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LARGE LANGUAGE MODELS AS ENABLERS OF INDUSTRIAL INFORMATION INTEGRATION IN CONSTRUCTION: AN ADOPTION MECHANISM STUDY

Yue-Hua CHEN[1,2✉], Xiao-Yang SONG[1], Jian-Peng CHANG[3,4], Mirosław J. SKIBNIEWSKI[5,6,7], Muhammet DEVECI[8,9,10], Zhen-Song CHEN[1,2✉✉]

[1]*School of Civil Engineering, Wuhan University, Wuhan, China*
[2]*Faculty of Business, City University of Macau, 999078, Macao Special Administrative Region of China, China*
[3]*Collaborative Innovation Center for Chongqing's Modern Trade Logistics & Supply Chain, Chongqing Technology and Business University, Chongqing 400067, China*
[4]*School of Management Science and Engineering, Chongqing Technology and Business University, Chongqing 400067, China*
[5]*Department of Civil & Environmental Engineering, University of Maryland, College Park, MD 20742-3021, United States*
[6]*Chaoyang University of Technology, Taichung 413310, Taiwan*
[7]*Polish Academy of Sciences Institute of Theoretical and Applied Informatics, Gliwice 44-100, Poland*
[8]*Department of Industrial Engineering, Turkish Naval Academy, National Defence University, 34942 Tuzla, Istanbul, Türkiye*
[9]*Sogang University, Seoul 04107, Republic of Korea*
[10]*Department of Computer Science and Engineering, College of Informatics, Korea University, 145 Anam-ro, Seongbuk-gu, Seoul, 02841, Republic of Korea*

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Abstract. Large language models (LLMs) are emerging enablers of industrial information integration, yet their adoption mechanisms in construction remain unclear. This study develops an integrated framework that combines the Technology Acceptance Model and the Information Systems Success model, extended with trust, prior LLM experience, perceived substitution crisis, and job specialization, to explain individual adoption of LLMs for information integration in construction. Data from a cross-sectional survey of 82 Chinese construction professionals are analyzed using partial least squares structural equation modeling and bootstrapping. Results show that perceived ease of use robustly strengthens attitude and provides directional evidence for strengthening perceived usefulness, while perceived usefulness strengthens attitude and attitude drives intention to use. Trust, reinforced by perceived information quality, shows a positive association with intention under the primary one-tailed criterion, but this relationship requires further validation under the two-tailed robustness check. System quality and information quality indirectly foster adoption by improving perceived ease of use, although the relationship between system quality and trust is supported only as directional evidence, while prior LLM experience enhances ease of use but not perceived usefulness or trust. Perceived substitution crisis and job specialization exhibit no significant effects. The findings highlight that successful LLM-enabled information integration depends on both technical quality and psychological appraisals, and they offer implications for designing trustworthy, human-centered LLM applications that advance intelligent, interconnected construction ecosystems. The study links micro-level user acceptance with macro-level digital transformation and integration strategic objectives.

Keywords: large language models, industrial information integration, construction industry, technology acceptance model, information systems success model.

✉Corresponding author. E-mail: *yuhchen@whu.edu.cn*
✉✉Corresponding author. E-mail: *zschen@ieee.org*

1. Introduction

The construction industry, a foundational pillar of national infrastructure and economic development, has long encountered structural barriers to industrial information integration. In contrast to manufacturing sectors with continuous production processes and mature data standards, construction is inherently project-based, temporary, and strongly multidisciplinary. This context gives rise to heterogeneous information systems, inconsistent data schemas, and weakly coupled workflows, which collectively impede efficient collaboration and data-driven decision mak-

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ing (Bicocchi et al., 2019; Czvetkó & Abonyi, 2023). Although initiatives such as Building Information Modeling (BIM), digital twins, and integrated project delivery have enhanced information visibility and coordination, the sector continues to exhibit fragmented knowledge management and limited interoperability along the supply chain (Love et al., 2014; Yang et al., 2024). The absence of a unified, domain-wide information architecture, coupled with a low level of intelligent coordination among stakeholders, thus remains a core bottleneck to realizing intelligent, interconnected, and data-driven industrial operations (Moshood et al., 2024).

Recent advances in large language models (LLMs) have introduced a new paradigm for addressing industrial information integration challenges (C. Zhang & H. Zhang, 2025). By using natural language as a universal interaction medium, LLMs enable human-machine communication that transcends traditional, menu-driven software interfaces. Their capacity for domain-aware interpretation, reasoning, and content generation allows them to mediate between heterogeneous information systems and diverse professional roles (Zhang et al., 2025). In the construction ecosystem, where collaboration critically depends on unstructured textual artefacts, including specifications, contracts, technical reports, and on-site records, LLMs are uniquely positioned to connect data silos and support cross-disciplinary coordination. Through semantic understanding and generative capabilities, they can consolidate fragmented digitalization efforts into cohesive, intelligent workflows, thereby advancing industrial information integration along the construction value chain (Li et al., 2025a).

LLMs, exemplified by systems such as GPT 4, BERT, and Llama 2, represent a new generation of generative artificial intelligence that integrates deep learning, natural language processing, and large-scale knowledge representation. Trained on massive text corpora, they exhibit strong abilities to comprehend and produce human-like language, as well as to perform contextual reasoning, pattern discovery, and adaptive problem solving (Jiang et al., 2024). As a result, LLMs are rapidly being deployed as cognitive engines and intelligent information mediators across multiple sectors. In education, they support personalized tutoring and automated feedback (Kamalov et al., 2023). In healthcare, they assist with diagnostic reasoning and patient communication (Goktas et al., 2023). In finance, they enhance decision support, risk assessment, and compliance monitoring (Huang et al., 2023). In autonomous driving, they enable more intelligent transportation systems and contribute to safer, more efficient self-driving technologies (Li et al., 2025b). Across these domains, LLMs are accelerating the convergence of human expertise, data analytics, and digital infrastructure, thereby laying a technical foundation for more integrated and intelligent industrial ecosystems.

Despite this momentum, LLM adoption in the construction industry remains nascent. Compared with sectors that rely on structured data and standardized processes, construction work is marked by situational complexity, tacit knowledge, and project-specific variability (Ghimire et al., 2024), all of which hinder the seamless embedding of AI into everyday workflows. Furthermore, the sector's traditionally conservative digital culture implies that adoption is shaped not only by technological readiness but also by human acceptance (Shojaei & Burgess, 2022). Although recent studies indicate that LLMs can assist with design conceptualization, document authoring, and project coordination (Postle & Salingaros, 2025), their effective use is highly dependent on practitioners' perceptions of usefulness, ease of use, and trustworthiness (Lin et al., 2025). If users perceive outputs as unreliable or cognitively demanding to interpret, they are unlikely to integrate LLM tools into their professional routines. Consequently, the success of LLM-driven industrial information integration in construction is contingent on understanding the psychological and behavioral mechanisms that govern adoption.

Existing research on AI adoption has grown rapidly, yet it has focused predominantly on relatively digitalized domains such as education, e-commerce, and healthcare, while paying limited attention to digitally lagging industries (Abioye et al., 2021). Construction, as a project-based and labor-intensive sector, constitutes a distinct context in which technology adoption is shaped by complex interactions among individual cognition, organizational support, and task characteristics. Consistent with this multi-level perspective, recent firm-level evidence based on machine-learning analysis of Chinese listed construction firms identifies top managers' digital-innovation mindset, inter-organizational collaboration, and boundary-spanning activities as leading drivers of digital transformation, ahead of technology inputs alone (Ding et al., 2025). Employees' willingness to adopt LLMs may be influenced not only by classical determinants identified in the Technology Acceptance Model (TAM), namely perceived usefulness (PU) and perceived ease of use (PEOU), but also by additional psychological and cognitive factors, including trust (TRU), perceived substitution crisis (PSC), prior LLM experience (LE), and job specialization (JS). Clarifying these multidimensional determinants is essential for designing targeted interventions that foster not only short-term experimentation but also sustained, value-generating use of LLMs.

To address these gaps, this study develops an integrated analytical framework that combines TAM with the Information Systems Success (ISS) model and augments them with constructs capturing TRU, LE, PSC, and JS. This combined model provides a more comprehensive account of the individual-level mechanisms driving LLM adoption in construction, which is critical for advancing intelligent and interoperable industrial ecosystems. Specifically, this study seeks to answer the following research questions:

- What are construction professionals' overall attitudes toward LLMs?
- Which key factors shape their attitudes toward (AT), and intentions to use (IU), LLMs?
- Does JS moderate the effect of PSC on IU, and if so, in what manner?

Building on these questions, the study seeks to extend technology adoption theories to the context of generative AI and to derive actionable insights for construction firms aiming to advance industrial information integration through human AI collaboration. The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops the research hypotheses. Section 3 describes the research design and methodology. Section 4 presents the empirical results. Section 5 discusses the key findings, their theoretical and managerial implications, and the study's limitations, and offers directions for future research. Section 6 concludes with a synthesis of the main insights.

2. Literature review and hypothesis development

2.1. Large language models in the construction industry

LLMs have rapidly emerged as transformative technologies within the construction sector (Zhang et al., 2025), a field long characterized by fragmented information flows, heterogeneous data formats, and labor-intensive documentation practices (Li et al., 2023). As in other knowledge-centric industries, LLMs have attracted considerable attention for their potential to reshape workflows, augment decision-making, and support both technical and non-technical personnel across project lifecycles. Early explorations highlight wide-ranging applications in areas such as engineering design, construction planning, site coordination, safety management, and regulatory interpretation (Zhang et al., 2025), reflecting a growing recognition that LLM-driven automation and reasoning capabilities could substantially enhance productivity and organizational learning in construction enterprises.

In terms of potential benefits, LLMs offer unprecedented capabilities for processing, generating, and summarizing natural-language information, which is a critical advantage in an industry where project knowledge is primarily communicated through specifications, standards, contracts, safety manuals, inspection reports, and daily logs (Wu et al., 2022). Recent studies indicate that LLMs can assist engineers and project managers by generating method statements, interpreting technical standards, producing alternative design narratives, and providing on-demand explanations of construction methods or regulatory requirements (Zhou et al., 2025). For non-technical personnel, such as administrative staff or marketing personnel, LLMs can help streamline routine tasks including drafting meeting minutes, preparing procurement documents, organizing communication records, and synthesizing information from disparate sources. This increased accessibility to domain knowledge, together with the 24/7 availability of an "AI project assistant", may foster more efficient communication, faster knowledge transfer, and more consistent documentation practices across project teams.

Beyond task-level automation, LLMs hold particular promise for advancing industrial information integration, a persistent challenge in construction projects. Heterogeneous systems, including BIM platforms, scheduling tools, procurement systems, quality inspection databases, and digital twin environments, rarely communicate seamlessly. LLMs, with their semantic understanding and text-to-structure conversion capabilities, can serve as integrative engines that connect otherwise siloed information (Shamshiri et al., 2024). Recent conceptual work argues that realizing this integrative potential at scale requires governable agent-native infrastructure that combines semantic knowledge organization, intelligence mediation, tool interaction, and policy-constrained workflow execution (Ma et al., 2026). For example, LLMs can map textual changes in design documents to corresponding BIM elements, translate site observations into structured maintenance logs, or summarize cross-system data for management decision-making (Shah et al., 2026; Wu et al., 2025). These capabilities suggest that LLMs may substantially improve interoperability and knowledge coherence across the construction value chain, acting as mediators that support smoother information flow and cross-platform alignment.

