Li, R., Oo, B.L., Lim and B.T.H., 2026. A theoretical framework for the adoption of artificial intelligence technologies in the construction industry. In: Waidyasekara, K.G.A.S., Jayasena, H.S., Chandanie, H. and Tennakoon, G.A. (eds). *Proceedings of the 14th World Construction Symposium*, 10-11 July 2026, Sri Lanka. pp. 121-134. DOI: https://doi.org/10.31705/WCS.2026.10. Available from: https://ciobwcs.com/papers/

A THEORETICAL FRAMEWORK FOR THE ADOPTION OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN THE CONSTRUCTION INDUSTRY

R. Li[1], B.L. Oo[2], and B.T.H. Lim[3]

ABSTRACT

Despite the extensive research on the applications of Artificial Intelligence (AI) technologies in the construction industry, little attention has been given to the theoretical perspective on varying levels of AI adoption by the industry stakeholders. This research aims to address this gap by proposing a theoretical framework for understanding the adoption of AI technologies in the construction industry. The framework was developed through a review of literature, and it draws on four underpinning theories, namely: the Technology–Organisation–Environment (TOE) framework, the Technology Acceptance Model (TAM), the Innovation Diffusion Theory (IDT) and the Stakeholder Theory (SKT). The TOE framework and IDT shape the influencing factors at the macro-level, while the TAM captures the factors at the micro-level along with SKT for defining the relevant stakeholders of the AI adoption in the construction industry. By connecting individual, organisational, and industrial factors at macro- and micro-levels that impact AI adoptions in the industry, the framework provides a better understanding of the complex interplay of the respective factors in informing future research.

Keywords: *Artificial Intelligence (AI); Construction Industry; Theoretical Framework.*

1. INTRODUCTION

AI technologies have been increasingly developed and adopted in various fields and industries in recent decades. In the Construction Industry (CI), AI applications have been playing an essential role in many aspects, including rendering optimisation (Khan et al., 2024), schedule management (Datta et al., 2024), risk mitigation (Kampelopoulos et al., 2025), and cost estimation (Bhargava et al., 2017). Many researchers opined that introducing AI applications across the entire Construction Project Life Cycle (CPLC) could contribute positively towards construction project deliveries (Regona et al., 2024; Abioye et al., 2021; Khan et al., 2024). Despite the growing expectations of AI technologies toward their potential abilities in construction project deliveries, their applications in the construction industry are still in their initial phase and remain

[1] PhD Candidate, School of Built Environment, The University of New South Wales, Australia, z5380160@ad.unsw.edu.au
[2] Associate Professor, School of Built Environment, The University of New South Wales, Australia, bee.oo@unsw.edu.au
[3] Associate Professor, School of Built Environment, The University of New South Wales, Australia, b.lim@unsw.edu.au

fragmented (Regona et al., 2024). Moreover, various studies reported the trends of resistance to AI adoption (Dauda et al., 2025; Ojha et al., 2022; Omar et al., 2022), suggesting a divergence between the development of new AI technologies and their adoption in practice. To explore the underlying elements or factors behind this discrepancy, existing studies have explored the barriers and challenges of AI applications in the CI. These studies usually summarised the findings from two perspectives. One is the technological limitations, including challenges such as cybersecurity (Olatunde et al., 2023; Maqbool et al., 2022), data integration and collaboration (Wang et al., 2021; Van Tam et al., 2024; Shang et al., 2023), and compatibility and longevity (Gamil et al., 2020). The other aspect is stakeholder- or employee-related factors, involving apprehension among stakeholders (Ojha et al., 2022; Wang et al., 2025; Shang et al., 2023), disinterest in learning a new technology (Musarat et al., 2024), and resistance to change (Musarat et al., 2024; Wang et al., 2021). Although these studies provide an insight into factors influencing AI adoption, little attention has been paid to the roles of key stakeholders who may impact the level of acceptance and application of AI technologies. Specifically, current research on AI applications in the CI lacks sufficient theoretical supports for comprehending the varying levels of adoption by the industry stakeholders. Additionally, the influencing factors and/or elements are often categorised as isolated or scattered, without integrating into a coherent theoretical structure. To address these research gaps, this study aims to propose a theoretical framework that integrates four underpinning theories to better understand the AI adoption in the CI from a multi-level perspective. To achieve this research aim, the research objectives are to: (i) to identify technology diffusion theories and models from different disciplines and explore their applicability to the CI; (ii) establish a theoretical structure for integrating individual, organisational, and industrial factors; and (iii) explore the potential connections of micro- and macro-level factors that affect AI adoption in the CI.

