported higher mean scores than SMEs in technology readiness, project resources impact, and legal impact. The EFA revealed three underlying constructs—organizational resources, goals, and strategy. Ten out of the fourteen key factors were successfully loaded into these constructs. The PLS-SEM analysis revealed that organizational strategy plays a significant role in ETC adoption decisions among those three underlying constructs. This underscores the importance of adopting a comprehensive, long-term strategic approach when considering ETC adoption in construction projects. These findings provide a nuanced understanding of the dynamics influencing ETC adoption, offering actionable insights for industry stakeholders aiming to leverage technology effectively in construction project management.

The study findings provide significant implications for AEC organizations considering ETC adoption. By identifying key factors, organizations can assess readiness and develop tailored strategies to overcome challenges effectively. This study emphasizes the critical role of organizational strategy in shaping ETC adoption decisions, stressing the need to align technology investments with broader organizational goals and address project-specific needs to optimize the adoption process. Facilitating cross-functional collaboration and communication is crucial for successful ETC adoption, enabling knowledge sharing across departments and enhancing the skills necessary for effective implementation. Embracing these implications empowers AEC organizations to navigate the ETC adoption journey, ensuring seamless integration and yielding improved project outcomes and enhanced market positioning. Policymakers and industry associations can leverage these insights to design initiatives supporting ETC adoption, such as introducing incentives like tax benefits or grants and promoting knowledge exchange and training programs among AEC organizations. These implications contribute to the current body of knowledge by elucidating adoption dynamics and enabling future research to evaluate strategies and develop models that inform decision-making for AEC organizations, policymakers, and industry associations, thereby enriching theoretical understanding and providing a practical framework for analyzing ETC adoption decisions in the evolving AEC landscape.

ACKNOWLEDGEMENT

This work was supported by Universiti Malaysia Pahang Al-Sultan Abdullah (RDU223314). The authors thank the participants for their time and participation in the survey to make this study possible. The authors are also grateful to the editors and anonymous reviewers for their insightful comments, which improved this paper's quality.

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