However, the integration of LLMs into construction enterprises is far from straightforward. The industry's low digital maturity, long-established reliance on experiential knowledge, and complex multi-stakeholder environment introduce unique adoption challenges (Wen et al., 2025). Many construction personnel, particularly those in non-technical roles, may have limited experience with advanced digital tools, which raises concerns about trustworthiness, accuracy, and the potential for AI-generated misinformation. LLM-specific risks, such as hallucination, limited interpretability, and context drift, further complicate adoption, as construction decisions often carry significant safety, financial, and contractual implications (Guo et al., 2025). These concerns may influence perceived system quality, usefulness, and ease of use differently across roles and levels of digital literacy. Moreover, the increasing automation of documentation and analysis tasks may trigger perceived substitution risks among employees, shaping both their acceptance of and resistance to LLM-enabled workflows.

Despite growing interest in LLMs within construction practice, scholarly research remains limited. Existing studies largely focus on technical demonstrations, including the automation of specific documents, the improvement of design workflows, and the prototyping of compliance tools, but they rarely investigate systematically how construction personnel perceive, evaluate, and ultimately adopt LLMs (Du et al., 2026; Peng & Liu, 2023; Xiao et al., 2024). Critically, no studies have yet addressed the heterogeneous needs of technical versus non-technical staff, or how JS influences PSC associated with AI systems. These gaps are particularly pronounced because the construction industry is characterized by low digital maturity, a conser-

vative industry culture, and role-specific psychological perceptions that strongly shape technology adoption. These contextual conditions make it especially important to understand personnel's acceptance behaviors and heterogeneous demands in construction, where adoption mechanisms may differ from those in more digitally advanced sectors. In light of these gaps, this study contributes to the literature by examining the adoption mechanisms of LLMs among construction enterprise personnel across diverse job categories.

2.2. Technology acceptance model

The TAM, originally proposed by Davis on the basis of the Theory of Reasoned Action (TRA), provides a parsimonious framework for explaining users' acceptance and use of new information technologies. TAM identifies two core cognitive beliefs, PU and PEOU, as fundamental determinants of technology adoption. PEOU is defined as "the degree to which a person believes that using a particular system would be free of effort", whereas PU is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). Within the TAM framework, behavioral IU a technology is the most proximal predictor of actual usage, and is shaped by users' attitudes toward the technology as well as their beliefs about its usefulness and ease of use. PU and PEOU jointly determine AT, while PEOU also exerts a direct positive effect on PU.

TAM has also provided an important theoretical basis for construction management research on digital technology adoption. Prior studies have applied TAM-related frameworks to examine BIM acceptance across national contexts (Lee & Yu, 2016), the acceptance of smart construction systems (Liu et al., 2018), and the adoption of electronic incident reporting systems in construction safety management (Saqib et al., 2023). These studies confirm the relevance of TAM for explaining construction professionals' technology acceptance, while also showing that adoption mechanisms in construction are often shaped by technology-specific attributes, task requirements, organizational settings, and user perceptions.

Building on this stream of research, TAM offers a suitable theoretical lens for examining LLM adoption in the construction industry. LLM-based applications can assist employees in efficiently generating design documentation, analyzing construction schedules, and retrieving technical references, and their natural language interaction interfaces lower technological entry barriers and enhance perceived usability. Given the complexity of construction tasks and their reliance on interdisciplinary collaboration, users' attitudes toward LLMs reflect not only personal preferences but also their assessment of the technology's potential to enhance collaborative efficiency and information processing. On this basis, the following hypotheses are proposed:

H1: *The PEOU of LLMs positively influences the PU of LLMs.*

H2: *The PEOU of LLMs positively influences the AT.*

H3: *The PU of LLMs positively influences the AT.*

H4: *The AT positively influences the IU.*

2.3. Perceived substitution crisis

PSC refers to employees' subjective concern that their job roles may be replaced by emerging technologies (Featherman & Pavlou, 2003), and has long been recognized as a major barrier to the adoption of information systems. This concern has gained renewed salience with the rapid advancement of AI, particularly the proliferation of LLMs. Verma and Singh (2022) argue that, as AI systems become increasingly embedded in organizational processes, employees engaged in routine or standardized tasks may experience heightened anxiety about technological displacement. In contrast to traditional information systems, LLMs exhibit learning capabilities and a degree of autonomous decision-making that enable them to perform not only predefined operations but also complex cognitive and creative tasks, thereby amplifying perceived threats to human occupational roles.

In the construction industry, tasks that previously relied heavily on professional expertise, such as drafting conceptual design sketches, preparing technical documents, and outlining project implementation plans, can now be completed with substantial assistance from LLM tools. While these capabilities improve efficiency and reduce cognitive workload, they also trigger deep-seated concerns among employees regarding job security and long-term career prospects.

In terms of measurement, PSC was operationalized by adapting prior PSC items from AI adoption and AI-enabled work contexts. Fan et al. (2020) originally introduced PSC as a construct in the adoption of artificial intelligence-based medical diagnosis support systems and defined it as concerns about being replaced by the target AI system. Their original operationalization covered perceived replacement by the AI system, dependence on the AI system, unemployment risk, and decline in professional diagnostic capability. Verma and Singh (2022) subsequently extended PSC to AI-enabled job contexts and measured it with items referring to employee replacement, dependence on AI systems, and unemployment risk. In the present study, the PSC measure was adapted a priori to the context of LLM use among construction professionals. No PSC item was removed after data collection. Rather, during questionnaire design, we retained the two facets that most directly reflected the core meaning of perceived occupational substitution threat, namely perceived employee replacement and unemployment risk. The dependence-related item was not retained because dependence on LLMs may indicate usage reliance, task support, or work habit formation rather than a direct perception of occupational

substitution. Similarly, the item concerning decline in professional diagnostic capability was not retained because it reflects perceived competence erosion rather than the more direct threat of job or role replacement. Therefore, these two items were judged to be less closely aligned with the focal definition of PSC adopted in this study. The wording of the retained items was contextualized by replacing AIMDSS or AIS with LLMs and by framing the perceived threat in the construction-work context, as reported in Appendix A. This adaptation narrows PSC to the core substitution-threat dimension relevant to LLM-enabled construction work. We acknowledge that using two items may limit the breadth of the PSC construct, and the results related to PSC should therefore be interpreted cautiously. Accordingly, this study posits the following hypothesis:

H5: *PSC negatively influences the IU.*

2.4. Trust

TRU is commonly defined as an individual's subjective expectation that a technology or service provider will perform tasks within an appropriate and expected scope (Maheshwari, 2024). In technology adoption research, TRU has consistently been identified as a critical antecedent of users' intention to adopt and continue using information systems (Gefen et al., 2003; Panagiotopoulos & Dimitrakopoulos, 2018; Pillai et al., 2024). Chang and Park (2024) further argue that TRU plays a particularly salient role in the early stages of technology use, especially when users lack prior experience, because positive beliefs about a system substantially increase their willingness to experiment with and adopt it. In the construction sector, where the deployment of LLMs is still nascent, the technology's black box characteristics, output uncertainty, and potential biases imply that users must establish a sufficient level of TRU before they are willing to engage with the system. For example, employees need confidence that LLM-generated construction proposals, material schedules, and contract drafts are accurate, consistent, and dependable; otherwise, even highly functional systems may not be translated into actual usage. TRU is therefore expected to be pivotal in shaping construction professionals' adoption decisions. When employees perceive the system as stable and reliable, and regard its outputs as credible, they are more inclined to actively employ LLMs to support a wide range of professional tasks. Accordingly, this study proposes the following hypothesis:

H6: *TRU in LLMs positively influences the IU.*

2.5. Information systems success model

The ISS model, first proposed by DeLone and McLean (1992) and subsequently revised in DeLone and McLean (2003), identifies three core dimensions, information quality (IQ), system quality (SQ), and service quality (SVQ), as key indicators of an information system's effectiveness, each reflecting a distinct aspect of system performance and value. This study deliberately excludes the SVQ dimension. Applications of LLMs in the construction sector are still nascent and have not yet been formally deployed or supported at the organizational level. Most use occurs informally at the individual level, with employees relying on publicly accessible platforms and lacking institutional support in the form of system implementation, training, or technical assistance. Under these conditions, there is no clearly defined service provider or organizational support infrastructure, so SVQ is difficult for users to perceive or evaluate. Forcibly incorporating this construct could introduce measurement bias and distort the structural model.

Accordingly, the analysis focuses on two technology-oriented attributes that users can directly experience, IQ and SQ, which are more relevant for evaluating the use and acceptance of LLMs in the construction industry. IQ refers to the intrinsic value of the content produced by the system, specifically whether the information is accurate, relevant, and supportive of effective task execution and decision making. SQ captures the technical performance of the system, including its reliability, responsiveness, and overall functionality. In the context of LLM adoption, when users perceive that the system provides high quality information, operates smoothly, and yields reliable outputs, they are more likely to regard it as useful, easy to use, and trustworthy. On this basis, the following hypotheses are proposed:

H7: *IQ positively influences the PU of LLMs.*

H8: *IQ positively influences the PEOU of LLMs.*

H9: *IQ positively influences TRU in LLMs.*

H10: *SQ positively influences the PU of LLMs.*

H11: *SQ positively influences the PEOU of LLMs.*

H12: *SQ positively influences TRU in LLMs.*

2.6. LLM experience

Usage experience is defined as the knowledge, skills, familiarity, and understanding of a technology's functions and limitations that individuals accumulate through prior use (Venkatesh et al., 2003). In research on technology adoption, usage experience is widely regarded as an important antecedent of user perceptions and behavioral intentions (Agarwal & Prasad, 1999). Empirical evidence suggests that repeated interaction with a system enhances users' operational proficiency and strategic use, thereby strengthening their perceived control and adaptability. Continued exposure also enables users to more accurately assess the strengths and weaknesses of a technology, which contributes to more informed and often more favorable expectations (Yan et al., 2022).

In the construction industry, employees' experience with LLMs is likely to shape three key perceptual processes: (1) PU, as experienced users are more capable of formulating effective prompts to obtain high quality outputs and thus are more inclined to view the system as valuable for task performance; (2) PEOU, as iterative interaction familiarizes users with system logic and prompt optimization, thereby enhancing perceived usability; and (3)

TRU, as familiarity with the system's behavioral patterns and output style increases confidence in its consistency and professional reliability. On this basis, the following hypotheses are proposed:

H13: *LE positively influences their PU.*

H14: *LE positively influences their PEOU.*

H15: *LE positively influences TRU in LLMs.*

2.7. Effect of job specialization as a moderator

JS refers to the degree of skill depth, knowledge complexity, and technical expertise required by a given position (Verma & Singh, 2022). Highly specialized positions typically demand advanced professional judgment, complex problem-solving capabilities, and long-term accumulation of industry-specific knowledge and technical proficiency. By contrast, positions with lower levels of specialization often involve standardized or procedural tasks and are therefore more vulnerable to the impact of automation and emerging digital technologies. In the context of technology adoption, users' attitudes and behavioral responses to new technologies are shaped not only by their perceptions of the technology itself, but also by their occupational background and positional characteristics, which may function as moderating factors (Massa et al., 2023). Existing studies indicate that individuals in highly specialized positions are more inclined to regard AI-based technologies as tools for enhancing efficiency rather than as threats to their employment (Kirov & Malamin, 2022). This tendency can be attributed to their confidence in the non-substitutability of their expertise and the perceived robustness of professional entry barriers. In contrast, employees occupying less specialized positions are more likely to perceive intelligent systems as potential "competitors", especially when such technologies can directly perform their routine tasks (Frey & Osborne, 2017). Accordingly, this study advances the following hypothesis:

H16: *JS significantly moderates the relationship between PSC and the IU; higher levels of specialization weaken the negative relationship between PSC and the IU.*

The proposed research model with the corresponding hypothesized paths is presented in Figure 1.