2. RESEARCH METHOD

A literature review was performed to investigate theories and models of technology diffusion from different contexts (e.g., technological, organisational, and environmental contexts) in exploring their potential applicability to AI adoption in the CI context. The search for related papers was conducted through Scopus and supplemented by Google Scholar. The criteria of paper selection are: (i) the paper should be a peer-reviewed journal article or conference paper; (ii) the paper should be written in English; and (iii) the paper should focus on AI adoption, advanced technology diffusion, or digital transformation in CI context. However, as limited studies present theoretical perspectives of AI adoption in the CI, the literature review process has selected the relevant theories and models across various disciplines and/or industries [e.g., information and communication technology (ICT) disciplines, and CI], which have been empirically validated. These theories and models cover individual perspectives and attitudes at the micro-level, with environmental, organisational, and technological contents at the macro-level. The insights of the literature review provided the theoretical foundation of the proposed framework.

3. NEW TECHNOLOGY ADOPTION THEORIES

Researchers who focus on the technological innovation field have evaluated and recommended several theories, which include the Technology-Organisation-

Environment (TOE) framework, Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Stakeholder Theory (SKT). These theories are identified as common theories in explaining the technology adoption and utilisation. Furthermore, the integrations of several theories were proposed in previous studies, such as TOE and TAM (Na et al., 2022), TOE and IDT (Wang et al., 2010; Oliveira et al., 2014), and TAM and IDT (Wang et al., 2010; Yuen et al., 2020). The trend implies that a single model or theory may not be sufficient to explain the processes of new technologies' adoption and acceptance. Indeed, with the exponential growth and development of advanced technologies, it is plausible that researchers seek to integrate a combination of diverse theories and/or models in comprehending innovation transmission. Considering these, the review of literature performed in this study presents how existing studies integrated various theories, and how these theories can be applied in the context of AI adoption in the CI.

3.1 TOE FRAMEWORK

The TOE framework was proposed by Tornatzky and Fleischer (1990) to explain the implementation of innovation at the organisation or firm level (Nguyen et al., 2022). The advantage of the TOE framework is that it enables the reflection from both internal and external dimensions of the decision-making process of new technologies' acceptance (Nguyen et al., 2022). They categorised the contexts that directly impact technology adoption of entrepreneurs in three aspects, i.e. (i) technology, (ii) organisation, and (iii) environment, as illustrated in Figure 1.

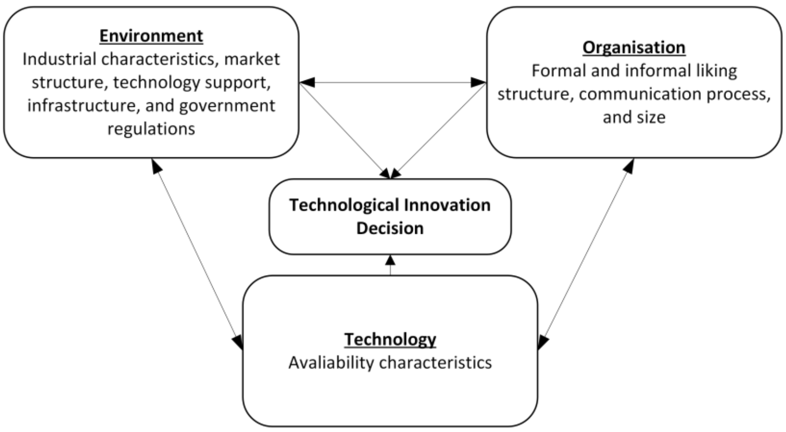

Figure 1: Technology-Organisation-Environment (TOE) framework
Source: Tornatzky and Fleischer (1990)

This model is identified as an organisation-dimension theory for explaining a firm's decision to utilise new technologies (Baker, 2011). These three elements interact with one another (Tornatzky & Fleischer, 1990), as further detailed below:

Technological context - It refers to all related technologies to the firm, including current equipment and systems the firm utilises, as well as the technologies that are currently available in the marketplace but not adopted (Baker, 2011).

