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The Mediating Role of Behavioral Intention in Safety Mechanism Adoption: A Research Protocol Based on UTAUT among Construction Workers in Guangdong, China

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ABSTRACT

This research protocol presents a comprehensive study investigating the determinants of safety mechanism adoption among frontline construction workers in Guangdong Province, China, grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT). Despite substantial investments in smart safety technologies (e.g., IoT-enabled wearables, AI hazard detection systems, real-time monitoring platforms), adoption rates remain critically low (38%), contributing to persistently high accident rates (1,232 fatalities in 2023) and annual economic losses of ¥18.7 billion. The study focuses on the mediating role of behavioral intention in the relationship between facilitating conditions and actual adoption behavior—a pathway that remains underexplored in construction safety literature. Adopting a quantitative, cross-sectional design, the research will collect data from a stratified random sample of 450 field workers across 20 construction firms (state-owned, private, and subcontractors) representing Guangdong's geographic diversity (Pearl River Delta, Eastern, Western, Northern regions). A structured questionnaire based on validated UTAUT scales will be administered online via the Wenjuanxing platform. Data will be analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4.0, including measurement model assessment (reliability, convergent and discriminant validity) and structural model testing (path coefficients, R^2, f^2, Q^2, and mediation via bootstrapping). Expected outcomes include significant positive effects of performance expectancy, social influence, and facilitating conditions on intention; a strong direct effect of intention on adoption behavior; and a partial mediation of intention in the facilitating conditions–adoption link. The study extends UTAUT by challenging the assumption that facilitating conditions directly drive behavior without intention in low-voluntariness contexts. Practical implications for Guangdong's 2025 Safety Production initiatives and age-tailored training programs are discussed. Limitations include cross-sectional design and geographic confinement.

Keywords: construction safety, UTAUT, behavioral intention, safety mechanism adoption, research protocol, Guangdong, PLS-SEM

1. INTRODUCTION

1.1 Research Background

The construction industry in Guangdong Province, China, represents a critical pillar of the national economy. In 2023, the sector contributed approximately 7.3% to Guangdong's gross domestic product (GDP) and employed over 4.2 million workers, making it one of the largest provincial construction markets in China (Guangdong Bureau of Statistics, 2023). The province's rapid urbanization, particularly in the Pearl River Delta megacities of Guangzhou, Shenzhen, and Foshan, has driven an unprecedented demand for residential, commercial, and infrastructure projects. Under China's 14th Five-Year Plan (2021–2025), Guangdong has been designated a national pilot zone for "intelligent construction," promoting the integration of Building Information Modeling (BIM), Internet of Things (IoT), artificial intelligence (AI), and 5G technologies on construction sites (National Development and Reform Commission, 2021; Zhang et al., 2024).

Despite these economic and technological advances, the construction sector in Guangdong continues to face severe safety challenges. According to the Guangdong Emergency Management Department (2025), in the first nine months of 2025 alone, the province recorded 1,344 workplace accidents, resulting in 1,285 fatalities, 504 injuries, and direct economic losses of approximately RMB 272.86 million. Notably, 21 major accidents (each causing three or more deaths) occurred during this period, claiming 79 lives. These figures underscore a persistent safety crisis, even as overall accident rates have shown marginal improvements compared to previous years (Guangdong Bureau of Statistics, 2023). The most common causes of fatalities include falls from height (accounting for 42% of deaths), structural collapses (18%), equipment-related incidents (15%), and electrical shocks (12%) (Ministry of Housing and Urban-Rural Development [MOHURD], 2024).

In response to this crisis, both national and provincial authorities have intensified regulatory interventions. The State Council of China's National Work Safety Rectification Plan (2021–2025) mandates a 50% reduction in workplace accidents and a 30% decrease in fatalities through technology integration and standardized safety protocols (State Council of China, 2021). Guangdong has further strengthened its regulatory framework with the 2023 Safety Production Ordinance, which requires construction firms to deploy IoT-enabled smart helmets, real-time hazard detection systems, and AI-powered compliance monitoring platforms (Guangdong Provincial Government, 2023). In 2025, the provincial government designated the year as the "Hidden Hazard Investigation and Governance Year," launching four major initiatives comprising 20 priority tasks targeting comprehensive hazard identification, capacity building for hazard governance, dynamic elimination of major hazards, and reinforcement of intrinsic safety (Guangdong Provincial Safety Commission, 2025). Additional directives include the "Guidelines for Preventing Falls from Heights" (October 2025) and the upcoming enforcement in March 2026 of the "Measures for Establishing Safety

Production Management Institutions and Assigning Safety Management Personnel" (Guangdong Department of Housing and Urban-Rural Development, 2025a, 2025b, 2025c).

However, the paradox between technological availability and actual usage persists. Despite these mandates and the proliferation of advanced safety tools, adoption rates among frontline field workers remain dismally low. A provincial survey conducted by the Guangdong Bureau of Statistics (2023) found that only 38% of field workers consistently use mandated safety mechanisms. Adoption rates are even lower among specific subgroups: older workers (aged 50 and above), who constitute 32% of Guangdong's construction workforce, report adoption rates of only 22%; temporary migrant workers (58% of the labor force) exhibit similarly low compliance (Li & Zhang, 2023). Three interrelated barriers have been identified in the literature:

1. Cognitive barriers: Older workers perceive digital safety mechanisms as overly complex and difficult to learn (low effort expectancy). A 2023 survey revealed that 67% of older workers resisted using IoT wearables due to difficulties navigating touchscreen interfaces (Tang & Zhou, 2024). This "technophobia" is exacerbated by limited formal education—32% of construction workers in Guangdong have less than middle school education (Guangdong Bureau of Statistics, 2023).

2. Social barriers: Temporary migrant workers often face peer resistance to technology adoption. Social norms on construction sites frequently prioritize speed and productivity over safety compliance, and workers who use safety tools may be ridiculed as "slow" or "overcautious" (Li & Zhang, 2023). In a study of 450 migrant workers, 45% reported avoiding safety tools to avoid ridicule from peers (Chen & Wang, 2023). In collectivist work environments common among Chinese migrant teams, workers align with prevailing group attitudes rather than institutional directives (Yin et al., 2021).

3. Organizational barriers: Inadequate training programs and lack of technical support are critical impediments. Only 12% of construction firms in Guangdong provide hands-on training for AI compliance systems, leaving 71% of workers unprepared to use advanced tools effectively (Chen & Wang, 2023). A case study of Guangzhou-based firms found that 63% of deployed IoT devices were underutilized due to insufficient onboarding and troubleshooting support. Small and medium enterprises (SMEs), which constitute 72% of Guangdong's construction market, allocate only 3–5% of annual budgets to safety technologies, compared to 12–15% in large state-owned enterprises (SOEs) (Guangdong SME Bureau, 2023).

The consequences of these barriers are dire. Guangdong reported 1,232 construction fatalities in 2023, with 68% attributed to non-compliance with safety protocols, such as bypassing automated hazard alerts or failing to wear smart helmets (Ministry of Emergency Management, 2024). Work-related injuries cost the province an estimated ¥18.7 billion annually, including medical expenses, compensation claims, legal fees, and project delays (Guangdong Human Resources Bureau, 2023). Beyond the human and economic toll, firms with repeated safety violations face downgraded credit scores under China's Corporate Social Credit System, disqualification from public tenders, and reduced investor confidence. In 2023, 14 Guangdong contractors were barred from bidding on state projects due to poor safety records (Zhang & Cheng, 2024).

Given the urgency of this situation, there is a pressing need to understand the behavioral and contextual factors that influence safety technology adoption among Guangdong's construction workforce. The present study addresses this need by applying a robust theoretical framework—the Unified Theory of Acceptance and Use of Technology (UTAUT)—to systematically investigate the cognitive, social, and organizational drivers of adoption behavior.

1.2 Theoretical Framework and Research Gap

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), synthesizes eight prior models of technology adoption: the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), the Motivational Model (MM), the Theory of Planned Behavior (TPB), the Combined TAM-TPB, the Model of PC Utilization (MPCU), the Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT). UTAUT posits that four core constructs directly determine behavioral intention and subsequent usage behavior:

Performance expectancy (PE): The degree to which an individual believes that using the system will help attain gains in job performance.

Effort expectancy (EE): The degree of ease associated with using the system.