3. Methodology

3.1. Sampling and data collection

This study examined the acceptance of LLMs among construction professionals using an internet-based survey. The questionnaire was administered via Credamo, a reputable online research platform in China, and data were collected over a five-week period from March to April 2025. To ensure relevance and validity, access to the survey was restricted to individuals employed in the construction sector, and respondents were required to verify their industry affiliation before participation. A non-probability convenience sampling strategy was used to efficiently recruit an adequate number of participants. The sample encompassed a broad range of occupational roles, including designers, construction technicians, marketing personnel, and administrative or managerial staff, spanning multiple functional departments within construction firms. All respondents were currently employed and possessed basic proficiency in digital tools, thereby meeting the study's inclusion criteria.

According to the research ethics policy of Wuhan University, this anonymous online questionnaire study involving adult participants did not require formal Institutional Review Board review or approval. The authors confirmed before data collection that this type of study did not fall within the scope requiring formal review under the rele-

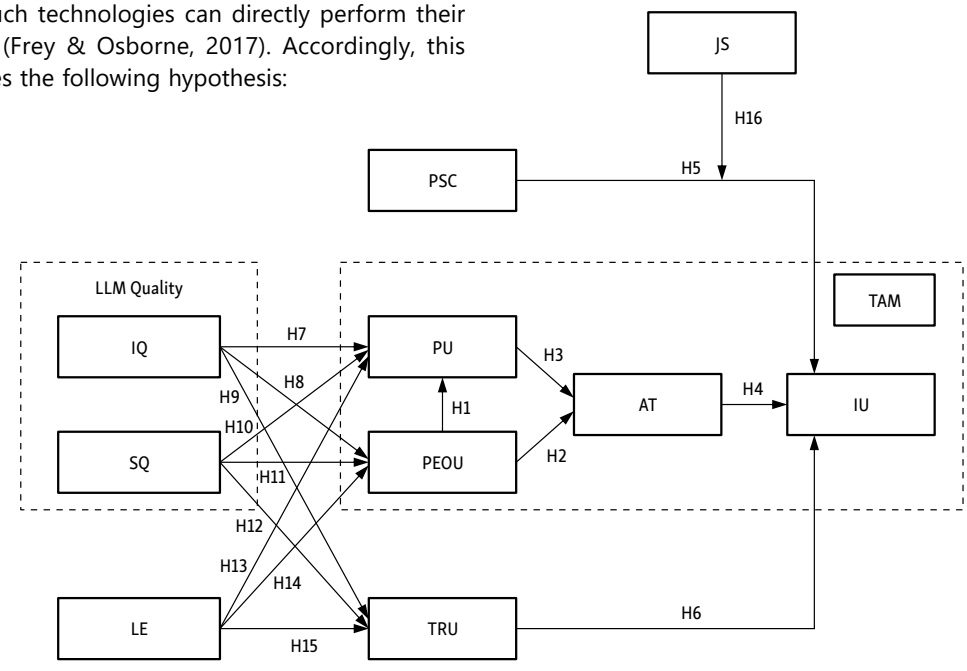


Figure 1. Proposed research model and hypotheses

vant institutional policy. The study involved minimal risk, collected no personally identifiable information or sensitive personal data, and did not involve any intervention with participants. The research was conducted in accordance with the ethical principles of the Declaration of Helsinki. Before starting the survey, all potential participants were informed about the purpose of the study, the voluntary nature of participation, and the anonymity and confidentiality of their responses. Electronic informed consent for participation was obtained from all participants via the online survey platform prior to data collection. To protect anonymity and privacy, no personally identifiable information (for example, names, email addresses, or telephone numbers) was collected. Participants who completed the questionnaire received a small incentive of 3 RMB (approximately 0.4 USD). Of the 128 questionnaires distributed, 82 were retained as valid, resulting in a valid response rate of 64.06%. Responses that failed attention checks or exhibited logical inconsistencies were excluded from subsequent analysis. Table 1 summarizes the demographic characteristics of the final sample. Among the respondents, 59.8% were male and 40.2% female. The sample was relatively young, with almost 87% of participants under the age of 40. The distribution of job roles was also reasonably balanced across key operational domains of the construction industry, providing a diverse and practically representative data basis for this study.

To assess whether the 82 valid cases were adequate for partial least squares structural equation modeling (PLS-SEM), two established criteria for sample size determination in variance-based structural equation modeling were applied in accordance with Hair et al. (2021a). First, the ten times rule specifies that the minimum sample size should be at least ten times the largest number of indicators per latent variable (maximum = 4) or the maximum number of structural paths pointing to any endogenous construct (maximum = 4 for PU), which yields a minimum required sample of 40. This threshold is comfortably exceeded by the 82 valid observations. Second, a G*Power 3.1.9.7 analysis was conducted with the following configuration: test family = F tests; statistical test = linear multiple regression (fixed model, R^2 deviation from zero); power analysis type = a priori (compute required sample size); number of predictors = 4; effect size f^2 = 0.15 (medium); significance level (α) = 0.10; and statistical power (1 − β) = 0.80. The results indicated a minimum required sample size of 69, which is exceeded by the actual sample by 18.8%. Taken together, these criteria demonstrate that the sample size is adequate for PLS-SEM, providing a robust basis for subsequent model estimation and structural path testing.

Table 1. Demographic characteristic variables of respondents

Variable	Value	Frequency	Percentage
Gender	Male	49	59.8%
	Female	33	40.2%
Age (years)	18–30	44	53.7%
	31–40	27	32.9%
	41–50	6	7.3%
	>50	5	6.1%
Educational level	High school or lower	3	3.7%
	Bachelor	68	82.9%
	Master	8	9.8%
	Doctorate	1	1.2%
	Others	2	2.4%
Position	Technical	58	70.7%
	Non-technical	24	29.3%
Monthly income (CNY)	<5000	15	18.2%
	5000–8000	29	35.4%
	8000–12000	29	35.4%
	>12000	9	11.0%
Work experience (years)	0–3	22	26.8%
	3–5	12	14.7%
	5–10	22	26.8%
	>10	26	31.7%

3.2. Questionnaire design, task familiarization protocol, and measures

The questionnaire comprised four sections. The first section collected demographic information, including gender, age, educational background, years of work experience, monthly income, and job nature (technical or non technical), in order to describe the sample structure and enable comparative analyses across subgroups.

The second section introduced a role-specific, two-stage task familiarization protocol. Based on their self-reported job category, respondents were assigned one construction-related task in the areas of design, construction technology, marketing communication, or administrative and managerial coordination. They first completed the task independently without LLM support and subsequently completed the same task with the assistance of Doubao, a publicly accessible LLM application in China. The purpose of this procedure was not to conduct a controlled performance experiment, but to ensure that respondents evaluated the subsequent measurement items after experiencing both independent and LLM-assisted task completion in a concrete work-related context. The overall questionnaire was expected to take approximately 15 minutes, and written responses were required in both stages. The full role-specific task scenarios and completion requirements are provided in Table A2 in Appendix B.

The third section contained the structured measurement scales, covering ten key latent constructs in the research model: PU, PEOU, AT, IU, TRU, PSC, IQ, SQ, LE, and JS. All items were adapted from well-established scales in the domestic and international literature (Choi & Ji, 2015; Davis, 1989; Fan et al., 2020; Herrenkind et al., 2019; C.-L. Hsu et al., 2007; P.-F. Hsu et al., 2015; Verma & Singh, 2022; Yan et al., 2022) and were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree), which helped ensure the reliability and construct validity of the instrument (see Table A1 in Appendix A).

The fourth section comprised three open-ended questions: "*In which scenarios do you consider LLMs most useful in the construction industry*?", "*What shortcomings of LLMs make you dissatisfied with their use*?", and "*What additional functions would you expect LLMs to provide in order to improve your work efficiency and quality*?". These qualitative responses were used to further explore users' real needs and expectations beyond the quantitative model and to enhance the practical relevance of the study.

3.3. Data analysis technique

This study adopted a multi-step analytical strategy. First, preliminary diagnostic analyses were conducted to assess common method bias and the suitability of the measurement items for factor analysis. Harman's single-factor test and the exploratory factor analysis (EFA) were conducted using IBM SPSS Statistics. Harman's single-factor test was used as an initial diagnostic for common method bias, whereas EFA was used as a supplementary diagnostic analysis to examine the underlying structure of the measurement items. Second, partial least squares structural equation modeling (PLS-SEM) was employed as the main analytical method to assess the measurement model and test the hypothesized relationships among the latent constructs.

For the supplementary EFA, principal axis factoring was used as the extraction method, and Promax rotation with Kaiser normalization was applied because the latent constructs in the adoption model were theoretically expected to be correlated. Considering the theory-driven structure of the proposed model, a ten-factor solution corresponding to the ten latent constructs was examined. The EFA results are reported in Section 4.2, and the detailed pattern matrix is provided in Appendix C (Tables A3 and A4).

This study employed structural equation modeling (SEM) using the partial least squares (PLS) approach to analyze the data. PLS-SEM was selected for its strong predictive orientation and methodological flexibility, which make it particularly suitable for exploratory research (Aktar & Pangil, 2017), especially given the integrated theoretical framework developed in this study. In contrast to covariance-based SEM (CB-SEM), PLS-SEM does not assume multivariate normality (Hair et al., 2019), can accommodate non-normally distributed data, and imposes comparatively less stringent requirements on sample size (Richter et al., 2016; Willaby et al., 2015). These features align well with the characteristics of the present dataset and research objectives.

Data analysis for the PLS-SEM model was conducted using SmartPLS version 4.1.1.1. PLS-SEM employs variance-based path modeling to estimate causal relationships among latent constructs and is well-suited to complex models that incorporate multiple mediating and moderating effects (Hair et al., 2014). Given that this study integrates TAM, the ISS model, and additional key constructs (LE, TRU, PSC, and JS) into a multi-path, cross-level framework, the adoption of PLS-SEM is both theoretically justified and methodologically appropriate (Hair et al., 2011).

4. Results

4.1. Common method bias

To assess potential common method bias (CMB) associated with the self-reported survey design, Harman's single-factor test was conducted following the classical procedure. All measurement items were subjected to an unrotated single-factor test. The first factor accounted for 27.68% of the total variance, which is well below the commonly used 50% threshold in prior studies (Fuller et al., 2016; Podsakoff et al., 2003). This indicates that no single factor dominates the covariance structure of the data, providing preliminary evidence that CMB is unlikely to pose a severe threat to the findings.