Organisational context - It refers to resources and characteristics of an organisation or firm, such as firm size, management structure among employees, and the amount of available resources (Baker, 2011). Specifically, these elements can impact a firm's decision to adopt new systems via various approaches, for instance, connecting internal subunits of an organisation or spanning internal boundaries to promote innovation.

Environmental context - It is the field where entrepreneurs operate their businesses, particularly, containing the industrial structure, regulatory status, and technological infrastructure support (Baker, 2011). Furthermore, this context includes the industry, competitors and government factors (Oliveira & Martins, 2011).

Kuan and Chau (2001) adopted the TOE model to explore the factors that led to the successful utilisation of electronic data interchange and verified the usefulness of the TOE framework in evaluating organisational decisions of IT technology adoption. Similarly, Oliveira and Martins (2011) used the TOE framework to compare the different influencing factors of e-business adoption between the telecommunications and tourism industries. The TOE framework has also been identified in other studies explaining various ICT systems adoption statuses (e.g., Malik et al., 2021; Mohammad et al., 2022; Nguyen et al., 2022). According to Hughes et al. (2025), with the adoption of the TOE framework, they proposed that the adoption of Generative AI (GenAI) in the CI is most likely to be driven by employees' talent in using GenAI and blocked by technological complexity. Their study provided an insight into the possibility of applying the TOE framework in research related to AI adoption in the CI. It is noted that the flexibility and comprehensiveness of the TOE model enable its adoption in different industries and technologies, including interdisciplinary research (Sun et al., 2025). Overall, the evidence from previous studies suggests that the TOE model can be well adopted with other theories in comprehending the adoption of new technologies.

3.2 TAM

The TAM, which was proposed by Davis et al. (1989), provides a fundamental framework for explaining how new technologies are accepted by individual users. Figure 2 illustrates two essential elements of this model: (i) Perceived Usefulness (PU) and (ii) Perceived Ease Of Use (PEOU). According to Davis (1989), the extend people tend to accept or reject using an advanced technology is related to their belief that it will assist them in completing their tasks better, which is PU in the TAM theory. Accordingly, if users deem that the new system is too hard to master, and the benefits of the application are outweighed by the difficulties of using it, they will prefer to resist the adoption of the advanced system. This is defined as PEOU. Researchers adopted scale development procedures and empirical validation to test the impacts of PU and PEOU on users' willingness to accept new technologies (Hur et al., 2017; Liu & Ye, 2021; Wang et al., 2021). Furthermore, these studies demonstrated that PEOU not only affect the utilisation of new technologies directly but also influences the utilisation through affecting PU.

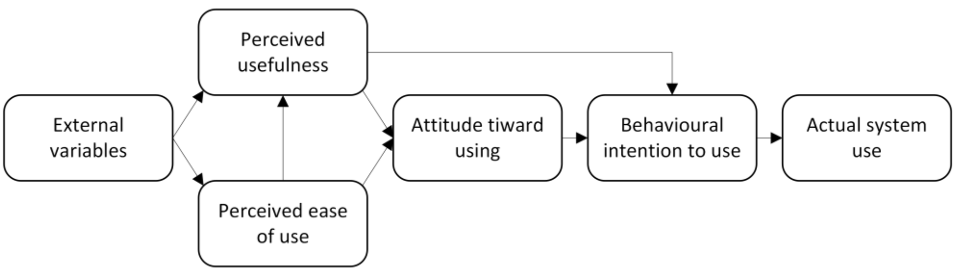

Figure 2: Technology Acceptance Model (TAM) framework
Source: Na et al. (2022)

The Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) indicates a significant consolidation of different theories in the investigation of new technology acceptance. By integrating eight models, including the TAM model, the Theory of Planned Behaviour (TPB), and the Model of Personal Computer Utilisation (MPCU), this theory identified four key elements that affect user intention and use behaviour: performance expectancy, effort expectancy, social influences, and facilitating conditions. Venkatesh et al. (2003) claimed that the empirical results demonstrated a higher accuracy in explaining the acceptance extension of users compared to earlier models. Hassan (2025) identified the usage of TAM in evaluating AI adoption in the Egyptian talent acquisition process. This study supported the feasibility of introducing TAM in AI adoption research, despite its research field is outside the CI. Although UTAUT successfully integrated relative models, it primarily retains an individual dimension focus, while providing limited insights into the impacts of multi-dimensional engagement.