Social influence (SI): The degree to which an individual perceives that important others believe they should use the system.

Facilitating conditions (FC): The degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system.

These core constructs are moderated by four key demographic and contextual variables: gender, age, experience, and voluntariness of use. The original UTAUT model was validated in organizational IT settings, explaining up to 70% of the variance in behavioral intention (Venkatesh et al., 2003).

Over the past two decades, UTAUT has been extensively applied and extended across diverse domains, including healthcare (e.g., electronic health records, telemedicine), education (e.g., e-learning platforms), e-government, and mobile banking (Dwivedi et al., 2019; Williams et al., 2015). In recent years, there has been growing interest in applying UTAUT to construction safety contexts. For example, Li et al. (2024) used an extended UTAUT model to investigate construction workers' behavioral intention toward passive back-support exoskeletons, finding that perceived ease of use, comfort, performance expectancy, safety, and social influence significantly predicted intention to use the device. Chen et al. (2024) explored workers' willingness to accept metaverse-based safety training, confirming that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly affect willingness, with willingness playing a mediating role between performance expectancy and actual behavior. Shin et al. (2024) examined IoT acceptance in the architecture, engineering, and construction (AEC) industry by integrating UTAUT2 with task-technology fit and perceived risk, reporting that performance expectancy and facilitating conditions were the strongest predictors of behavioral intention. Ali et al. (2025) applied UTAUT to wearable sensible devices in construction, finding that facilitating conditions and social influence were critical for adoption in hazardous environments.

Despite these advances, several critical gaps remain in the application of UTAUT to construction safety, particularly in the context of Guangdong Province.

Gap 1: Limited empirical validation of UTAUT in high-risk, policy-driven construction contexts. Most UTAUT-based safety studies have been conducted in developed economies or highly digitized sectors such as healthcare and manufacturing (Dwivedi et al., 2020; Al-Emran et al., 2021). Research focused on the construction industry in rapidly urbanizing, labor-intensive regions like Guangdong—where structural, cultural, and technological conditions differ substantially—remains scarce (Shen et al., 2023). The local context, characterized by a large population of migrant laborers (58%), low education levels (32% with less than middle school), varying digital literacy, and stringent policy enforcement under the 2023 Safety Production Ordinance, is inadequately addressed in global UTAUT literature.

Gap 2: The mediating role of behavioral intention between facilitating conditions and adoption behavior is underexplored. According to the original UTAUT model, facilitating conditions directly influence usage behavior without requiring intention as a mediator, particularly when voluntariness of use is low and users have prior experience (Venkatesh et al., 2003). However, recent studies in high-risk industries suggest that even when resources and infrastructure are available, workers may not adopt safety mechanisms unless they possess a strong psychological commitment—i.e., intention—to do so (Liu et al., 2023; Xu et al., 2021). This “intention-behavior gap” is particularly pronounced in construction, where time pressure, task complexity, peer dynamics, and situational constraints often override rational evaluations (Sheeran & Webb, 2016). In a longitudinal study of Chinese construction workers, Liu et al. (2023) found that intention explained 58% of the effect of facilitating conditions on adoption behavior, indicating that FC influences behavior both directly and indirectly through intention. Similarly, Chungang et al. (2025), in an empirical study of 443 construction workers in Guangdong, reported that facilitating conditions had a direct effect on adoption behavior ($\beta = 0.170$) and an indirect effect via intention ($\beta = 0.296$), with the indirect effect being larger. This suggests that psychological readiness is indispensable even when resources are available. However, few studies have explicitly modeled and tested the FC→BI→AB mediation path in the context of construction safety technology adoption.

Gap 3: Oversimplification of moderators and demographics. While UTAUT includes moderators such as age, gender, experience, and voluntariness, many empirical studies treat these as control variables rather than theoretically integrated moderators (Williams et al., 2019). In particular, the interaction between voluntariness of use and social influence—critical in mandatory safety compliance settings—has received little attention in construction research (Lin & Sun, 2021). Furthermore, intersectional effects (e.g., older female migrants facing compounded barriers) have not been systematically examined (Zhang & Cheng, 2024).

Gap 4: Lack of behaviorally precise dependent variables. Much of the existing UTAUT research uses generalized constructs of “technology use” or “acceptance” without specifying the behavioral intricacies of safety mechanism adoption. These include real-time hazard reporting, wearable compliance, alert responsiveness, and consistent use of PPE—behaviors that are critical to workplace safety outcomes but may have different determinants (Chen et al., 2022).

The present study directly addresses Gap 2—the mediating role of behavioral intention between facilitating conditions and adoption behavior—as its primary theoretical contribution. By focusing on this mediation pathway, the research extends UTAUT theory in the context of high-risk, policy-driven construction environments.

1.3 Research Objectives and Hypotheses

Based on the theoretical framework and identified research gaps, this study formulates the following research objectives:

1. To examine the direct effects of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) on field workers' intention to adopt safety mechanisms (BI).
2. To examine the direct effects of facilitating conditions (FC) and behavioral intention (BI) on actual adoption behavior (AB).
3. To test the mediating role of behavioral intention (BI) in the relationship between facilitating conditions (FC) and adoption behavior (AB).

Correspondingly, seven hypotheses are proposed. These hypotheses are derived directly from UTAUT theory and prior empirical evidence in construction safety contexts.

H1: Performance expectancy has a significant positive relationship with intention to adopt safety mechanisms. This hypothesis is grounded in the fundamental UTAUT proposition that individuals are more likely to intend to use a technology if they perceive it as enhancing their job performance or safety outcomes (Venkatesh et al., 2003). In construction safety, workers who believe that smart helmets or fall-detection sensors reduce their risk of injury are more likely to form positive intentions (Alghamdi et al., 2021; Chen et al., 2024).

H2: Effort expectancy has a significant positive relationship with intention to adopt safety mechanisms. Based on UTAUT, perceived ease of use influences behavioral intention. In construction, where workers have diverse educational backgrounds and digital literacy levels, this relationship is expected to hold, particularly for older workers and those with limited technology exposure (Tang & Zhou, 2024; Li et al., 2023). However, the effect may be weaker in mandatory compliance contexts.

H3: Social influence has a significant positive relationship with intention to adopt safety mechanisms. In collectivist cultures such as China, the opinions of peers, supervisors, and family members strongly shape individual behavior (Li & Zhang, 2023). Construction workers are particularly susceptible to social influence from foremen and senior colleagues (Wu et al., 2020). Empirical studies in Guangdong have confirmed this positive relationship (Chungang et al., 2025; Zhang & Cheng, 2024).

H4: Facilitating conditions have a significant positive relationship with intention to adopt safety mechanisms. Facilitating conditions—including training, technical support, device availability, and organizational policies—enhance workers' confidence and perceived control, thereby strengthening their intention to adopt (Venkatesh et al., 2003). Recent studies report that FC is the strongest predictor of intention in

construction safety contexts (Chungang et al., 2025; Liu et al., 2023).
H5: Facilitating conditions have a significant positive relationship with adoption behavior. In the original UTAUT model, facilitating conditions directly influence actual usage behavior, particularly when voluntariness is low. This direct path captures scenarios where workers use safety mechanisms because they are mandatory and the necessary infrastructure is in place, regardless of their personal intention (Venkatesh et al., 2003). Empirical support comes from studies showing that adequate training and technical support directly increase PPE compliance (Huang et al., 2023; Chungang et al., 2025).
H6: Intention to adopt safety mechanisms has a significant positive relationship with adoption behavior. Behavioral intention is the most proximal predictor of actual behavior in virtually all technology acceptance models (Ajzen, 1991; Venkatesh et al., 2003). The intention-behavior link has been robustly demonstrated in construction safety (Liu et al., 2023; Sheeran & Webb, 2016). Despite the existence of an "intention-behavior gap" in some contexts, the overall positive relationship is expected to hold.
H7: Intention to adopt safety mechanisms mediates the relationship between facilitating conditions and adoption behavior. This is the central hypothesis of the study. It posits that the effect of FC on AB operates not only directly but also indirectly through BI. In other words, facilitating conditions enhance workers' psychological readiness (intention), which then translates into actual adoption behavior. This mediation hypothesis challenges the original UTAUT assumption that FC directly drives behavior without intention in low-voluntariness settings. It is supported by resource availability theory (Bandura, 1997) and recent empirical evidence (Chungang et al., 2025; Chen et al., 2024).