Because Harman's single-factor test has been criticized for its limited sensitivity in detecting CMB (Fuller et al., 2016; Podsakoff et al., 2003), a supplementary full collinearity assessment was further conducted. Following the full collinearity approach proposed for PLS-SEM, the Variance Inflation Factor (VIF) values for all latent constructs were examined as an additional diagnostic for common method variance (Kock, 2015a). The results indicate that all VIF values ranged from 1.000 to 1.847, well below the recommended threshold of 3.3 (Diamantopoulos & Siguaw, 2006). These results suggest that CMB is unlikely to exert a severe influence on the structural path estimates. Nevertheless, given the cross-sectional and self-reported nature of the survey data, the possibility that residual common method effects influenced some structural path estimates cannot be completely ruled out.

4.2. Exploratory factor analysis

Before assessing the PLS-SEM measurement model, an exploratory factor analysis (EFA) was conducted as an additional diagnostic analysis of the measurement structure. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.767, and Bartlett's test of sphericity was significant (χ^2 = 1111.112, df = 435, p < 0.001), indicating that the data were suitable for factor analysis (Hair et al., 2010). Principal axis factoring was used as the extraction method, while Promax rotation was applied because the latent constructs were theoretically expected to be correlated (Fabrigar et al., 1999). Given the theory-driven specification of the proposed model, a ten-factor solution corresponding to the ten latent constructs was examined. The ten factors explained 60.041% of the total variance.

The pattern matrix yielded a partially interpretable but non-simple factor structure. Relatively clear within-construct clustering was observed for LE, PSC, and JS. The four LE items loaded on Factor 3, with loadings ranging from 0.493 to 0.687. PSC1 and PSC2 loaded on Factor 5, with loadings of 0.843 and 0.804, respectively, and neither item exhibited a secondary loading above the reporting threshold of 0.30. The three JS items primarily loaded on Factor 4, with loadings ranging from 0.593 to 0.856, although JS2 also exhibited a secondary loading of 0.486 on

Factor 10. By contrast, several theoretically related adoption constructs were not clearly separated. Most PU and AT items loaded on the same factor, several TRU, IQ, and SQ items showed overlapping loading patterns, and the PEOU and IU items were distributed across multiple factors. Several factors were also defined by only one or two salient items. Accordingly, the EFA results provide limited and mixed support for the proposed ten-construct measurement structure and are interpreted as a supplementary diagnostic rather than as independent confirmation of the full measurement model. Such caution is warranted because EFA solutions can be affected by methodological decisions, sample characteristics, factor correlations, and deviations from a simple structure (de Winter et al., 2009; Fabrigar et al., 1999). Detailed EFA loadings are reported in Appendix C.

4.3. Measurement model

In PLS-SEM, the first step is to assess the measurement model to ensure that each construct exhibits adequate reliability and validity (Anderson & Gerbing, 1988). Internal consistency reliability was evaluated using Cronbach's alpha (CA) and composite reliability (CR), while convergent validity was assessed via standardized factor loadings and average variance extracted (AVE). Table 2 reports the factor loadings, CA, CR, and AVE for all constructs.

CA values are generally expected to exceed 0.70 (Hair et al., 2010). In this study, the CA values of PU, PEOU, AT, IU, IQ, and SQ were below this conventional threshold, with PU (α = 0.578) and PEOU (α = 0.509) showing the lowest values. Therefore, the internal consistency of these constructs should not be regarded as strong based on CA alone. However, Cronbach's alpha was not used as the sole criterion for evaluating construct reliability, because alpha assumes tau-equivalence and its value can be affected by the number of items, item interrelatedness, and dimensionality (Tavakol & Dennick, 2011). Accordingly, the measurement quality was assessed jointly using CA, CR, AVE, standardized factor loadings, and the supplementary EFA results reported in Section 4.2 (Hair et al., 2021b). Moreover, all CR values exceeded the recommended cutoff of 0.70 (Sekaran & Bougie, 2016), providing supportive evidence of internal consistency reliability. As shown in Table 2, all item loadings were greater than the commonly accepted threshold of 0.50 (Hair et al., 2010) and were statistically significant. The recommended minimum value for AVE is 0.50 (Hair et al., 2017), and the lowest AVE in this study was 0.504, implying that each construct explained at least 50.4% of the variance in its indicators. Taken together, these results provide partial support for retaining the constructs, particularly because PU and PEOU are theoretically central components of the TAM framework. Nevertheless, the relatively low CA values, especially for PU and PEOU, indicate that the measurement reliability evidence is acceptable but not strong, and the corresponding structural relationships should be interpreted with caution.

Table 2. Scales for reliability and validity of measurement model

Constructs	Items	FL	CA	CR	AVE
PU	PU1	0.780	0.578	0.779	0.543
	PU2	0.634			
	PU3	0.786			
PEOU	PEOU1	0.624	0.509	0.751	0.504
	PEOU2	0.775			
	PEOU3	0.722			
AT	AT1	0.794	0.661	0.816	0.596
	AT2	0.781			
	AT3	0.740			
IU	IU1	0.846	0.610	0.789	0.560
	IU2	0.590			
	IU3	0.784			
TRU	TRU1	0.808	0.798	0.881	0.712
	TRU2	0.861			
	TRU3	0.861			
LE	LE1	0.687	0.790	0.862	0.610
	LE2	0.793			
	LE3	0.813			
	LE4	0.824			
IQ	IQ1	0.808	0.600	0.788	0.559
	IQ2	0.594			
	IQ3	0.818			
SQ	SQ1	0.809	0.635	0.802	0.575
	SQ2	0.748			
	SQ3	0.714			
PSC	PSC1	0.824	0.724	0.873	0.776
	PSC2	0.934			
JS	JS1	0.800	0.773	0.864	0.680
	JS2	0.873			
	JS3	0.799			

Next, following the classical criterion proposed by Fornell and Larcker (1981), we evaluated discriminant validity to determine whether each latent construct represents a unique concept rather than overlapping with others. According to this criterion, the square root of a construct's Average Variance Extracted (AVE) should exceed its correlation coefficients with all other constructs. This method remains widely used and is considered a standard approach for assessing discriminant validity in PLS-SEM (Hair et al., 2020). As shown in Table 3, the square roots of all constructs' AVEs appear in bold on the diagonal of the correlation matrix. By comparing these diagonal values with the off-diagonal correlation coefficients, it can be seen that the square root of each construct's AVE is greater than its correlation coefficients with other constructs, indicating good discriminant validity among the constructs. In addition, as reported in Section 4.1, the VIF values for all latent constructs ranged from 1.000 to 1.847, below the recommended threshold of 3.3 (Diamantopoulos & Siguaw, 2006), suggesting that serious multicollinearity among the constructs is not a concern.

Table 3. Discriminant validity and correlation matrix

Construct	AT	IQ	IU	JS	LE	PEOU	PSC	PU	SQ	TRU
AT	**0.772**									
IQ	0.500	**0.747**								
IU	0.542	0.399	**0.748**							
JS	0.293	0.293	0.370	**0.825**						
LE	0.404	0.428	0.568	0.424	**0.781**					
PEOU	0.540	0.535	0.493	0.262	0.416	**0.710**				
PSC	–0.020	–0.166	–0.146	–0.150	–0.028	–0.120	**0.881**			
PU	0.654	0.350	0.448	0.262	0.264	0.397	–0.029	**0.737**		
SQ	0.443	0.635	0.446	0.303	0.380	0.548	–0.127	0.344	**0.758**	
TRU	0.526	0.671	0.443	0.298	0.368	0.417	–0.176	0.452	0.531	**0.844**

4.4. Structural model

Evaluation of the structural model constitutes the second step in the PLS-SEM procedure and focuses on assessing the hypothesized relationships among latent constructs and the overall model performance. Key indicators include the coefficient of determination (R^2), the cross-validated redundancy measure (Q^2), the Standardized Root Mean Residual (SRMR), and the statistical significance as well as substantive relevance of the path coefficients. The R^2 values reflect the explanatory power of the model. Results from the PLS algorithm show that the R^2 values for the five endogenous variables, AT (0.521), TRU (0.473), PEOU (0.387), IU (0.377), and PU (0.195), are all above or close to 0.25, which indicates that the model achieves a moderate level of explanatory power (Shmueli et al., 2016). The Q^2 values are used to evaluate predictive relevance (Hair et al., 2020). According to Bagozzi and Yi (1989), a model is considered to possess predictive capability when the Q^2 value for each dependent variable is greater than zero. Using a ten-fold cross-validation procedure, the Q^2 values obtained were 0.234 for AT, 0.418 for TRU, 0.305 for PEOU, 0.167 for IU, and 0.073 for PU. All values exceed zero, which indicates acceptable predictive relevance. Overall, these results suggest that the structural model exhibits satisfactory explanatory and predictive performance.

The structural model was examined using SRMR as a global model-fit diagnostic. The SRMR value of the model was 0.101. In empirical research, an SRMR value below 0.10 is frequently adopted as a reference threshold for model fit assessment, particularly within the context of PLS-SEM applications (Cuesta-Valiño et al., 2023). Because the SRMR value in this study slightly exceeded this threshold, it was not interpreted as definitive evidence of satisfactory global model fit. We therefore do not claim that the model achieves fully satisfactory global fit on the basis of SRMR alone, nor do we treat the reliability, validity, collinearity, R^2, and Q^2 results as substitutes for an unequivocal fit assessment. Rather, these indicators are used to show that the measurement and predictive properties of the model are acceptable while the marginal SRMR exceedance remains a limitation. Accordingly, the structural estimates are presented as exploratory evidence of the proposed adoption mechanism rather than as conclusive confirmation of a fully fitted covariance structure.

To further examine the significance of the structural paths, a bootstrapping procedure with 5,000 resamples was conducted. Because all hypotheses were directionally specified, one-tailed tests at the 0.10 significance level were used as the primary hypothesis assessment (Cho & Abe, 2013). This specification is also consistent with recommendations for exploratory PLS-SEM studies when limited sample size or model complexity may increase the risk of Type II errors (Hair et al., 2021a). However, a relatively liberal significance level increases the probability of rejecting the null hypothesis and is directly related to the risk of Type I error (Neyman & Pearson, 1992). In addition, one-tailed tests typically yield lower *p*-values than two-tailed tests and may influence whether hypotheses are accepted or rejected (Kock, 2015b). Therefore, two-tailed *p*-values at the 0.10 significance level were additionally reported as a robustness check, particularly for borderline paths. Detailed results are reported in Table 4. The robustness check indicates that H2, H3, H4, H8, H9, H11, and H14 remained significant under the two-tailed test, whereas H1, H6, and H12 were significant only under the one-tailed criterion and are therefore interpreted as weak directional evidence rather than robust statistical support.