3.3 IDT

The IDT was proposed to explain how individuals decide to adopt or reject an innovation by identifying five stages of innovation adoption, namely: knowledge, persuasion, decision, implementation, and confirmation (Rogers 1995). However, Moore and Benbasat (1991) demonstrated that IDT should emphasise the characteristics of the innovation, instead of the attitude of potential users. Based on this perspective, they proposed eight elements as the determining factors of IDT i.e. (i) relative advantage, (ii) ease of use, (iii) compatibility, (iv) image, (v) result demonstrability, (vi) visibility, (vii) voluntariness, and (viii) trialability. Similarly, Poong et al. (2009) proposed that result demonstrability, compatibility and relative advantage can positively impact the stakeholders' intention to conduct the innovation. In a statistical model by Yuen et al. (2020), they found that relative advantage, compatibility, complexity, and trialability have a positive influence on users' acceptance level of innovation. They summarised the findings of relevant studies and proposed five elements that can be used to evaluate and predict users' adoption of innovation i.e. (i) relative advantage, (ii) compatibility, (iii) complexity, (iv) experimental, and (v) observability. Steiber et al. (2021) applied the IDT to deepen the understanding of the elements affecting an industrial firm's digital transformation. They suggested that the IDT is effective in identifying factors that affect the adoption level of innovation from its own side. According to the above-mentioned studies, IDT established a connection between technology adoption and acceptance with the innovation itself at the organisational level.

3.4 THE INTEGRATIONS OF TOE FRAMEWORK, TAM AND IDT

The TOE framework has been widely adopted to explore organisation-level factors influencing technology adoption and acceptance. At the individual level, TAM provides the perspective of how individuals' intentions impact the new technologies' adoption through PU and PEOU (Davis et al, 1989). Meanwhile, IDT has been used in the field of Information and Communications Technology (ICT) research to evaluate the extension of new technologies in organisations (Meade & Islam, 2006; Yuen et al., 2020). Existing studies attempted to integrate them together to gain a better understanding of the processes of new technologies' adoption from different perspectives. Table 1 illustrates the integration of these frameworks and theories, including TOE with TAM, TAM with IDT, and TOE with IDT.

Table 1: The summary of models and theories integrations

Model or framework	Fields or industries	Reference
TOE + TAM	CI	Na et al. (2022); Na et al. (2023)
TAM + IDT	ICT field	Wang et al. (2010); Al-Rahmi et al. (2019); Yuen et al. (2020)
TOE + IDT	ICT field	Soares-Aguiar and Palma-dos-Reis (2008); Wang et al. (2010); Oliveira et al. (2014)

In the CI context, Na et al. (2022) contributed to the connection between individual and organisational factors by examining the relationships across PU, PEOU, and external factors. Their findings emphasised the importance of PU in shaping user intention of advanced technology, while organisational and environmental factors influenced adoption outcomes at the same time. In addition, they confirmed that PU and PEOU are influenced by external factors, including technological, organisational, and environmental contexts. Specifically, challenges and motivations from the contextual dimension can affect stakeholders' attitudes through PU and PEOU. Additionally, Na et al. (2023) found that PU could positively influence the intention of using new systems, implying the potential utilisation of TAM and TOE models in explaining the adoption of AI technologies in the CI. Despite the wide utilisation and acceptance of the integrated structure of the TOE framework and TAM in explaining new technology adoption, this integration still provides limited consideration of innovation diffusion. Despite the integration of the TOE framework and TAM, researchers also suggested that the integration of the TAM and IDT shows a high level of suitability for examining new technology adoption (Wang et al., 2010; Yuen et al., 2020). By applying a combination of TAM and IDT models, Al-Rahmi et al. (2019) tested the applicability of this integration by investigating the factors affecting the use of the e-learning system among students empirically. Next, Yuen et al. (2020) used the integrated model of IDT and TAM to evaluate the adoption of autonomous vehicles among users and investigate the factors that impact the acceptance intentions of users. Besides, researchers have tried to integrate the TOE framework with IDT theory in the ICT field. The integration was applied in examining the adoption of these advanced technologies' systems: electronic procurement systems (Soares-Aguiar & Palma-dos-Reis, 2008), radio frequency identifications (Wang et al., 2010) and cloud computing systems (Oliveira et al., 2014). Overall, these theoretical integrations have been widely applied across different fields, including the CI context and the ICT fields. By combining organisational, technological, and individual perspectives, previous studies provide a comprehensive explanation of technology adoption processes across different domains. Nevertheless, these studies rarely consider the influences from users or relevant stakeholders of new technologies adoption. This gap is particularly distinct in the CI context, where multiple actors are involved in construction project deliveries. Thus, a clear definition of stakeholders is necessary to provide a comprehensive theoretical perspective.