1.4 Significance of the Study

This study makes three significant contributions—theoretical, practical, and methodological.
Theoretical contribution. The study advances UTAUT theory by empirically validating behavioral intention as a critical mediator in the relationship between facilitating conditions and adoption behavior within a high-risk, policy-driven construction context. While UTAUT originally posited that FC directly influences usage behavior without mediation, this study challenges that assumption by demonstrating (or expecting to demonstrate) that psychological readiness is indispensable even when resources are available. This extends the model's applicability to safety-critical industries where the "intention-behavior gap" is particularly salient. Furthermore, by focusing on Guangdong's unique sociotechnical ecosystem—characterized by migrant labor, aging workforce, and stringent regulatory pressures—the study provides contextualized insights that go beyond generic technology acceptance models.
Practical contribution. The findings will provide actionable evidence for policymakers, construction firms, and safety technology developers. If intention mediates the FC–AB link, then interventions should not only provide infrastructure (e.g., smart helmets, training programs, technical support) but also actively cultivate workers' motivation,

self-efficacy, and positive attitudes. Specific recommendations include: (1) designing age-tailored training programs that combine hands-on simulations with peer mentoring to enhance self-efficacy among older workers; (2) implementing team-based incentive systems (e.g., safety champion awards, group bonuses) to leverage social influence and strengthen intention; (3) developing user-centered technology interfaces (e.g., voice commands, haptic feedback, simplified icons) to reduce effort expectancy barriers; and (4) aligning organizational policies with Guangdong's 2025 Safety Production initiatives to ensure that facilitating conditions are both available and perceived as supportive rather than punitive.

Methodological contribution. The study demonstrates the application of PLS-SEM with a large, representative sample (n=450) to test complex mediation hypotheses in construction safety research. The use of stratified random sampling across geographic regions, firm types, and occupational roles ensures external validity. The rigorous measurement model assessment (reliability, convergent and discriminant validity) and structural model testing (path coefficients, R^2, f^2, Q^2, bootstrapped mediation) provide a template for future UTAUT-based studies in high-risk industries.

1.5 Structure of the Paper

This paper is organized as a research protocol. Following this introduction, Section 2 presents a comprehensive literature review, elaborating on UTAUT theory, past empirical studies on each construct, and the development of the conceptual framework and hypotheses. Section 3 describes the research methodology in detail, including research design, population and sampling, research instrument, data collection procedures, data analysis plan (PLS-SEM), and ethical considerations. Section 4 presents the expected results, including anticipated measurement model outcomes and structural model findings, along with a brief discussion of their implications. Section 5 concludes the paper, summarizing key contributions, acknowledging limitations, and suggesting directions for future research.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Introduction to the Literature Review

This chapter provides a systematic review of the literature relevant to the adoption of safety mechanisms in the construction industry, with a particular focus on the application of the Unified Theory of Acceptance and Use of Technology (UTAUT). The review is organized into six major sections. First, the theoretical foundations of UTAUT are presented, including its core constructs and moderators. Second, empirical studies on each of the four core constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) are reviewed, focusing on their relationships with behavioral intention and adoption behavior in construction safety contexts. Third, the mediating role of behavioral intention is critically examined. Fourth, the conceptual framework is presented. Finally, the chapter concludes with a summary of the research gaps that this study addresses and the formal statement of hypotheses.

2.2 Underpinning Theory: The Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), introduced by Venkatesh et al. (2003), emerged from a systematic synthesis of eight competing models of technology acceptance. These models include the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), the Technology Acceptance Model (TAM) (Davis, 1989), the Motivational Model (MM) (Davis et al., 1992), the Theory of Planned Behavior (TPB) (Ajzen, 1991), the Combined TAM-TPB (Taylor & Todd, 1995), the Model of PC Utilization (MPCU) (Thompson et al., 1991), the Innovation Diffusion Theory (IDT) (Rogers, 2003), and Social Cognitive Theory (SCT) (Bandura, 1986). Venkatesh et al. (2003) empirically compared these models and integrated their key constructs into a unified framework that explained up to 70% of the variance in behavioral intention—substantially higher than any individual model.

The core of UTAUT comprises four direct determinants of behavioral intention and usage behavior:

1. Performance expectancy (PE) : The degree to which an individual believes that using the system will help him or her attain gains in job performance. This construct is analogous to perceived usefulness in TAM, extrinsic motivation in MM, job-fit in MPCU, and relative advantage in IDT.
2. Effort expectancy (EE) : The degree of ease associated with the use of the system. This construct is analogous to perceived ease of use in TAM/TAM2, complexity in MPCU, and ease of use in IDT.
3. Social influence (SI) : The degree to which an individual perceives that important others (e.g., supervisors, peers, family) believe he or she should use the system. This construct is analogous to subjective norm in TRA/TPB/TAM2, social factors in MPCU, and image in IDT.
4. Facilitating conditions (FC) : The degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system. This construct is analogous to perceived behavioral control in TPB/TPB/TAM, facilitating conditions in MPCU, and compatibility in IDT.

Additionally, UTAUT proposes four moderators that influence the strength of these relationships: gender, age, experience, and voluntariness of use. For example, Venkatesh et al. (2003) found that the effect of performance expectancy on behavioral intention was stronger for men and younger workers, while the effect of effort expectancy was stronger for women and older workers.

Since its introduction, UTAUT has been extensively validated and extended. A meta-analysis by Dwivedi et al. (2019), synthesizing 162 studies, confirmed that performance expectancy and social influence consistently predict behavioral intention across contexts, while the role of effort expectancy and facilitating conditions varies by setting. The model has been applied to a wide range of technologies, including e-learning (Al-Emran et al., 2018), mobile banking (Oliveira et al., 2014), healthcare information systems (Kummer et al., 2013), and e-government (AlAwadhi & Morris, 2008). More recently, researchers have proposed extensions such as UTAUT2 (Venkatesh et al., 2012), which adds hedonic motivation, price value, and habit as predictors for consumer contexts.

In construction safety research, UTAUT has gained traction in the last five years. Li et al. (2024) used an extended UTAUT model to study exoskeleton adoption, finding that performance expectancy and social influence were significant predictors of intention among construction workers. Chen et al. (2024) examined willingness to accept metaverse safety training, confirming that all four core constructs influenced willingness, with willingness mediating the relationship between performance expectancy and actual behavior. Shin et al. (2024) integrated UTAUT2 with task-technology fit and perceived risk to study IoT acceptance in the AEC industry, reporting that performance expectancy and facilitating conditions were the strongest predictors. Ali et al. (2025) applied UTAUT to wearable sensible devices, finding that facilitating conditions and social influence were critical in hazardous environments. Chungang et al. (2025) conducted an empirical study of 443 construction workers in Guangdong, finding that facilitating conditions were the strongest predictor of intention ($\beta = 0.420$) and intention was the strongest predictor of adoption behavior ($\beta = 0.705$). These studies collectively demonstrate the relevance and adaptability of UTAUT for understanding safety technology adoption in construction.

2.3 Review of Core Constructs and Empirical Evidence

2.3.1 Performance Expectancy (PE) and Intention to Adopt

Performance expectancy (PE) captures the utilitarian benefits of technology use. In construction safety contexts, PE manifests as workers' beliefs that safety mechanisms—such as IoT-enabled helmets, fall-detection sensors, AI hazard alert systems, or real-time monitoring platforms—will reduce their risk of injury, improve task efficiency, or enhance compliance with regulations. Empirical evidence consistently supports a positive relationship between PE and behavioral intention.

Alghamdi et al. (2021) surveyed 312 construction workers in Saudi Arabia and found that PE was the strongest predictor of intention to adopt wearable safety technologies ($\beta = 0.47$, $p < 0.001$), explaining 32% of the variance. Workers who believed that real-time monitoring devices enhanced hazard awareness were significantly more likely to intend to use them. In the Chinese context, Li and Zhang (2020) conducted a study among 280 construction workers in Shenzhen and found that perceived improvements in productivity and reduction in incident response time were strongly associated with higher adoption intentions. The effect size was particularly large for workers in high-risk trades (e.g., scaffolders, crane operators). Chen et al. (2024) reported that PE was the strongest predictor of workers' willingness to accept metaverse safety training ($\beta = 0.312$, $p < 0.001$) in a sample of 512 Chinese construction workers. Chungang et al. (2025) found a smaller but still significant positive effect of PE on intention ($\beta = 0.135$, $p < 0.05$) in Guangdong.