Within the TAM framework, PEOU exerted a robust positive effect on AT (β = 0.333), PU had a strong positive effect on AT (β = 0.522), and AT robustly predicted IU (β = 0.403). The positive relationship between PEOU and PU (β = 0.245) was consistent with the hypothesized direction but remained significant only under the one-tailed criterion. Regarding information quality, system quality, and trust, IQ robustly enhanced both PEOU (β = 0.256) and TRU (β = 0.534), while SQ robustly improved PEOU (β = 0.314) and showed only weak directional evidence for enhancing TRU (β = 0.162). TRU also showed a positive association with IU (β = 0.175), but this relationship remained significant only under the one-tailed criterion and should therefore be interpreted cautiously. Among the usage-experience paths, only H14 remained supported, indicating that LE improved PEOU (β = 0.187), whereas its effects on PU (H13) and TRU (H15) were not statistically significant. In addition, PSC did not exhibit a significant negative ef-

Table 4. Path-level structural model results and hypotheses testing

Dependent variable	Path	Hypothesis	Path coefficient	One–tailed *p*	Two–tailed *p*	Results
PU	PEOU → PU	H1	0.245	0.083(*)	0.166(ns)	Weak directional support
	IQ → PU	H7	0.122	0.168(ns)	0.336(ns)	Not supported
	SQ → PU	H10	0.106	0.275(ns)	0.551(ns)	Not supported
	LE → PU	H13	0.069	0.243(ns)	0.487(ns)	Not supported
AT	PEOU → AT	H2	0.333	0.000(***)	0.000(***)	Supported
	PU → AT	H3	0.522	0.000(***)	0.000(***)	Supported
IU	AT → IU	H4	0.403	0.003(**)	0.006(**)	Supported
	PSC → IU	H5	–0.111	0.187(ns)	0.374(ns)	Not supported
	TRU → IU	H6	0.175	0.097(*)	0.194(ns)	Weak directional support
	JS×PSC → IU	H16	0.106	0.239(ns)	0.479(ns)	Not supported
PEOU	IQ → PEOU	H8	0.256	0.012(**)	0.025(**)	Supported
	SQ → PEOU	H11	0.314	0.007(**)	0.013(**)	Supported
	LE → PEOU	H14	0.187	0.036(**)	0.072(*)	Supported
TRU	IQ → TRU	H9	0.534	0.000(***)	0.000(***)	Supported
	SQ → TRU	H12	0.162	0.091(*)	0.182(ns)	Weak directional support
	LE → TRU	H15	0.078	0.224(ns)	0.447(ns)	Not supported

Note. One-tailed *p*-values were used for the primary assessment of directionally specified hypotheses, and two-tailed *p*-values are reported as a robustness check. Significance symbols are shown separately for each *p*-value column: *$p < 0.1$; **$p < 0.05$; ***$p < 0.001$; ns: not significant. Paths significant only under the one-tailed 0.10 criterion are labeled as weak directional support.

fect on IU, and the moderating effect of JS on the relationship between PSC and IU was not supported. These findings suggest that concerns about job substitution and job specialization effects have not yet translated into significant deterrent or moderating mechanisms in construction professionals' LLM adoption.

4.5. Moderation analysis

H16 posited that JS would significantly moderate the relationship between PSC and IU, such that higher JS would attenuate the negative impact of PSC on IU. To test this moderating effect, an interaction term (PSC × JS) was created by multiplying PSC with JS and incorporated into the structural model as an additional predictor of IU. As reported in Table 4, the interaction term did not exert a statistically significant effect on IU under either the primary one-tailed criterion or the two-tailed robustness check (β = 0.106), indicating that, within the present sample, JS did not significantly moderate the relationship between PSC and IU. Accordingly, H16 was not supported.

To visualize the potential interaction pattern, a simple slope analysis was conducted by splitting the sample into high and low JS groups (mean ± 1 SD) and plotting the corresponding moderation graph. As shown in Figure 2, the negative effect of the PSC on IU appears stronger among respondents with low JS and weaker among those with high JS. However, given that the overall interaction effect was not statistically significant under either testing criterion, the moderating role of JS in this relationship must be interpreted with caution and remains empirically inconclusive.

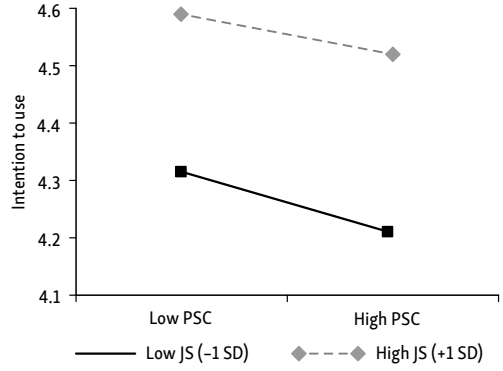


Figure 2. Moderating effects of JS on the relationship between PSC and IU

4.6. Importance-performance map analysis (IPMA)

Figure 3 presents the results of the IPMA. Following the approach commonly adopted in prior IPMA studies (Martilla & James, 1977), the two-dimensional space is partitioned into four quadrants using the mean values of importance and performance as cut-off criteria. The results show that AT, PU, and PEOU fall into the high importance, high performance quadrant, indicating that these core TAM constructs are both strong drivers of adoption intention and already functioning at a relatively satisfactory level in practice. By contrast, IQ and TRU are located in the high importance, low performance quadrant, suggesting that although they are critical for fostering IU, their current performance is suboptimal and they should therefore be prioritized for improvement.

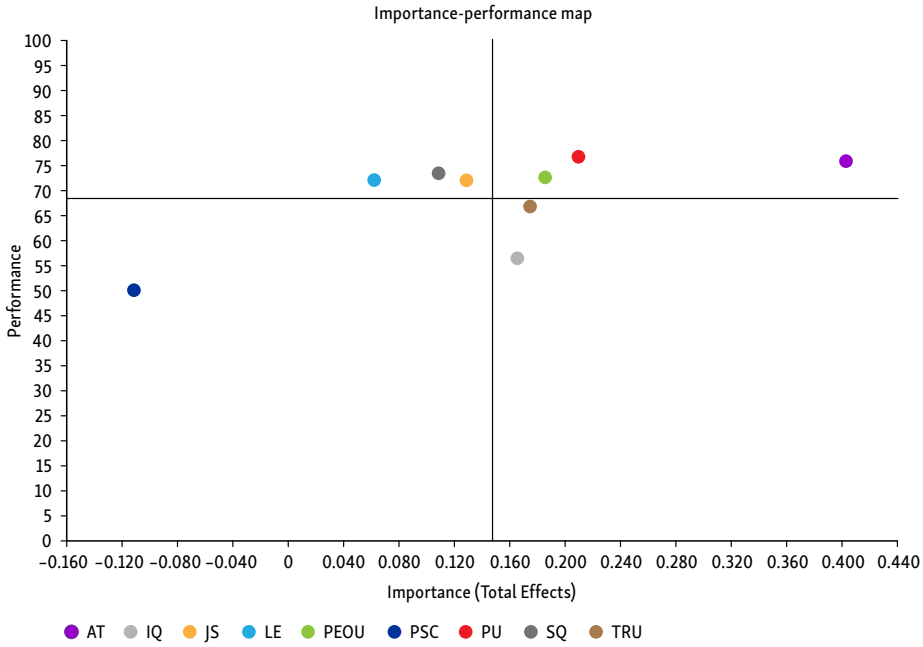


Figure 3. Importance-performance map for IU

LE, SQ and JS are positioned in the low importance, high performance quadrant. While these constructs exhibit comparatively high performance, their marginal contribution to intention is limited, implying that additional investments in these areas may yield relatively modest gains. Finally, PSC appears in the low importance, low performance quadrant, indicating that, although concerns about technological replacement are present, they neither substantially inhibit nor promote adoption at this stage. Overall, the IPMA results underscore that strengthening TRU and enhancing IQ constitute the most urgent levers for improving LLM adoption in the construction industry, while the strong performance of AT, PU, and PEOU should be maintained.

4.7. Results from open-ended questions

To obtain a more nuanced understanding of how construction professionals perceive and engage with LLMs, as well as their practical needs, qualitative data were collected through three open-ended questions. These questions focused on: (1) potential application scenarios of LLMs in daily work, (2) current obstacles in using LLMs, and (3) expectations for future functions and services.

To improve the methodological transparency of the qualitative analysis, the responses were analyzed using an inductive thematic content analysis approach. The qualitative analysis was based on the open-ended responses from the 82 valid questionnaires. The coding process involved repeated reading of the responses, identification of recurring meanings, and grouping of similar codes into broader themes. Because the open-ended component was designed to supplement and contextualize the PLS-SEM results rather than to function as a stand-alone qualitative study, no separate inter-rater reliability coefficient was calculated. To avoid overstating the qualitative evidence, the coding results are reported as descriptive supplementary evidence rather than as an independent qualitative reliability test. Because a single response could mention more than one idea, multiple codes could be assigned to the same response. Therefore, the reported frequencies represent the number of respondents mentioning each theme, and the percentages were calculated based on the 82 valid questionnaires. The qualitative themes were further mapped onto the PLS-SEM findings to clarify whether they validate, extend, or help explain the quantitative results.

As shown in Table 5, the most frequently mentioned application scenario was document drafting and text processing, which was reported by 42 respondents (51.2%). Respondents described LLMs as useful for preparing technical schemes, reports, bidding documents, meeting materials, summaries, and other text-intensive outputs. This finding supports the quantitative result that perceived usefulness plays an important role in shaping users' attitudes toward LLM use. Design support and creative generation were also frequently mentioned by 39 respondents (47.6%), indicating that LLMs are perceived as useful for generating design ideas, optimizing preliminary schemes, and supporting conceptual design. Another 39 respondents (47.6%) referred to project or construction management and planning, including schedule planning, risk prediction, construction process optimization, and resource coordination. These themes extend the interpretation of perceived usefulness by showing that construction professionals value LLMs not only for general office tasks but also for knowledge-intensive project activities.

Respondents also emphasized technical knowledge retrieval and standards consultation. This theme appeared in 29 responses (35.4%) and included references to build-

Table 5. Themes identified from open-ended responses

Open-ended question	Theme	Frequency	Percentage
Application scenarios	Document drafting and text processing	42	51.2%
Application scenarios	Design support and creative generation	39	47.6%
Application scenarios	Project/construction management and planning	39	47.6%
Application scenarios	Technical knowledge retrieval and standards consultation	29	35.4%
Application scenarios	Cost, quantity calculation, and data analysis	15	18.3%
Obstacles	Insufficient domain knowledge and professional accuracy	37	45.1%
Obstacles	Limited project-specific and practical applicability	21	25.6%
Obstacles	Prompting burden and limited intent understanding	20	24.4%
Obstacles	System or functional limitations	17	20.7%
Obstacles	Generic or insufficiently personalized outputs	17	20.7%
Obstacles	Outdated or non-real-time information	13	15.9%
Future expectations	Domain-specific knowledge bases, standards, and case resources	32	39.0%
Future expectations	Multimodal drawing, CAD/BIM, or model interpretation	24	29.3%
Future expectations	Decision support, data analysis, calculation, and optimization	22	26.8%
Future expectations	Improved interaction, intent understanding, or personalization	21	25.6%
Future expectations	Project-specific customization and contextual simulation	14	17.1%
Future expectations	Real-time data updating and monitoring	14	17.1%
Future expectations	Tool/software integration and workflow automation	8	9.8%

ing codes, technical standards, professional information search, and construction-related problem solving. This finding helps validate the significant role of information quality in the structural model. In particular, users' reliance on LLMs for technical knowledge and standards-related queries suggests that accurate, understandable, and relevant information is essential for improving perceived ease of use and trust. In addition, 15 respondents (18.3%) mentioned cost, quantity calculation, and data analysis, suggesting that some users expect LLMs to support more analytical and calculation-related construction tasks.