3.5 SKT

The SKT was proposed by Freeman (1984), who demonstrated that the achievement of a firm depends on the value it creates for their various stakeholders. According to this perspective, organisations are required to consider and manage the relationships between both individuals and groups that can affect or are affected by organisational activities.

Freeman (1984) first categorised the different stakeholders based on their level of involvement and influence on the business. Primary (also known as internal) stakeholders are defined as the groups or individuals that directly affect the decision-making process of creating the company's value. In other words, primary stakeholders are directly influenced by a firm's interests or outcomes. For the secondary stakeholder, who is not directly involved in organisational operations but could still influence or be influenced by a firm's decisions and practices. However, Freeman et al. (2010) demonstrated that there is no clear boundary between the primary and secondary stakeholders.

The complex construction project management process indicates that the coordination with stakeholders is a significant challenge (Agyemang et al., 2025). Due to this, the adoption of AI technologies should be considered as a multi-aspect decision, as it is influenced by various stakeholder groups. Newcombe (2003) introduced the SKT into the construction field to identify stakeholders in construction projects by using a case study with power/predictability and power/interest matrices to demonstrate that clients in a construction project include multi-party alliances. Accordingly, in the CI, the primary stakeholders have usually been referred to as investors, employees, contractors, suppliers, clients, and shareholders, as shown in Figure 3.

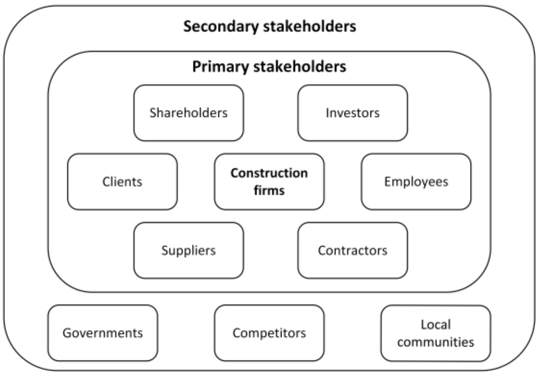

Figure 3: Stakeholders in the CI context
Source: Newcombe (2003)

The secondary stakeholders in the CI usually include governments, local communities, and competitors. Olander and Landin (2005) applied SKT to construction project management processes by proposing a stakeholder impact analysis method to examine their influences on construction projects. Agyemang et al. (2025) emphasised that the multi-organisational and fragmented natures of construction projects lead to a complex situation of multi-stakeholders. Existing research has conducted SKT to analyse construction interest conflicts (Olander & Landin, 2005), decision-making process influences (Shahbaz et al., 2018), and risk management approaches (Zanjirchi & Moradi, 2012). Evidently, SKT has been widely adopted in construction research to shed light on the coordination of stakeholders' relationships and mitigate conflicts between different parties from a theoretical perspective. However, there is a lack of application of SKT for explaining new technologies' adoption in the CI. In this study, SKT is embedded in the proposed theoretical framework as detailed next.