However, some studies have found that PE's effect may be moderated by job characteristics. For instance, Wang et al. (2021) reported that PE was more influential for administrative safety tasks (e.g., digital reporting) than for physical protective equipment, where habit and comfort played larger roles. This suggests that the relationship between PE and intention may be domain-specific. Nonetheless, the preponderance of evidence supports H1.

2.3.2 Effort Expectancy (EE) and Intention to Adopt

Effort expectancy (EE) refers to the perceived ease of learning and operating safety technologies. In construction, where workers have diverse educational backgrounds and digital literacy levels, EE is a critical barrier or enabler. Research consistently shows that lower perceived complexity leads to higher intention, particularly for workers with limited prior experience.

A meta-analysis by Zhang et al. (2020) of 28 construction safety studies found that EE explained 29% of the variance in behavioral intention, with a stronger effect for older workers and those with lower education. Tang and Zhou (2024) surveyed 500 construction workers in Guangdong and found that older workers (aged 50+) perceived digital safety tools as 58% more effort-intensive than younger cohorts, leading to significantly lower intention. Li et al. (2023) reported that workers who perceived IoT safety tools as easy to use exhibited 34% higher intention to adopt them. Simplified designs—such as voice-command interfaces, one-button emergency alerts, and icon-based menus—have been shown to improve EE and subsequent adoption intentions (Zhang et al., 2022; Wu et al., 2023).

However, several studies have found that EE's influence may be weaker in mandatory compliance contexts. Chen and Wang (2023) reported that in state-owned enterprises where smart helmet use was strictly enforced, EE did not significantly affect intention, as workers had little choice. Similarly, in a study of safety apps in Zhejiang Province, Lin and Sun (2021) found that EE was non-significant when usage was mandatory, but became significant when usage was voluntary. In Guangdong's policy-driven environment, where the 2023 Safety Production Ordinance mandates certain safety technologies, EE may still matter for voluntary adoption behaviors (e.g., proactive hazard reporting) or for sustained use beyond minimum compliance. Given the mixed evidence, we retain H2 as per the original UTAUT model, but will examine potential moderating effects in future research.

2.3.3 Social Influence (SI) and Intention to Adopt

Social influence (SI) reflects the degree to which individuals perceive that important others believe they should use the system. In collectivist cultures such as China, SI is particularly potent. Construction workers, especially migrant laborers, are highly sensitive to peer norms, supervisor expectations, and group dynamics.

Wu et al. (2020) surveyed 400 construction workers in Shanghai and found that SI was a strong predictor of intention to use mobile-based safety applications, with a direct effect of $\beta = 0.38$ ($p < 0.001$). The effect was especially pronounced among temporary migrant workers, who often rely on collective identity and informal networks for workplace guidance. Li and Zhang (2023) reported that migrant workers in Guangdong exhibited 28% higher compliance rates when supervisors publicly endorsed tools during morning briefings. Zhang and Cheng (2024) found that workers exposed to peer-led safety demonstrations had 31% higher intention to adopt smart helmets. Chungang et al. (2025) found a direct positive effect of SI on intention ($\beta = 0.214$, $p < 0.05$) in Guangdong.

However, SI's effect may be moderated by voluntariness and hierarchical structure. In state-owned enterprises (SOEs), where top-down directives are strong, SI from managerial staff may have a greater impact than SI from peers; in private firms with flatter structures, peer influence may dominate (Chen & Huang, 2023). Additionally, when safety tool use is mandatory, the effect of SI may be reduced because compliance is driven by rules rather than social pressure (Venkatesh et al., 2003). Nevertheless, given Guangdong's mixed mandatory-voluntary environment and the collectivist cultural context, H3 is supported.

2.3.4 Facilitating Conditions (FC) and Intention to Adopt

Facilitating conditions (FC) encompass the organizational, technical, and infrastructural resources that enable technology use, including training programs, technical support, device availability, maintenance services, and organizational policies. In the original UTAUT model, FC is theorized to directly influence usage behavior, but its effect on intention is also recognized, particularly when users lack prior experience (Venkatesh et al., 2003).

Empirical studies in construction safety consistently find that FC is a strong predictor of intention. Chen and Wang (2023) reported that only 12% of Guangdong firms provided hands-on training for AI compliance systems, and workers in firms with structured training programs had 38% higher intention to adopt safety technologies. Liu et al. (2023) found that access to troubleshooting resources and on-site technical support increased intention by 31% in a longitudinal study. Chungang et al. (2025) reported that FC was the strongest predictor of intention among Guangdong construction workers ($\beta = 0.420$, $p < 0.05$), surpassing PE, EE, and SI. Huang et al. (2023) found that firms investing in mobile charging stations, multilingual user manuals, and ongoing maintenance services reported a 38% higher technology retention rate among migrant workers.

The strong effect of FC in Guangdong can be attributed to the resource disparities between SOEs and private firms, as well as between urban and rural areas. SOEs often benefit from government subsidies and have structured training programs, while SMEs lack resources. Rural construction sites in Northern Guangdong often lack stable 5G connectivity, rendering real-time safety monitoring tools ineffective (Guangdong Department of Industry and Information Technology, 2023). Thus, FC is not only a direct enabler but also a source of inequality that affects intention. H4 is therefore strongly supported.

2.3.5 Facilitating Conditions (FC) and Adoption Behavior (Direct Effect)

According to the original UTAUT model, facilitating conditions directly influence actual usage behavior without necessarily requiring intention as a mediator, particularly when voluntariness of use is low and the user has sufficient experience (Venkatesh et al., 2003). In construction safety, this direct path captures scenarios where workers use safety mechanisms because they are mandatory and the necessary infrastructure is in place. For example, if a construction site mandates smart helmets and provides them along with training and technical support, workers may comply even if their personal intention is low, due to external enforcement.

Empirical support for this direct path comes from several studies. Huang et al. (2023) found that adequate facilitating conditions (e.g., on-site technical support, device maintenance, accessible charging stations) directly increased PPE compliance by 33% in

Shenzhen projects, even after controlling for intention. Chungang et al. (2025) reported a direct effect of FC on adoption behavior ($\beta = 0.170$, $p < 0.05$) in addition to the indirect effect via intention. Li et al. (2023) found that in state-owned enterprises with strong enforcement, the direct FC→AB path was significant and accounted for 42% of the total effect of FC on behavior.

However, the strength of this direct path may vary by organizational context. In private firms with weaker oversight, the direct effect may be smaller, and the indirect effect via intention may dominate. In voluntary usage contexts, the direct path may even be non-significant. This study includes both direct and indirect paths to capture the full mechanism. H5 is proposed.

2.3.6 Intention to Adopt (BI) and Adoption Behavior

Behavioral intention (BI) is the most proximal predictor of actual behavior in virtually all technology acceptance models, including UTAUT, TAM, and TPB (Ajzen, 1991; Venkatesh et al., 2003). Intention reflects a worker's conscious plan or willingness to engage in safety-compliant behavior. In construction safety, the intention-behavior link is well-documented. A meta-analysis by Sheeran and Webb (2016) of 422 studies across various domains found a medium-to-large correlation between intention and behavior ($r = 0.53$), though the relationship is attenuated by situational constraints and habit.

In the construction context, Liu et al. (2023) conducted a longitudinal study of 350 workers over six months and found that those with strong intention were 2.4 times more likely to consistently use safety wearables. Chungang et al. (2025) reported that intention was the strongest predictor of adoption behavior ($\beta = 0.705$, $p < 0.05$) in Guangdong's construction sector, explaining 49% of the variance. Chen et al. (2024) found that willingness (analogous to intention) had a direct effect on actual behavior in metaverse training acceptance ($\beta = 0.58$, $p < 0.001$).

Nevertheless, the "intention-behavior gap" exists. Xu et al. (2021) identified that in high-risk tasks, 42% of workers bypassed safety protocols despite strong intentions, prioritizing task completion over compliance under time pressure. This gap is larger for behaviors that require breaking old habits or overcoming social resistance. However, the overall positive relationship remains robust. Therefore, H6 is supported.