The obstacle-related responses further clarify the limitations of current LLM applications in construction. The most frequently mentioned obstacle was insufficient domain knowledge and professional accuracy, reported by 37 respondents (45.1%). Respondents noted that LLMs may misunderstand professional terminology, provide inaccurate technical information, or lack sufficient depth in construction-specific knowledge. This finding helps explain why information quality is important for both perceived ease of use and trust. Limited project-specific and practical applicability was mentioned by 21 respondents (25.6%), who indicated that LLMs often fail to account for site conditions, regional differences, project-specific constraints, or practical constructability. This qualitative evidence helps explain why information quality and system quality did not directly improve perceived usefulness: technical quality alone may not translate into perceived usefulness unless outputs are sufficiently adapted to real construction contexts.

Prompting burden and limited intent understanding were identified by 20 respondents (24.4%). These respondents reported that useful outputs often depend on precise prompt formulation, repeated clarification, or trial-and-error interaction. This theme extends the quantitative role of perceived ease of use by showing that ease of use in LLM adoption is not limited to interface simplicity; it also involves reducing the cognitive and operational burden of prompt construction. System or functional limitations were mentioned by 17 respondents (20.7%), including response delay, file-size restrictions, limited long-text processing, and insufficient support for external inputs. These responses support the positive effect of system quality on perceived ease of use. In addition, 17 respondents (20.7%) referred to generic or insufficiently personalized outputs, while 13 respondents (15.9%) emphasized outdated or non-real-time information. These findings indicate that construction professionals expect LLM outputs to be more context-aware, up-to-date, and professionally verifiable.

Regarding future expectations, the most frequently mentioned theme was the development of domain-specific knowledge bases, standards, and case resources, which appeared in 32 responses (39.0%). Respondents expected LLMs to connect with building codes, technical databases, project cases, and professional knowledge repositories. This theme reinforces the importance of information quality and indicates that domain grounding is a key condition for improving the practical relevance of LLM applications in construction. Multimodal drawing, CAD/BIM, or model interpretation was mentioned by 24 respondents (29.3%), indicating that users expect LLMs to move beyond text-based interaction and support drawing review, model interpretation, visualization, and automated design-related outputs. Decision support, data analysis, calculation, and optimization were mentioned by 22 respondents (26.8%), suggesting that users expect LLMs to provide more structured analytical support for construction decision making.

Improved interaction, intent understanding, or personalization was mentioned by 21 respondents (25.6%), further extending the interpretation of perceived ease of use in the LLM context. Respondents expected LLMs to better infer user intent, support smoother interaction, and provide more personalized outputs. Project-specific customization and contextual simulation were mentioned by 14 respondents (17.1%), and real-time data updating and monitoring were also mentioned by 14 respondents (17.1%). These expectations are consistent with the obstacle-related finding that current LLMs are often perceived as insufficiently adapted to specific construction contexts. Finally, 8 respondents (9.8%) explicitly mentioned tool/software integration and workflow automation, such as integration with BIM, CAD, Excel, Word, or other construction software ecosystems.

Overall, the qualitative findings triangulate the PLS-SEM results in three ways. First, they validate several significant quantitative findings, particularly the roles of information quality, system quality, perceived ease of use, and perceived usefulness. Second, they extend the interpretation of key constructs by clarifying their practical meanings in construction work, such as prompting burden for perceived ease of use, output verifiability for trust, and project-specific applicability for perceived usefulness. Third, they help explain weaker or non-significant quantitative relationships. For example, the frequent emphasis on professional accuracy and project-specific applicability helps explain why technical quality alone may not directly generate perceived usefulness, while the limited emphasis on job replacement concerns is consistent with the non-significant effect of perceived substitution crisis. Thus, the open-ended responses serve as supplementary explanatory evidence that contextualizes the structural model rather than as a separate qualitative study, and the theme frequencies should be interpreted as descriptive indicators within this sample rather than as population-level prevalence estimates.

5. Discussion

5.1. Results discussion

LLMs are widely regarded as transformative tools in knowledge-intensive industries, yet their integration into construction practice remains nascent. In the context of Chinese construction professionals, the triangulation of quantitative evidence from the PLS-SEM analysis with qualitative insights from open-ended responses yields several nuanced findings that extend current understanding of generative AI adoption in digitally conservative sectors.

First, the core attitude-formation mechanism of TAM is generally supported, although the relationship between PEOU and PU should be interpreted cautiously. PEOU exerted a robust positive effect on AT, and PU also strongly enhanced AT, indicating that construction professionals' attitudes toward LLMs are shaped by both usability perceptions and perceived task value. AT further emerged as a robust predictor of IU. This pattern suggests that, despite the novelty and complexity of LLMs, construction professionals still follow cognitive acceptance pathways broadly consistent with prior TAM-based studies on construction technology adoption and related digital technologies (Lee & Yu, 2016; Liu et al., 2018; Saqib et al., 2023). However, the positive relationship between PEOU and PU was significant only under the one-tailed 0.10 criterion and should therefore be understood as weak directional evidence rather than robust statistical support. Qualitative feedback further specifies what "ease of use" entails in this context, namely clear prompt requirements, low trial-and-error costs, and smooth interface interactions. Many respondents reported frustration with repeatedly adjusting inputs to obtain usable outputs. Thus, ease of use in construction is not limited to interface simplicity; it also concerns reducing hidden cognitive and operational burdens in interaction between humans and LLMs.

Second, TRU showed a positive association with IU that was significant under the primary one-tailed 0.10 criterion but did not remain significant under the two-tailed 0.10 robustness check. The positive direction of this path is theoretically consistent with Chang and Park's (2024) argument that, in the absence of extensive experience and formal training, users may rely on subjective TRU when deciding whether to embrace new technologies. Given the high risk and high responsibility inherent in construction work, trustworthy system outputs may encourage employees to consider incorporating LLMs into everyday decision making, a mechanism also discussed in education and healthcare settings (Bilquise et al., 2024; Prakash & Das, 2021). Nevertheless, because the relationship between TRU and IU was supported only under the primary one-tailed criterion, this relationship should be interpreted as directional evidence rather than robust statistical support and requires further validation in future studies with larger and more representative samples.

Third, IQ and SQ affect adoption-related perceptions in differentiated ways, but neither significantly improves PU. IQ robustly enhanced both PEOU and TRU, indicating that accurate, relevant, and understandable outputs help users perceive LLMs as easier to use and more trustworthy. SQ robustly improved PEOU, suggesting that responsiveness, stability, and functional fluency mainly reduce the perceived operational burden of using LLMs. However, the relationship between SQ and TRU provided only weak directional evidence. Together, these results reveal a misalignment between technical performance and task fit in the construction context. Even when LLMs perform well in terms of response speed or surface-level accuracy, users may still hesitate to regard them as useful if outputs lack domain depth or contextual relevance. This finding resonates with research on task technology fit (Wang et al., 2025) and suggests that future LLM deployment in construction should prioritize domain-specific training and the embedding of industry knowledge, rather than focusing solely on generic performance metrics.

Fourth, prior LE increases PEOU, but does not significantly influence PU or TRU. Although this may appear counterintuitive, it is consistent with the actual usage patterns revealed by qualitative data. Many participants reported sporadic, low-stakes use, for example, for text editing, translation, or general information search, rather than for core, high-complexity construction tasks. Such shallow engagement can lower the perceived learning barrier, thereby improving ease of use, but does not provide sufficient exposure to fundamentally reshape beliefs about professional value or reliability. As Yan et al. (2022) emphasized, the transformative impact of experience on technology perceptions typically requires sustained and complex interactions, which are not yet common in construction.

Fifth, PSC does not significantly affect IU, which differs from the findings of Wang et al. (2025). This result should be interpreted cautiously rather than as evidence that substitution concerns are irrelevant in LLM adoption. Prior research suggests that perceived substitution-related technological threats can function as inhibitors of AI-use intention (Wang et al., 2025), and employees' awareness of smart technologies, artificial intelligence, robotics, and algorithms may generate concerns about job replacement and future employability (Brougham & Haar, 2018). However, in the present study, PSC did not operate as a statistically detectable direct inhibitor of IU. One possible explanation is that construction professionals may still perceive current LLMs as assistive and dependent on human expertise rather than as fully substitutive technologies, which is consistent with the argument that users evaluate emerging technologies in relation to their perceived task capability and practical limitations (Fan et al., 2020). The open-ended responses support this cautious interpretation: respondents frequently mentioned insufficient domain knowledge and professional accuracy, limited project-specific applicability, prompting burden, and system or functional limitations. These limitations may weaken the extent to which substitution concerns are translated into lower use intention, because current LLMs may not yet be perceived as capable of replacing construction professionals' site experience, contextual judgment, and professional responsibility. Nevertheless, this explanation remains tentative and should be tested in future research using direct measures of perceived LLM maturity, task substitutability, complementarity between humans and AI, and job-security concern.

Finally, the hypothesized moderating effect of JS on the relationship between substitution crisis and IU is not statistically supported. Nonetheless, the simple slope analysis reveals the anticipated pattern: employees in highly specialized roles appear less threatened by LLMs, whereas those in routine positions exhibit greater sensitivity. The lack of significance is likely attributable to the modest sample size and uneven distribution of JS levels (Shah & Goldstein, 2006). Future research with larger and more diverse samples is needed to validate the robustness and boundary conditions of this moderating mechanism.

5.2. Theoretical implications

Building on an integrated framework of the TAM and the ISS model, this study offers several theoretical contributions to understanding the adoption of LLMs in the construction industry, a domain traditionally characterized by digital fragmentation and low information integration (Moshood et al., 2024).

First, this study extends the explanatory scope of TAM to the emerging context of generative AI-driven tools. Although LLMs differ from traditional information systems in terms of autonomy, opacity, and language-based reasoning (Heersmink et al., 2024), PEOU and PU remain important components of the attitude-formation mechanism. Specifically, PEOU and PU both showed robust positive effects on AT, and AT robustly predicted IU, indicating that users' willingness to adopt LLMs is strongly shaped by their overall attitude toward the technology. However, the relationship between PEOU and PU provided only weak directional evidence, suggesting that the internal relationship between ease of use and usefulness requires further validation in the construction context. Therefore, the findings support the adaptability of TAM to generative AI adoption, while also showing that some internal TAM relationships may be less stable in complex, text-intensive professional settings. By revealing how perceptions of usefulness and ease of use operate in construction-related collaboration between humans and AI, the study enriches technology adoption theory under the paradigm of generative AI use.

Second, the study advances ISS theory by examining the roles of IQ and SQ in non-institutionalized AI use contexts. When LLMs are adopted at the individual level rather than deployed through formal organizational systems, users evaluate them mainly on informational reliability and interaction fluency rather than institutional support. The results show that IQ robustly enhances both PEOU and TRU, while SQ robustly improves PEOU and provides only weak directional evidence for enhancing TRU. Neither IQ nor SQ significantly improves PU. This pattern points to a distinctive cognitive mechanism: users interpret information quality as a basis for both usability and trust, whereas system quality primarily contributes to perceived usability rather than directly generating perceived task utility. This extends ISS theory by uncovering differentiated psychological pathways through which IQ and SQ contribute to technology acceptance in early-stage AI adoption.