4. THE PROPOSED THEORETICAL FRAMEWORK

As revealed in Section 2, existing studies tend to propose theoretical integrations at a single level. For instance, combining TOE and IDT to represent the macro level, and using TAM to represent the micro level. Thus, limited studies exist that integrate macro- and micro-dimensional perspectives. Furthermore, SKT has been noted for frequently conducting research in the CI to identify and define stakeholders. However, its collaboration with the theories of technology adoption remains limited. Accordingly, this study proposes an integrated theoretical framework on the adoption of AI technologies in the CI that is underpinned by four theories as illustrated in Figure 4.

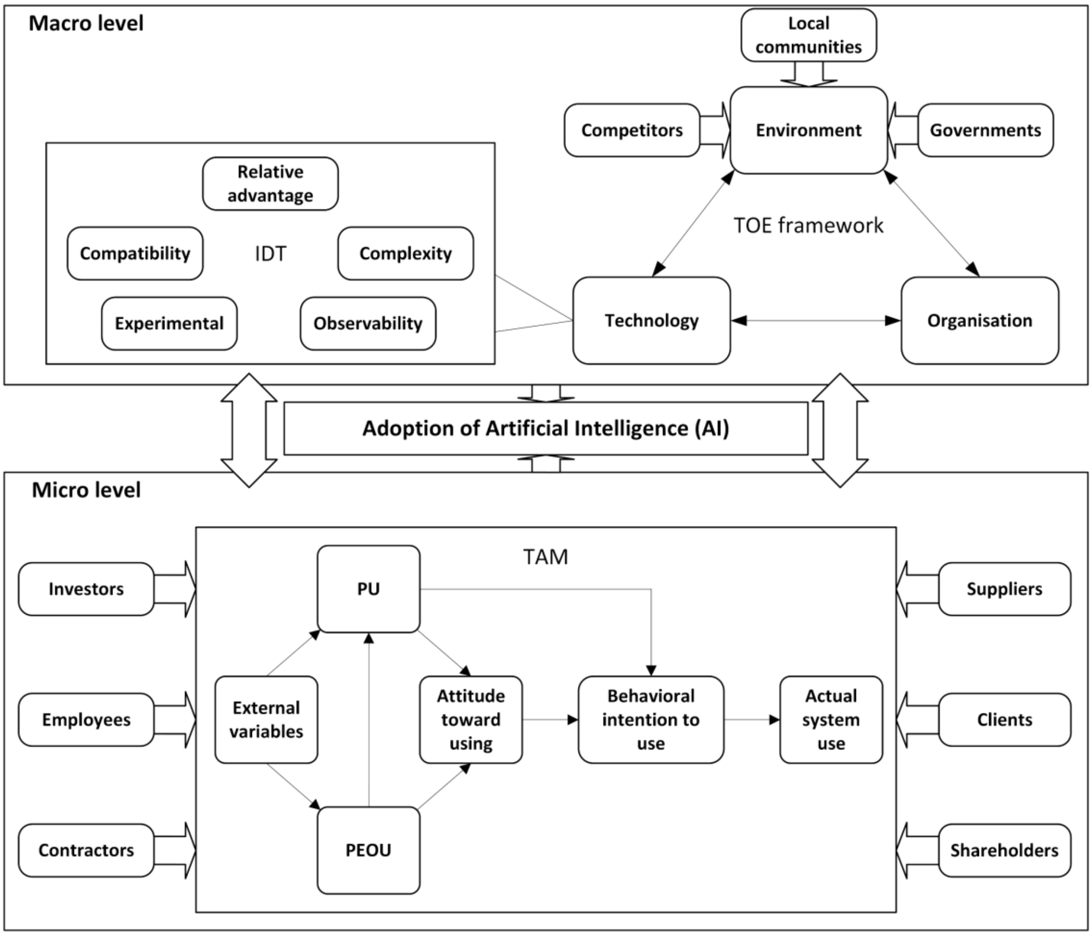

Figure 4: The proposed theoretical framework
Source: Authors' own work

The framework captures both the micro and macro-level factors from organisational and individual levels that influence the adoption of AI technologies in the CI as discussed next.