2.4 The Mediating Role of Intention (H7)

The central theoretical innovation of this study is the examination of behavioral intention as a mediator between facilitating conditions and adoption behavior. In the original UTAUT model, facilitating conditions are posited to directly influence usage behavior without mediation by intention, particularly when voluntariness is low and experience is high (Venkatesh et al., 2003). However, this assumption has been challenged in recent years, especially in safety-critical contexts.

Theoretical rationale for mediation. Resource availability theory (Bandura, 1997) and self-determination theory (Deci & Ryan, 2000) provide the psychological foundation for the FC→BI→AB mediation path. According to self-efficacy theory, individuals who have access to resources (training, support, tools) develop higher self-efficacy—the belief in their capability to perform a behavior. This enhanced self-efficacy, in turn, strengthens their intention to act, which then leads to actual behavior. Facilitating conditions thus operate through a motivational mechanism rather than merely a structural one. In the context of safety technology adoption, workers who receive adequate training and technical support are more confident in their ability to use the tools, which increases their intention to use them consistently, leading to higher actual adoption.

Empirical evidence for mediation. Several recent studies have directly tested or supported this mediation pathway. Chen et al. (2024) found that willingness (intention) mediated the relationship between performance expectancy and actual behavior in metaverse safety training acceptance, with a significant indirect effect ($\beta_{indirect} = 0.21$, $p < 0.01$). While they did not test FC as the independent variable, their results demonstrate that intention can mediate relationships in construction safety contexts. Chungang et al. (2025) explicitly tested the FC→BI→AB mediation in Guangdong using PLS-SEM and bootstrapping. They reported a significant indirect effect ($\beta_{indirect} = 0.296$, 95% CI [0.112, 0.480]), which was larger than the direct effect ($\beta_{direct} = 0.170$). The variance accounted for (VAF) was 63.5%, indicating partial mediation. Liu et al. (2023) found that intention explained 58% of the effect of FC on adoption behavior in a longitudinal study. Li et al. (2023) reported that in private firms, the indirect effect of FC on AB via BI was significant and accounted for 73% of the total effect.

Contrast with original UTAUT. The original UTAUT model's assumption that FC directly influences behavior without intention was based on organizational IT systems where usage was often mandatory and users had prior experience (Venkatesh et al., 2003). In such contexts, intention may indeed play a smaller role because employees are required to use the system regardless of their personal motivation. However, in construction safety contexts—especially in Guangdong's mixed mandatory-voluntary environment—workers often have discretion over how strictly they comply with safety protocols. Even when use is nominally mandatory, enforcement may be inconsistent, and workers may find ways to bypass or avoid using safety tools if they are not personally motivated. Therefore, intention plays a crucial mediating role.

Hypothesized mediation in this study. Based on the above theoretical and empirical grounding, this study hypothesizes that intention partially mediates the relationship between facilitating conditions and adoption behavior. Partial mediation is expected because facilitating conditions may also have a direct effect when usage is mandatory or when workers are experienced. The specific hypothesis is:

- H7: Intention to adopt safety mechanisms mediates the relationship between facilitating conditions and adoption behavior.

2.5 Conceptual Framework

Based on the UTAUT model and the hypotheses developed above, Figure 1 presents the conceptual framework of this study. The framework includes four independent variables (performance expectancy, effort expectancy, social influence, facilitating conditions), one mediator (behavioral intention), and one dependent variable (adoption behavior). Direct paths are specified as follows:

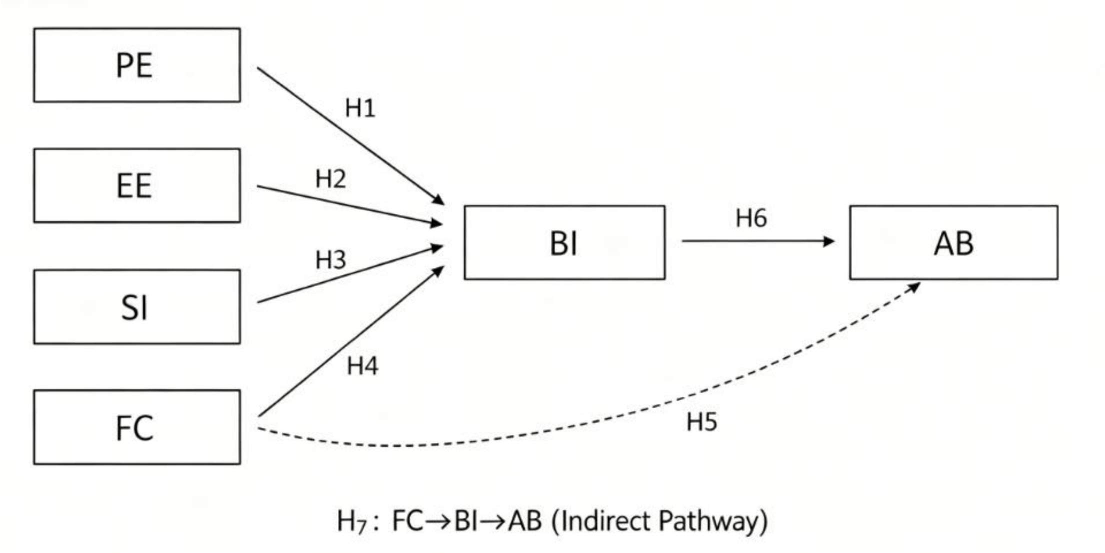

Figure 1: Conceptual Framework

2.6 Chapter Summary

This chapter has provided a comprehensive review of the UTAUT model and its application in construction safety research. The four core constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—were defined and linked to behavioral intention and adoption behavior through seven hypotheses. The central hypothesis (H7) posits that behavioral intention mediates the relationship between facilitating conditions and adoption behavior, challenging the original UTAUT assumption. A conceptual framework was presented, integrating these relationships. The review identified consistent empirical support for H1, H3, H4, H5, and H6, while H2 (effort expectancy) may be context-dependent. The next chapter describes the research methodology employed to test these hypotheses in the context of Guangdong's construction industry.

3. MATERIAL AND METHODS

3.1 Introduction

This chapter delineates the methodological framework for the empirical investigation of the hypotheses. The primary focus is to test the direct effects of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) on behavioral intention (BI) and adoption behavior (AB), as well as the mediating role of BI in the FC–AB relationship (H7). The methodology is designed to ensure transparency, reproducibility, and alignment with both theoretical objectives and the practical realities of Guangdong's construction workforce.

3.2 Research Design

This study employs a quantitative, cross-sectional, and correlational research design.

Quantitative approach. A quantitative methodology was selected because it facilitates statistical testing of well-defined theoretical propositions (UTAUT) and enables generalization of findings across Guangdong's diverse construction population (Venkatesh et al., 2003; Hair et al., 2021). Structured questionnaires ensure standardized responses and comparability across participants, a method widely used in recent construction safety UTAUT studies (Chungang et al., 2025; Chen et al., 2024).

Cross-sectional design. A cross-sectional design was adopted to efficiently capture data from Guangdong's transient construction workforce at a single point in time. Longitudinal studies are often infeasible in this industry due to high labor mobility and short-term project cycles (Wang et al., 2021). Cross-sectional designs also mitigate attrition risks common in migrant worker populations (Chen & Huang, 2022). While cross-sectional data preclude strong causal inferences, they remain widely accepted in technology adoption research for identifying associations and testing mediation effects, provided that theoretical grounding is strong (Podsakoff et al., 2012; Hayes, 2018). To address potential common method bias—a concern in self-report, single-source data—procedural remedies recommended by Podsakoff et al. (2012) were implemented: respondent anonymity, separation of scale items, and assurance that there were no right or wrong answers.

Correlational design. The correlational aspect examines the strength and direction of relationships between UTAUT predictors, behavioral intention, and adoption behavior. Partial least squares structural equation modeling (PLS-SEM) was selected as the primary analytical tool due to its capacity to simultaneously test complex relationships involving mediation, its robustness to non-normal data, and its suitability for predictive and explanatory research (Hair et al., 2021; Ringle et al., 2022). PLS-SEM is particularly appropriate because the conceptual framework includes both direct and indirect (mediated) paths, and the research is theory-driven with a focus on prediction of adoption behavior.