Third, by incorporating psychological and cognitive variables such as TRU, prior experience, PSC, and JS, this study deepens understanding of human cognition in AI adoption. TRU showed a positive association with IU that was significant under the primary one-tailed 0.10 criterion, but it did not remain significant under the two-tailed 0.10 robustness check. Therefore, trust may function as a psychological bridge that helps compensate for technological opacity (Gefen et al., 2003), but this relationship should be interpreted as directional evidence rather than

robust statistical support. Prior experience significantly improves PEOU but does not affect PU or TRU, suggesting that early-stage experience mainly shapes operational fluency rather than higher-order cognitive reassessment. The non-significant effect of PSC suggests that, at the current stage, users may be more likely to frame LLMs as supportive assistants than as direct occupational threats (Fan et al., 2020); however, this interpretation remains tentative and should be further examined as LLM capabilities and workplace integration continue to evolve. These results collectively indicate that AI adoption models must account for evolving psychological appraisals across different stages of technological maturity.

Fourth, although the moderating effect of JS was statistically nonsignificant, it introduces a novel occupational perspective into the theory of technology adoption. Simple slope analysis and qualitative evidence suggest that professional self-efficacy and perceived irreplaceability can dampen technology-related anxiety among highly specialized workers, whereas those in routine roles remain more sensitive to perceived substitution. This highlights the value of integrating occupational identity and professional stratification into future extensions of TAM-based frameworks, particularly in industries with pronounced professional hierarchies.

Finally, the study contributes to the emerging literature that links micro-level adoption behavior with macro-level industrial information integration. By empirically demonstrating how individual TRU, PEOU, and PU jointly shape willingness to engage with LLMs, it provides theoretical grounding for understanding how human factors enable broader integration of information flows in construction. This cross-level perspective enriches information systems research by situating technology acceptance within the larger objective of building intelligent, interconnected industrial ecosystems.

In summary, the theoretical contributions of this study lie in: (1) extending the classical TAM to generative AI contexts, (2) revealing TRU-centered pathways within ISS theory under decentralized adoption, (3) uncovering the staged and cognition-dependent nature of perceived substitution effects, and (4) conceptually bridging micro-level user cognition with macro-level information integration. Together, these contributions offer a refined theoretical foundation for future research on AI-enabled transformation in digitally lagging industries such as construction.

5.3. Managerial implications

The findings of this study yield several actionable implications for construction firms, particularly those operating in digitally transforming construction environments similar to China, seeking to promote effective adoption of LLMs. By integrating quantitative evidence from the structural model, prioritization insights from IPMA, and qualitative feedback from open-ended responses, the study supports targeted interventions that address the specific mechanisms revealed by the empirical results.

First, strengthening IQ is fundamental to building user TRU. The SEM results show that IQ significantly affects both PEOU and TRU, while IPMA identifies it as a high-importance but low-performance attribute. Qualitative responses clarify why IQ is perceived as insufficient: users criticize LLM outputs as overly generic, lacking creativity, misinterpreting technical terminology, and failing to account for site-specific constraints. These deficiencies erode TRU and discourage employees from relying on LLMs for core professional tasks. Managers should therefore prioritize domain-specific fine-tuning of LLMs, for example, by integrating building codes, construction standards, and project case repositories. In parallel, firms should invest in contextual adaptation mechanisms that enable LLMs to generate outputs that reflect on-site conditions and align with industry logic (Mustapha, 2025). Such measures directly address users' dissatisfaction and help reposition LLMs from general-purpose assistants to trusted professional tools.

Second, cultivating TRU requires organizational and institutional arrangements in addition to technical improvements. TRU showed directional support as a predictor of usage intention under the primary one-tailed criterion and was also identified as a highly important, low-performance construct in IPMA. Beyond improving output quality, firms must manage the psychological and organizational dimensions of TRU. Open-ended responses indicate that employees are reluctant to rely on LLM outputs because of uncertainty about reliability and unclear accountability when errors occur. Management can mitigate these concerns by implementing verification protocols for LLM-generated documents, clarifying liability policies, and increasing transparency in AI-assisted workflows. Providing secure, enterprise-level access to LLM platforms can also reduce worries about data leakage and further enhance employees' willingness to trust the system (Diro et al., 2025).

Third, enhancing PU requires focusing on high-frequency, high-friction tasks while aligning with employees' expectations for future functionality. The quantitative results confirm the central role of PU in shaping attitude, while attitude further predicts intention. Qualitative data identify where users currently perceive tangible value: document drafting, information retrieval, project planning, and design assistance. These tasks are both common and cognitively demanding, making them ideal entry points for LLM applications. At the same time, respondents express demand for richer domain-specific capabilities, including integration with codes and technical databases, the use of historical project cases, the ability to interpret architectural drawings, connectivity with BIM platforms, and more intelligent conversational interaction. Firms should therefore concentrate training and demonstration activities on current "pain point" scenarios where performance gains are easily observable, while coordinating system development and organizational support with these forward-looking expectations. By simultaneously showcasing efficiency

improvements in existing tasks and introducing enhanced features that address concrete user needs, management can accelerate the PU and broader adoption of LLMs.

Fourth, PEOU should be reinforced through structured organizational support. Although ease of use already performs relatively well according to IPMA, qualitative feedback reveals that employees often struggle with prompt formulation and must engage in repeated trial and error to obtain satisfactory outputs. Managerial interventions should therefore go beyond intuitive system interfaces and provide complementary organizational resources. Training programs on effective prompt design, curated libraries of task-specific prompts, and peer learning or community sharing mechanisms can substantially reduce the cognitive load associated with LLM interaction. These measures help consolidate the perception that LLMs are not only technically accessible but also practically effortless to apply in daily work.

Finally, the non-significant effect of PSC offers a counterintuitive but important insight. Both the structural model and IPMA place PSC in the low importance, low performance quadrant, indicating that replacement concerns currently neither strongly hinder nor promote adoption. Qualitative data show that employees are well aware of LLMs' limitations, such as generic outputs, insufficient domain depth, and weak adaptation to site conditions, and maintain confidence in their own professional judgement. These limitations may partly explain why LLMs are currently perceived more as assistants than as competitors (Fan et al., 2020). For managers, this means that substitution anxiety was not the most immediate adoption barrier observed in this sample; it should not be dismissed, but it should be managed alongside more salient barriers related to information quality, reliability, and task alignment. Instead, the focus should be on enhancing LLM performance, particularly IQ, reliability, and task alignment, so that employees can experience concrete benefits in their daily work. Nevertheless, as LLM capabilities improve, substitution concerns may re-emerge. Proactive preparation, such as promoting human AI complementarity and strengthening employees' skills in evaluation, contextual reasoning, and creative design, will be crucial for sustaining adoption over the long term (Zirar et al., 2023).

In sum, the managerial implications of this study suggest that successful LLM adoption in the construction industry depends less on generic promotion and more on addressing specific barriers identified by users. Enhancing IQ through domain-specific fine-tuning and contextual adaptation, building TRU via technical reliability and institutional safeguards, prioritizing high-frequency and high-friction tasks to demonstrate usefulness, reducing cognitive burdens through training and prompt sharing mechanisms, and treating substitution concerns as secondary while preparing for future human-AI complementarity together constitute a pragmatic roadmap for fostering LLM adoption. By aligning interventions with the concrete needs and concerns revealed by both quantitative and qualitative evidence, construction firms can move beyond symbolic adoption and realize substantive value from LLM integration.

5.4. Limitations and future research

Despite its preliminary contributions to theory development and empirical evidence, this study has several limitations that should be addressed in future research. First, the relatively small sample size and the use of convenience sampling may constrain the external validity of the findings (Shahzad et al., 2025; Sun, 2024). Although the sample includes multiple categories of construction-related job roles, the total of 82 respondents is insufficient to fully represent the broader construction workforce. More importantly, the sample was drawn exclusively from Chinese construction professionals recruited through a single online survey platform, Credamo. This sampling context may have systematically shaped the observed adoption mechanism. On the one hand, China's construction industry has been strongly influenced by policy-driven digital transformation, BIM promotion and mandate-like institutional pressures, and intelligent construction initiatives (Zhang et al., 2023), which may make respondents more familiar with digitalization-related narratives and more receptive to LLM-enabled information integration. China's project-based construction organizations may also be shaped by relatively collectivist and hierarchy-conscious work norms, under which employees' attitudes toward emerging technologies can be influenced by organizational expectations, peer adoption, and perceived alignment with collective project goals. On the other hand, online-platform recruitment may overrepresent respondents who are younger, more digitally literate, and more willing to experiment with emerging technologies. These contextual features may partly elevate perceived usefulness, perceived ease of use, and attitude toward LLM use, while limiting the generalizability of the findings to construction professionals in countries or regions with different digital maturity, regulatory environments, labor-market structures, and organizational cultures.

In addition to these sampling and contextual constraints, the SRMR value slightly exceeded the conventional 0.10 threshold, suggesting that the global model fit should also be interpreted with caution. Subsequent studies should enlarge the sample and adopt more representative random or stratified sampling strategies to improve generalizability and statistical power. They should also conduct cross-national or cross-regional comparative studies to examine whether the adoption paths identified in this study remain stable across different institutional, cultural, and technological contexts, and further validate the proposed model using alternative model specifications and additional fit and predictive assessment criteria.

Second, the data are primarily self-reported, which may be affected by CMB and social desirability tendencies (Podsakoff et al., 2003). While screening items and anonymity were incorporated into the survey design to miti-

gate these issues, future research could integrate multiple data sources, for example, behavioral usage logs, semi-structured interviews, or field observations, to strengthen reliability and ecological validity.

Relatedly, the two-stage task familiarization protocol may have influenced respondents' subsequent self-reported perceptions. Although respondents first completed a role-specific task without LLM assistance and then completed the same task with Doubao assistance, this procedure was not a randomized controlled experiment. The fixed task order may have introduced order or contrast effects, and the four role-specific tasks differed in content, cognitive demand, and output format. In addition, the study did not evaluate objective task performance, such as completion time, output accuracy, output quality, or productivity improvement. Therefore, the task protocol should be interpreted as a contextual anchoring procedure for self-reported evaluations rather than as evidence of the objective performance benefits of LLM use. Future research should adopt randomized and standardized task experiments with independent output-quality assessment.

Third, most constructs were measured using generic scales adapted from prior studies. Although localization adjustments were made, certain variables, such as PSC and LE, still lack measurement instruments specifically designed for the construction context, which may limit their sensitivity to industry-specific psychological responses and behavioral patterns. In particular, PSC was measured with two a priori adapted items focusing on perceived replacement and unemployment risk. Although this focused operationalization was aligned with the substitution-threat definition adopted in this study and was supported by the measurement model and supplementary EFA results, a two-item measure may still provide limited coverage of the broader psychological responses associated with AI-enabled work transformation. Related aspects, such as usage dependence or perceived competence erosion, were not included in the final PSC measure and should be further examined in future scale-development research. Relatedly, several constructs, particularly PU and PEOU, showed relatively low Cronbach's alpha values, indicating that the measurement reliability of these central TAM constructs should also be further examined. Although the CR, AVE, item-loading, and supplementary EFA results provided partial support for retaining the constructs, the corresponding structural relationships should still be interpreted cautiously. Future research should develop and independently validate a broader construction-specific PSC scale using larger samples and complementary EFA and CFA procedures. It should also develop and validate construction-specific measures for other context-sensitive constructs, such as LE, to enhance measurement precision and explanatory power. In addition, although this study examined the moderating role of JS, the interaction effect was not statistically significant, which may reflect limited sample heterogeneity or overly coarse occupational categories (Shah & Goldstein, 2006). Future research could employ more fine-grained occupational classifications and incorporate additional individual-level moderators, such as technology anxiety, computer self-efficacy, and perceived organizational support, to provide a more nuanced account of LLM adoption.