4.1 MACRO-DIMENSION THEORIES INCORPORATION

To explain the factors that affect the adoption of AI technologies in the CI, the TOE model and IDT are embedded in the macro-level of the structure, which represents the macro-level theories (i.e., the top structure of Figure 4). The TOE framework involves three contexts at the macro level: technology, organisation, and environment. The technological context, which concerns both current utilised and unutilised AI technologies' characteristics that are relevant to construction firms (Na et al., 2023). For instance, the technological context could include immature AI technologies (Ojha et al., 2022), current software limitations to integrate AI systems (Perera et al., 2023), and a lack of robustness between current technological systems and AI technologies (Gamil et al., 2020). On the other hand, the organisational context refers to the internal characteristics of construction firms that influence their capability to adopt or apply AI technologies. It includes the coordination and communication between different firms' structural levels (Peter, 2023), in the absence of adequate management guidelines (Gamil et al., 2020). This aspect addresses the structural and managerial conditions from construction firms' perspective on AI adoption. Next, the environmental context refers to the external environment surrounding construction firms, incorporating the industry itself, competitors, and government rules and regulations. These include the fragmented and complex natures of the CI (Ojha et al., 2022) and the lack of professional skills toward AI adoption (Peter, 2023). Furthermore, the factors across these three contexts are interdependent (Baker, 2011). For example, in a situation where a construction firm is exploring the opportunity of adopting a new AI technology, which would involve the assessment of the feasibility and compatibility of the new technology with its existing operating system. Managerial support, availability of skilled employees, and cost of new technology adoption determine whether the firms' capacity to adopt the respective new AI technologies. Meanwhile, external environmental impacts, including client requirements, competitive dynamics, and regulatory requirements of compliance, may be referred to as incentives or constraints that influence firms' decision-making process. Although the TOE framework identifies three contexts that influence the adoption of AI technologies, it does not explain how the intrinsic perspective of AI technologies impacts the adoption process. Therefore, to broaden the coverage of factors that influence, the IDT is introduced in this framework.

As a theory that contributes to explaining the characteristics of new technologies, IDT is frequently used in research related to the adoption of advanced technologies as a widely recognised theory (Oliveira et al., 2014; Malik et al., 2021; Na et al., 2022). In this framework, the IDT proposed by Yuen et al. (2020) is applied, which introduces five characteristics i.e. (i) relative advantage, (ii) compatibility, (iii) complexity, (iv) experimental, and (v) observability. The IDT is a refinement of the TOE model in the proposed framework, providing a particular perspective from AI technologies on the macro scale. Additionally, the impact of technologies can diffuse to all contexts at the organisational dimension, which reflects the interdependence of contexts of TOE. Moreover, IDT connects the macro-level and micro-level. For example, the observability of technologies helps users shape their attitude toward adopting AI. Specifically, this factor impacts stakeholders' PU and PEOU of AI technologies, further influencing their intention to adopt AI technologies.

4.2 MICRO-DIMENSION THEORIES INCORPORATION

In Figure 4, the bottom structure indicates the micro-level theories involved in this framework. The model adopted at this level is TAM, surrounded by relevant stakeholders. Authors opined that the TAM is the most popular theory for predicting and explaining user acceptance of innovations (Na et al., 2022; Na et al., 2023; Davis & Granic, 2024). TAM suggests that individuals' attitude toward technologies' adoption is based on PU and PEOU. According to Davis and Granic (2024), compared to the PEOU, PU is the primary determinant. Particularly, PEOU affects user acceptance through influencing PU. They also demonstrated that users tend to tolerate the difficulties of the advanced technology, provided it can improve the usefulness of their current operating technologies. In this study, PU refers to stakeholders' belief in how much AI technologies can enhance the workflow performance and efficiency in construction project deliveries. Taking an example of the diffusion of BIM technology in the CI since the 1990s, given its high efficiency as an all-in-one solution to construction issues in different project phases, including designing, constructing, and operating, stakeholders perceived the adoption of BIM as beneficial for construction project deliveries (Khan et al., 2024). PEOU refers to stakeholders' belief that it is easy to adopt AI technologies without substantial requirements or investments. As a key stakeholder entity, it is expected that investors are more likely to support the adoption of AI technologies, which offer a predictable high Return On Investment (ROI), for those with low ROI, the investor's attitude tends to be apprehensive.