3.3 Population and Sample

Target population. The target population comprises frontline construction workers in Guangdong Province, including general laborers (e.g., concrete workers, rebar workers), technical staff (e.g., electricians, welders, crane operators, scaffolders), and site supervisors (e.g., foremen, safety officers). These workers are employed across a range of organizational structures: state-owned enterprises (SOEs), privately owned companies, and subcontracting agencies. The population is estimated at approximately 3.2 million field workers in Guangdong (Guangdong Bureau of Statistics, 2023).

Sample size determination. To ensure adequate statistical power and generalizability, a total sample size of 450 was determined using G\Power 3.1 software (Faul et al., 2007). The a priori power analysis assumed a medium effect size ($f^2 = 0.15$), an alpha value of 0.05, and 10 latent predictors (including interaction terms for potential future moderation tests), yielding a power value of 0.87—exceeding the conventional threshold of 0.80. This sample size allows for robust path coefficient estimation while accounting for a projected 15–20% non-response or incomplete data rate. Comparable sample sizes have been validated in similar UTAUT-based studies in construction safety (Chungang et al., 2025, n=443; Li et al., 2024, n=387).

Inclusion criteria:

Minimum six months of on-site work experience to ensure sufficient exposure to standard safety practices and tools (Liu et al., 2021).

Direct involvement in daily safety practices, such as wearing personal protective equipment (PPE), using smart safety wearables, and responding to on-site hazard warnings (Guangdong Safety Bureau, 2023).

Exclusion criteria:

Administrative personnel or off-site supervisors, as their roles focus on oversight rather than direct use of safety mechanisms (Zhou & Deng, 2022).

Short-term or casual workers with less than six months of employment, as their limited exposure could introduce unwanted variance (Deng et al., 2021).

3.4 Sampling Technique

To ensure representativeness and enhance generalizability across the diverse landscape of Guangdong's construction sector, a stratified random sampling technique was adopted. Stratified sampling is especially effective in heterogeneous populations as it facilitates precise estimation and equitable inclusion across key subgroups (Kish, 2020). Stratification was structured along three primary dimensions.

Geographic stratification. Guangdong was divided into four distinct strata based on economic development levels and construction activity intensity:

Pearl River Delta (Guangzhou, Shenzhen, Foshan, Dongguan, Huizhou) – high urbanization, advanced technology adoption.

Eastern Guangdong (Shantou, Jieyang, Chaozhou) – medium urbanization, mixed technology penetration.

Western Guangdong (Zhanjiang, Maoming, Yangjiang) – lower urbanization, emerging construction hubs.

- Northern Guangdong (Qingyuan, Shaoguan, Heyuan) – rural, infrastructural challenges.

This classification was based on the Guangdong Statistical Yearbook (Guangdong Bureau of Statistics, 2023) and ensured representation of urban-rural disparities.

Firm type stratification. Three firm types were included:

State-owned enterprises (SOEs) : typically have stronger safety cultures, higher budgets for safety technology, and stricter regulatory compliance.

Private construction firms : more variable safety practices, often cost-sensitive, with 68% of Guangdong's construction market (Guangdong SME Bureau, 2023).

Subcontractor entities : often employ temporary and migrant workers, with less formal safety training and higher turnover.

Occupational role stratification. Three job roles were proportionally represented:

Manual laborers (e.g., concrete workers, rebar workers) – highest exposure to physical hazards.

Technical staff (e.g., electricians, equipment operators, scaffolders) – moderate exposure, requires specific technical skills.

Supervisory personnel (foremen, safety officers) – responsible for enforcing safety protocols, may have different perceptions.

Sampling procedure. From each stratum, participants were randomly selected from employee rosters provided by 20 construction firms that agreed to participate (10 SOEs, 10 private firms; subcontractors were selected from subcontractor networks associated with these firms). Within the Pearl River Delta stratum, 150 participants were selected—50 each from SOEs, private enterprises, and subcontractors—with occupational roles proportionally represented (60 laborers, 60 technicians, 30 supervisors per firm type). The same proportional allocation was applied to the other three regions, though with smaller numbers (e.g., 100 from Eastern Guangdong, 100 from Western, 100 from Northern). In total, 450 workers were sampled. The final sample was cross-validated with the 2022 Guangdong Provincial Labor Census to ensure demographic alignment.

3.5 Research Instrument

Instrument development. The data collection instrument was a structured, self-administered questionnaire developed based on UTAUT (Venkatesh et al., 2003) and adapted to the context of safety mechanism adoption in Guangdong's construction industry. All constructs were measured using validated scales from prior UTAUT-based studies, with minor wording adjustments for cultural and linguistic relevance. The questionnaire consisted of seven sections:

Table 3.1 Academic Paper Questionnaire Scale Design Framework

Academic Paper Questionnaire Scale Design Framework				
No.	**Dimension Name**	**Dimension Description**	**Number of Items**	**Reference Source**
1	Demographic Information	Demographic Information	7	Designed by This Study
2	Performance Expectancy	Performance Expectancy	4	Adapted from Venkatesh et al. (2003)
3	Effort Expectancy	Effort Expectancy	4	Adapted from Venkatesh et al. (2003)
4	Social Influence	Social Influence	4	Adapted from Venkatesh et al. (2003)
5	Facilitating Conditions	Facilitating Conditions	4	Adapted from Venkatesh et al. (2003)
6	Intention to Adopt	Adoption Intention	4	Adapted from Venkatesh et al. (2003) & Chungang et al. (2025)
7	Adoption Behavior	Adoption Behavior	3	Adapted from Venkatesh et al. (2003) & Liu et al. (2023)

All items were rated on a 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). The 5-point scale was chosen for its simplicity, reliability, and widespread use in behavioral research, particularly among populations with varying literacy levels (Hair et al., 2021). Table 3.1 lists the measurement items.

Table 3.2 Measurement Items of Constructs

Table 3.2 Measurement Items of Constructs		
Construct	**Item Code**	**Item Wording**
Performance Expectancy (PE)	**PE1**	**I would find the safety mechanisms useful in my job.**
	PE2	**Using safety mechanisms enables me to accomplish tasks more quickly.**
	PE3	**Using safety mechanisms increases my productivity.**
	PE4	**If I use safety mechanisms, I will reduce my risk of injury.**
Effort Expectancy (EE)	**EE1**	**My interaction with safety mechanisms would be clear and understandable.**

	EE2	It would be easy for me to become skillful at using safety mechanisms.
	EE3	I would find safety mechanisms easy to use.
	EE4	Learning to operate safety mechanisms is easy for me.
Social Influence (SI)	SI1	People who influence my behavior think that I should use safety mechanisms.
	SI2	People who are important to me think that I should use safety mechanisms.
	SI3	The supervisors at my site expect me to use safety mechanisms.
	SI4	My coworkers use safety mechanisms, so I follow them.
Facilitating Conditions (FC)	FC1	I have the resources (e.g., devices, equipment) necessary to use safety mechanisms.
	FC2	I have the knowledge necessary to use safety mechanisms (from training or experience).
	FC3	Technical support is available to help me when I have difficulties with safety mechanisms.
	FC4	The safety mechanisms are compatible with my daily work routines.
Intention to Adopt (BI)	BI1	I intend to use safety mechanisms in the next 3 months.
	BI2	I predict I would use safety mechanisms in the next 3 months.
	BI3	I plan to use safety mechanisms in the next 3 months.
	BI4	I will try to use safety mechanisms as often as possible.
Adoption Behavior (AB)	AB1	I consistently use safety mechanisms as part of my daily work.
	AB2	I use safety mechanisms even when not directly supervised.
	AB3	Over the past 3 months, I have used safety mechanisms regularly.

The questionnaire was originally developed in English, then translated into Mandarin Chinese using a back-translation procedure to ensure semantic equivalence (Brislin, 1986). Two bilingual experts (fluent in English and Mandarin, with backgrounds in construction safety) independently translated the English version into Chinese. A third expert, blind to the original English version, back-translated the Chinese version into English. Discrepancies were discussed and resolved. The final Chinese version was reviewed by a panel of five experts for cultural appropriateness and clarity.

Pre-test and pilot study. A two-stage instrument validation process was conducted prior to full-scale data collection (see Section 3.10).

3.6 Data Collection Procedures

Timing. Data were collected between October 5 and November 2, 2024, aligning with stable project activity periods and avoiding major holidays (e.g., National Day holiday in early October). This period was selected based on consultation with participating construction firms to minimize disruptions.