Finally, the cross-sectional research design restricts the ability to infer causality or capture dynamic changes over time (Menard, 2002; Rindfleisch et al., 2008). As LLM technologies evolve and become more deeply embedded in organizational workflows, employee attitudes and perceptions are likely to shift. Longitudinal panel designs or experimental and quasi-experimental approaches would enable researchers to track adoption trajectories and examine how psychological mechanisms evolve across different stages of technology adoption.

6. Conclusions

LLMs, as a core technology within generative artificial intelligence, exhibit substantial potential to advance industrial information integration in the construction sector. This study examined the individual-level mechanisms underpinning LLM adoption among construction professionals and derived practical guidance for facilitating their integration into everyday workflows. The results yield four main conclusions.

First, the TAM-based attitude-formation mechanism is generally supported in the generative AI context. PEOU and PU both exert robust positive effects on AT, and AT further emerges as a robust predictor of intention to use LLMs. However, the relationship between PEOU and PU is supported only under the primary one-tailed 0.10 criterion and should therefore be interpreted as directional evidence rather than robust statistical support. Beyond the TAM paths, TRU also shows a positive association with intention to use LLMs under the primary one-tailed 0.10 criterion, but this relationship does not remain significant under the two-tailed 0.10 robustness check and therefore requires further validation. Second, IQ and SQ contribute to adoption-related perceptions through differentiated pathways. IQ robustly enhances both PEOU and TRU, while SQ robustly improves PEOU and provides only weak directional evidence for enhancing TRU. Neither IQ nor SQ directly improves PU, suggesting that technical quality alone may not be sufficient to generate perceived task utility in construction settings. Third, prior experience with LLMs significantly improves PEOU, but does not directly influence PU or TRU, reflecting the exploratory and early-stage nature of LLM application in the construction domain. Fourth, PSC and JS exert no significant effects at this stage, indicating that LLMs are currently regarded more as supportive assistants than as potential replacements for professional roles.

Overall, the findings indicate that promoting LLM adoption in construction enterprises requires more than technical deployment. It depends on improving IQ, strengthening trust-building mechanisms through reliable outputs

and institutional safeguards, and enhancing user readiness through targeted training and organizational support. Given that several paths were supported only under the primary one-tailed criterion, the findings should be interpreted as exploratory evidence rather than conclusive confirmation. By clarifying the psychological and cognitive mechanisms underlying individual adoption among Chinese construction professionals and outlining feasible strategies for enterprises, this study provides a foundation for embedding LLMs into construction workflows and for advancing intelligent collaborative environments in which humans and AI systems jointly support industrial information integration and accelerate the digital transformation of the construction industry. However, the generalization of these findings to other national contexts should be made cautiously because LLM adoption may be shaped by local digital maturity, policy environments, labor-market conditions, and organizational cultures, including the extent to which technology use is encouraged through collective project norms or top-down digitalization initiatives.

Declaration of competing interests

None.

Data availability statement

The authors do not have permission to share the data.

Declaration of generative AI in scientific writing

During the preparation of this manuscript, the authors used ChatGPT (an AI large language model developed by OpenAI) solely for language polishing and stylistic refinement. The tool was not used to generate content, results, arguments, or to perform substantive intellectual work. After using ChatGPT, the authors reviewed, edited, and verified all generated text, and take full responsibility for the content and integrity of the paper.

No AI tool is listed as an author, contributor, or co-author, and all authorship responsibilities remain with the human authors.

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APPENDIX

A. Measures

Table A1. Measurement constructs, items, and sources

Constructs	Items	Sources
Perceived usefulness (PU)	PU1: Using LLM improves my performance at work.	Davis (1989)
	PU2: Using LLM increases my productivity at work.	
	PU3: Overall, LLM are useful at work.	
Perceived ease of use (PEOU)	PEOU1: Learning to use LLM is easy.	Davis (1989)
	PEOU2: The interface of LLM is concise.	
	PEOU3: I find LLM easy to use.	
Attitude towards use (AT)	AT1: I believe that using LLM is a good idea at work.	Davis (1989)
	AT2: I believe that using LLM is advisable at work.	
	AT3: I am satisfied with the use of LLM at work.	
Intention to use (IU)	IU1: I intend to use LLM in the future.	Choi and Ji (2015); Hsu et al. (2007)
	IU2: I expect that I would use LLM in the future.	
	IU3: I will strongly recommend others to use LLM.	
Trust (TRU)	TRU1: I find LLM to be reliable.	Herrenkind et al. (2019)
	TRU2: I find LLM to be trustworthy.	
	TRU3: All in all, I trust LLM.	
LLM experience (LE)	LE1: I often use LLM to seek answers to various knowledge questions.	Yan et al. (2022)
	LE2: I frequently turn to LLM to refine and improve my writing.	
	LE3: I often utilize LLM to understand and learn new concepts in different fields.	
	LE4: I frequently rely on LLM to have conversations and discussions on diverse topics.	
Information quality (IQ)	IQ1: LLM provides output that seems to be exactly what I need.	Hsu et al. (2015)
	IQ2: Information from LLM is easy to understand.	
	IQ3: Information from LLM is accurate.	
System quality (SQ)	SQ1: LLM reacts and responds quickly to the user's entry.	Hsu et al. (2015)
	SQ2: LLM meets my requirements.	
	SQ3: LLM rarely fails.	
Perceived substitution crisis (PSC)	PSC1: I think that LLM will replace employees in the future.	Fan et al. (2020), Verma and Singh (2022)
	PSC2: I think the rise and development of LLM will likely lead to unemployment.	
Job specialization (JS)	JS1: My job requires high specialization of purpose, tasks, or activities.	Verma and Singh (2022)
	JS2: My job requires highly specialized knowledge and skills.	
	JS3: My job requires in-depth advanced technological expertise.	

B. Role-specific two-stage task familiarization protocol

Table A2. Role-specific task scenarios and completion requirements

Job category	Display condition	Stage 1 Non-LLM task	Stage 1 completion requirement	Stage 2 LLM-assisted task	Stage 2 completion requirement
Design-related personnel	Displayed when respondents selected "design-related personnel" as their job role.	Respondents were asked to design a small community activity center on a rectangular site measuring 80 m × 50 m. The center was required to include a meeting room for 200 people, a fitness room of at least 300 m^2, and a library with a capacity of 5,000 books. The architectural style was specified as modern and minimalist, with emphasis on natural lighting and ventilation. Respondents were asked to provide one design concept and spatial layout idea in text form.	Respondents completed the task independently without LLM assistance. A minimum response length of 50 Chinese characters was required.	Respondents were instructed to use Doubao to complete the same design task again and to reflect on the LLM's response speed, output quality, usefulness, and limitations.	A minimum response length of 100 Chinese characters was required.
Construction technical personnel	Displayed when respondents selected "technical personnel" as their job role.	Respondents were given a six-story residential building project. The foundation stage included earthwork excavation for 10 days, pile foundation construction for 20 days, and foundation reinforcement and concrete pouring for 15 days. The main structure stage required 10 days per floor, including formwork, reinforcement, and concrete pouring. The decoration stage included wall plastering and door/window installation. Resource allocation information was also provided. Respondents were asked to analyze possible efficiency bottlenecks and risk points and propose optimization measures to shorten the construction period without increasing total cost.	Respondents completed the task independently without LLM assistance. A minimum response length of 50 Chinese characters was required.	Respondents were instructed to use Doubao to complete the same construction-technical task again and to evaluate the LLM's response process, quality, usefulness, and limitations.	A minimum response length of 100 Chinese characters was required.
Marketing personnel	Displayed when respondents selected "marketing personnel" as their job role.	Respondents were asked to draft a professional and polite email reply to a client who was dissatisfied with the meeting room layout in a previously submitted community activity center design proposal. The client considered the access passages too narrow and requested redesign. The reply needed to acknowledge the client's comments, state that a revised proposal would be provided within three working days, and briefly explain preliminary improvement directions such as widening passages and optimizing seat arrangement.	Respondents completed the task independently without LLM assistance. A minimum response length of 50 Chinese characters was required.	Respondents were instructed to use Doubao to complete the same email-drafting task again and to evaluate the LLM's response quality, usefulness, and limitations.	A minimum response length of 100 Chinese characters was required.
Administrative or managerial personnel	Displayed when respondents selected "administrative or managerial personnel" as their job role.	Respondents were asked to prepare a meeting agenda for a large commercial building project that was experiencing schedule delays and technical difficulties in structural construction and waterproofing. The meeting duration was three hours, and participants included engineering department leaders, technical experts, and procurement department leaders. The agenda needed to allocate time for progress reporting, problem analysis, solution discussion, and decision-making.	Respondents completed the task independently without LLM assistance. A minimum response length of 50 Chinese characters was required.	Respondents were instructed to use Doubao to complete the same meeting-agenda planning task again and to evaluate the LLM's response process, quality, usefulness, and limitations.	A minimum response length of 100 Chinese characters was required.

Note. The two-stage task protocol was used to familiarize respondents with a role-relevant LLM-use scenario before they completed the formal measurement scales. It was not designed as a randomized controlled experiment, and the objective quality, accuracy, or productivity of task outputs was not evaluated. Task responses were used only as a procedural step to ensure that respondents had direct experience with both independent and LLM-assisted task completion before answering the perceptual questionnaire items.

C. Exploratory factor analysis results

Table A3. Summary of exploratory factor analysis results

Item	Result
Kaiser–Meyer–Olkin measure	0.767
Bartlett's test of sphericity	χ^2 = 1111.112, df = 435, p < 0.001
Extraction method	Principal axis factoring
Rotation method	Promax rotation with Kaiser normalization
Number of factors retained	10
Total variance explained	60.041%
Loading suppression threshold	|λ| < 0.30 suppressed

Table A4. Pattern matrix of exploratory factor analysis

Item	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8	Factor 9	Factor 10
PU1		0.667								
PU2		0.328								0.308
PU3		0.629								
PEOU1								0.828		
PEOU2							0.702			
PEOU3						0.813				
AT1		0.663								
AT2		0.314				0.375				
AT3		0.574								
IU1										0.497
IU2		0.511	0.432							
IU3	0.405									0.509
TRU1	0.659									
TRU2	0.707									
TRU3	0.426									
LE1			0.675							
LE2			0.687							
LE3			0.592							
LE4			0.493							
IQ1	0.413					0.492				
IQ2									0.660	
IQ3	0.798									
SQ1	0.654						0.381			
SQ2							0.392			
SQ3	0.720									
PSC1					0.843					
PSC2					0.804					
JS1				0.730						
JS2				0.593						0.486
JS3				0.856						

Note. Extraction method = principal axis factoring; rotation method = Promax with Kaiser normalization. Loadings with absolute values below 0.30 are suppressed. The factor order follows the SPSS pattern matrix, and items are ordered by construct for readability.