Although the TAM explains the impact of users' intentions and attitudes on AI adoption at the micro level, it does not specify how users or stakeholders should be identified or classified. This gap highlights the necessity of introducing SKT. The embedding of SKT enables the identification of the individuals and groups that are relevant to AI adoption. It is noted that the relationships between SKT and other theories are not singular, it is applied in scattered boxes at both levels to present the stakeholders that are appropriate for the level. It can be observed that competitors, governments, and local communities are identified as being able to affect the environment at the macro level, while investors', employees', contractors', suppliers', clients', and shareholders' influences reflect on the process of TAM at the micro level. The primary stakeholders, also named as the internal stakeholders, are involved at the micro-level, as they influence the adoption of AI technologies through their individual intentions. The secondary stakeholders (external stakeholders) affect the applications of AI technologies by influencing the factors among the TOE. For example, the government requirements of digital transformation can transform into external pressures on construction firms within the environmental context, prompting them to reconsider their decision on AI adoption.

Additionally, the bidirectional arrows crossing the central structure that refers to the AI adoption in the CI represent the interaction between the two structures in Figure 4. Notably, factors for different dimensions are not isolated; they are influenced by each other. Taking an example, the compatibility of AI technologies reflects the characteristics of technologies themselves and further shapes the intentions of adopting these technologies by construction firms. Compatibility reflects the capability of AI technologies to integrate into existing systems. When the management level decides to adopt an AI technology, it must evaluate whether the new technology aligns with the company's current infrastructure and systems. Thus, a higher degree of compatibility reduces the uncertainty of AI adoption' process, thereby accelerating the diffusion of AI adoption within the firm. Thus, this framework provides a multi-dimensional explanation at both the macro- and micro-levels of AI adoption in the CI by combining environmental, organisational and individual elements.

Conclusively, existing frameworks (e.g., TOE-IDT structure) focus on AI adoption primarily explore the adoption intention through single-level influences, rather than conducting cross-level analysis for different factors. However, the proposed framework extends existing integrated structures by combining the focus on individual and system dimensions within the CI. In addition, it incorporates stakeholders' participation to explain the potential interactions from different contexts. This allows for a more dynamic and sensible explanation of AI adoption in the CI, as different phases of the CPLC may include specific demands of AI applications.

5. CONCLUSIONS

This study proposes a theoretical framework for a better understanding of the factors influencing the adoption of AI technologies in the CI. It incorporates the TOE framework, TAM, IDT, and SKT to provide both macro- and micro-level perspectives of influencing factors. Given the complex and fragmented nature of construction projects that would result in heterogeneous technological demands across different phases of CPLC, the AI adoption in the CI is rather unique compared to other sectors. By integrating models and theories from different dimensions, this framework enables a deeper understanding of how influencing factors from different contexts interact, negotiate, and translate into AI adoption in the CI. Furthermore, this framework identifies factors that can be operationalised into measurable variables for quantitative or mixed-method research. For instance, future research may explore stakeholders' trust in AI, ethical concerns of AI utilisation, and resistance to technological innovation, which are influenced by AI technologies complexity from the technological context; management group support from organisational context; and industry competition from environmental context. By integrating these dimensions, the framework enables future research to link and evaluate the interactions of those influencing factors toward AI adoption in the AI. In terms of contribution, theoretically, this study proposes an integrated framework of how environmental contexts, organisational decisions, technological characteristics, and individual intentions interplay in the AI adoption process. It provides a theoretical basis for understanding the AI adoption process from multiple dimensions and a dynamic perspective. Practically, it provides a foundational structure for evaluating the complex AI adoption processes in the CI involving multiple stakeholders. Additionally, the framework deepens the understanding of AI adoption from both macro- and micro-level perspectives. Moreover, this framework provides a fundamental structure for identifying the interactions among various influencing factors, enabling the evaluation of effective points of intervention across multiple levels. Thereby, it supports a well-informed decision-making process of AI adoption from the construction firms' perspective. Meanwhile, the identification of macro-level influences is more inclined to facilitate policy interventions for AI adoption. However, a significant limitation of this framework is that it has not yet been empirically tested, which indicates that its predictive and explanatory capabilities still require validation. To address this limitation, future research can apply Structural Equation Modelling (SEM) or regression-based method to test direct, mediating, and moderating effects among variables to evaluate the generalisability and comprehensiveness of this framework.

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