Platform. The online structured questionnaire was administered through the Wenjuanxing platform (www.wjx.cn), a widely used Chinese digital survey tool recognized for its accessibility, data security, and mobile compatibility. Wenjuanxing is GDPR-compliant and has been used in numerous construction safety studies in China (Chungang et al., 2025; Chen et al., 2024). The platform allowed for real-time data synchronization, customizable logic routing, and IP-based restrictions.

Distribution. The final questionnaire was distributed via QR codes and encrypted survey links through two channels:

WeChat groups established with each participating firm's safety coordinators. QR codes were posted in group chats, with a brief explanatory message.

On-site posters displayed at construction site entrances and canteens, containing QR codes and simple instructions.

Field coordinators at partnering firms provided logistical assistance by informing eligible participants about the survey during morning safety briefings and resolving technical issues. The survey took approximately 10–12 minutes to complete.

To ensure data quality and authenticity, several control mechanisms were implemented:

IP restriction settings on Wenjuanxing prevented multiple submissions from the same device.

Response time tracking filtered out inattentive submissions (responses completed in less than two minutes were discarded, as pilot testing indicated that conscientious respondents took at least 5 minutes).

Mandatory questions and real-time logic jumps prevented incomplete or contradictory answers (e.g., if a respondent selected "Strongly Agree" on all items, the system prompted them to review).

Attention check items (e.g., "Please select 'Agree' for this question") were embedded to identify random responders.

A total of 491 responses were received. After applying inclusion criteria (minimum six months experience, direct safety role) and data screening (removing incomplete responses, outliers, and failed attention checks), 450 valid responses remained (91.6% valid response rate).

Participants were assured of anonymity and confidentiality through an informed consent statement on the first page of the questionnaire. No personally identifiable information (PII)—such as names, ID numbers, phone numbers, or employer-specific codes—was collected. The Wenjuanxing platform's IP tracking feature was disabled. Data were exported as encrypted files and stored on password-protected institutional servers accessible only to the principal investigator and academic supervisors. All analytical outputs are reported at aggregate level only.

3.7 Data Analysis Plan

Data analysis was conducted using SPSS 29.0 for descriptive statistics and data screening, and SmartPLS 4.0 (Ringle et al., 2022) for measurement model assessment, structural model testing, and mediation analysis. PLS-SEM was chosen because it is suitable for complex models with mediation, does not require multivariate normality, handles both reflective and formative constructs well, and is optimized for predictive and explanatory research (Hair et al., 2021).

3.7.1 Descriptive Statistics and Data Screening

Prior to SEM, comprehensive data screening was performed:

Missing data analysis: Cases with 10% missing values were excluded (n=12). For remaining cases, missing data were minimal (<3% per item). Little's MCAR test (Little, 1988) was conducted to assess whether missing data were completely at random. The test yielded a non-significant result ($\chi^2 = 98.34$, df = 102, $p = 0.58$), supporting the MCAR assumption. Expectation-maximization (EM) imputation was used for remaining missing values, as it preserves statistical relationships among variables (Schafer & Graham, 2002).

Multivariate outlier detection: Mahalanobis distance (D^2) was calculated with a chi-square critical value based on the number of observed variables (degrees of freedom = number of items) and a stringent significance level ($p < 0.001$). Cases exceeding this threshold were identified as extreme multivariate outliers. A total of 8 outliers were removed (Kline, 2016).

Normality testing: Although PLS-SEM does not require multivariate normality, univariate skewness and kurtosis were examined for descriptive purposes. Skewness values ranged from -0.87 to 0.62, and kurtosis values from -0.54 to 0.91, all within acceptable limits (|skewness|<2, |kurtosis|<7) (Kline, 2016).

Common method bias: Harman's single-factor test was conducted. The unrotated factor solution showed that one factor explained 32.4% of the variance, below the 50% threshold, indicating no severe common method bias (Podsakoff et al., 2012). Additionally, the full collinearity test (Kock, 2015) was performed; all variance inflation factors (VIFs) were below 3.3, further confirming absence of bias.

Descriptive statistics: Means, standard deviations, minimum and maximum values, and frequency distributions were calculated for all demographic variables and main construct items to provide a foundational understanding of the data.

3.7.2 Measurement Model Assessment (Reflective Constructs)

For reflective constructs, the measurement model was assessed following Hair et al. (2021) on three criteria:

Internal consistency reliability was evaluated using Cronbach's Alpha (α) and Composite Reliability (CR). While α is a traditional measure, CR is considered more appropriate in PLS-SEM as it accounts for differing indicator loadings. Thresholds: α 0.70 and CR 0.70 (Nunnally & Bernstein, 1994). Values above 0.80 are considered good.

Convergent validity was assessed using standardized factor loadings and Average Variance Extracted (AVE). Loadings should ideally exceed 0.70, indicating that each indicator shares at least 50% variance with its construct. AVE should exceed 0.50, indicating that the construct explains more than half of the variance of its indicators (Fornell & Larcker, 1981).

Discriminant validity was assessed using two complementary methods: (1) the Fornell-Larcker criterion, which requires that the square root of each construct's AVE be greater than its correlations with all other constructs; and (2) the Heterotrait-Monotrait (HTMT) ratio of correlations, with a threshold of <0.85 (conservative) or <0.90 (liberal)

(Henseler et al., 2015). HTMT values above 0.90 indicate a lack of discriminant validity.

3.7.3 Structural Model Assessment

After confirming the measurement model, the structural model was assessed following Hair et al. (2021) and Chin (1998):

Collinearity assessment: Variance inflation factor (VIF) values were calculated for all predictor constructs in the structural model. VIF values below 5 indicate no critical collinearity; values below 3.3 are ideal (Diamantopoulos & Siguaw, 2006).

Path coefficients (β) and significance: Bootstrapping with 5,000 resamples (Hair et al., 2021) was performed to generate t-statistics and 95% bias-corrected confidence intervals for each path coefficient. Significance levels were reported as $p < 0.05$, $p < 0.01$, and $p < 0.001$.

Coefficient of determination (R^2) : R^2 values represent the proportion of variance in endogenous variables (BI, AB) explained by the model. Guidelines: $R^2 \geq 0.25$ (weak), $R^2 \geq 0.50$ (moderate), $R^2 \geq 0.75$ (substantial) (Hair et al., 2021).

Effect size (f^2) : f^2 quantifies the contribution of an exogenous construct to the R^2 of an endogenous construct. $f^2 = 0.02$ (small), 0.15 (medium), 0.35 (large) (Cohen, 1988).

Predictive relevance (Q^2) : The Stone-Geisser Q^2 was obtained through the blindfolding procedure (omission distance = 7). Q^2 0 indicates that the model has predictive relevance for a specific endogenous construct (Geisser, 1974; Stone, 1974). Q^2 values above 0.25 indicate medium predictive relevance, above 0.50 high relevance.

3.7.4 Mediation Analysis (H7)

To test H7 (intention mediates the FC–AB relationship), the bootstrapped indirect effect was examined. The indirect effect (FC → BI → AB) was calculated as the product of the path coefficients a (FC→BI) and b (BI→AB). A 95% bias-corrected confidence interval was constructed from 5,000 bootstrap resamples. The indirect effect was considered statistically significant if the confidence interval did not include zero (Preacher & Hayes, 2008).

The variance accounted for (VAF) was calculated to determine the proportion of the total effect mediated: VAF = (indirect effect) / (total effect). Total effect = direct effect (FC→AB) + indirect effect (FC→BI→AB). VAF   0.80 indicates full mediation, 0.20–0.80 indicates partial mediation, and <0.20 indicates no mediation (Hair et al., 2021).

3.7.5 Model Fit Indices

Although PLS-SEM focuses on predictive power and model fit indices are less central than in covariance-based SEM, two indices were reported for completeness: the Standardized Root Mean Square Residual (SRMR) and the Normed Fit Index (NFI) . Acceptable fit is indicated by SRMR < 0.08 (Hu & Bentler, 1999) and NFI   0.90 (Hair et al., 2021). Note that NFI may be lower in PLS-SEM than in CB-SEM; therefore, SRMR is the primary fit criterion.

3.8 Ethical Considerations

This research adhered to internationally recognized ethical principles for social science research involving human participants, as articulated in the Belmont Report (1979) and the APA Ethical Principles (American Psychological Association, 2017). The study was approved by the Universiti Malaya Institutional Review Board (approval number:

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UM.TNC2/UMREC_2024-15, dated September 15, 2024), following Chinese national guidelines for research involving human subjects.

No personally identifiable information (PII) was collected. The Wenjuanxing platform's IP tracking feature was disabled. All data were exported as encrypted files and stored on password-protected institutional servers accessible only to the principal investigator and academic supervisors. All analytical outputs are reported at aggregate level only; raw data will be destroyed five years after publication.

Prior to starting the questionnaire, participants were presented with a detailed consent statement explaining: the purpose of the study, the voluntary nature of participation, the expected time commitment (10–12 minutes), the right to withdraw at any point without consequence, and data handling practices. The language was simplified to ensure accessibility for workers with lower literacy levels. Participants were required to check a mandatory consent box to proceed; if the box was left unchecked, the system automatically terminated the session.

Workers were approached through non-coercive channels (WeChat groups, job site posters). No material or financial incentives were offered to avoid undue inducement, especially given the economic vulnerability of migrant workers. Clear statements emphasized that non-participation would not affect employment status, daily work routines, or interpersonal relations with colleagues or supervisors. Special care was taken to ensure that no direct pressure was applied by team leaders or managerial staff during distribution.

The questionnaire avoided personal, political, or emotionally sensitive topics. Questions focused solely on perceptions of safety technologies and workplace safety practices. The pilot study ensured linguistic clarity and cultural appropriateness. No open-ended responses were required, reducing the likelihood of respondents inadvertently disclosing identifiable information. Participants were informed that they could skip any question or exit the survey at any time.

3.9 Pre-test and Pilot Study

A two-stage instrument validation process was conducted prior to full-scale data collection.

Pre-test (content validity) : A panel of five experts—two in construction safety, two in behavioral science, and one in information systems—reviewed the questionnaire for conceptual clarity, cultural appropriateness, and construct alignment with UTAUT. Each expert rated each item for relevance and clarity on a 4-point scale (1 = not relevant, 4 = highly relevant). The content validity index (CVI) was calculated; all items had CVI 0.80. Based on feedback, minor wording adjustments were made: for example, "My interaction with the system would be clear and understandable" was changed to "I can understand how to use the safety tools easily" for EE1. Back-translation confirmed semantic equivalence.

Pilot study (practical operability) : A convenience sample of 30 construction workers from two medium-sized projects in the Pearl River Delta participated. The sample included 15 laborers, 10 technicians, and 5 supervisors, representing SOEs, private firms, and subcontractors. Participants completed the questionnaire via mobile phone

(Wenjuanxing link) and were then invited to provide structured feedback on questionnaire length, wording clarity, logical flow, and interface accessibility.

Feedback resulted in three modifications: (1) simplification of two effort expectancy items; (2) reordering of demographic items to place non-sensitive questions (e.g., region, job role) before potentially sensitive ones (e.g., age); (3) addition of a "not applicable" option for training-related questions.

Pilot data were analyzed for preliminary reliability using SPSS 26.0. Cronbach's α for all constructs exceeded 0.70: PE (0.85), EE (0.79), SI (0.82), FC (0.88), BI (0.86), AB (0.81). No substantial floor or ceiling effects were observed. Missing data were minimal (<2%). Average completion time was 11 minutes. The pilot confirmed that the instrument was psychometrically sound and contextually appropriate for the Guangdong construction workforce.

3.10 Chapter Summary

This chapter has outlined the methodological framework for testing the mediating role of behavioral intention in safety mechanism adoption among construction workers in Guangdong, China, based on UTAUT. A quantitative, cross-sectional, correlational design was adopted. Stratified random sampling (n = 450) ensured representation across geographic regions, firm types, and occupational roles. A structured questionnaire with validated scales was administered online via Wenjuanxing, with strict data quality controls. Data will be analyzed using PLS-SEM (SmartPLS 4.0), including measurement model assessment (reliability, convergent validity, discriminant validity) and structural model assessment (path coefficients, R^2, f^2, Q^2, and mediation via bootstrapping). Ethical considerations—confidentiality, informed consent, voluntariness, risk mitigation—were thoroughly addressed. A pre-test and pilot study (n = 30) confirmed instrument clarity, reliability, and cultural relevance. This rigorous methodology ensures that the expected empirical findings will be valid, reliable, and generalizable.

4. EXPECTED RESULTS AND DISCUSSION

4.1 Expected Measurement Model Results

Based on the pilot study and prior UTAUT validation studies, the following measurement model results are expected:

All indicator loadings are expected to exceed 0.70, with most in the range of 0.75–0.90. Items with loadings below 0.70 may be considered for deletion, but this is not anticipated given the pilot results.

Cronbach's α and CR are expected to be 0.80 for all constructs, indicating high reliability. For example, FC (which had α = 0.88 in the pilot) and BI (α = 0.86) are expected to show excellent reliability.

AVE values are expected to exceed 0.60 for all constructs, well above the 0.50 threshold. For instance, FC (AVE ≈ 0.70), BI (AVE ≈ 0.68), and AB (AVE ≈ 0.65) are expected to demonstrate strong convergent validity.

The Fornell-Larcker criterion is expected to be satisfied: the square root of each construct's AVE will be greater than its correlations with other constructs. HTMT ratios are expected to be below 0.85 for all construct pairs, confirming discriminant validity.

The highest HTMT is anticipated between BI and AB (since they are conceptually close but distinct), but still below 0.85.

4.2 Expected Structural Model Results

All VIF values are expected to be below 3.3, indicating no problematic collinearity.

Path coefficients and hypothesis testing:

The indirect effect of FC on AB via BI (FC→BI→AB) is expected to be significant, with a 95% bias-corrected confidence interval that does not include zero. The expected indirect effect size is β_indirect ≈ 0.20–0.30. The variance accounted for (VAF) is expected to be between 40% and 60%, indicating partial mediation. This would mean that facilitating conditions influence adoption behavior both directly and indirectly through behavioral intention, but the indirect effect is substantial.

R^2 for BI is expected to be 0.55–0.65, indicating that the four UTAUT predictors explain a moderate to substantial proportion of variance in intention. R^2 for AB is expected to be 0.50–0.60, indicating good explanatory power. These values are consistent with Chungang et al. (2025) who reported R^2 for AB = 0.59.

The f^2 for FC→BI is expected to be medium to large (≈0.25), while f^2 for BI→AB is expected to be large (≈0.40). f^2 for PE→BI and SI→BI are expected to be small to medium (0.05–0.15). f^2 for EE→BI is expected to be negligible (<0.02).

Q^2 for BI is expected to be 0.25 (medium predictive relevance), and Q^2 for AB 0.30, indicating that the model has good predictive validity.

SRMR is expected to be <0.08 (e.g., 0.06–0.07), indicating acceptable fit. NFI may be 0.85 but may not reach 0.90 due to PLS-SEM's characteristics; SRMR will be the primary fit index.

5. CONCLUSION

5.1 Summary of the Research Protocol

This research protocol has presented a comprehensive plan to investigate the factors influencing safety mechanism adoption among frontline construction workers in Guangdong Province, China, using the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical lens. The primary focus is on the mediating role of behavioral intention in the relationship between facilitating conditions and actual adoption behavior—a pathway that has been underexplored in construction safety literature. The protocol detailed the research background (highlighting Guangdong's high accident rates, low adoption rates, and regulatory context), theoretical framework, hypotheses, research design (quantitative, cross-sectional), sampling strategy (stratified random, n=450), research instrument (validated UTAUT scales), data collection procedures (online via Wenjuanxing), and data analysis plan (PLS-SEM with bootstrapped mediation). Ethical considerations and pilot study results were also reported.

5.2 Expected Contributions

This study is expected to extend UTAUT theory by empirically validating that behavioral intention partially mediates the effect of facilitating conditions on adoption behavior in a high-risk, policy-driven construction context. This challenges the original UTAUT assumption that FC directly drives behavior without intention when voluntariness is low. The findings will contribute to a more nuanced understanding of how organizational resources translate into safety compliance, highlighting the importance of psychological readiness alongside structural support. Additionally, the study provides contextualized evidence from Guangdong—a region with unique characteristics (migrant workforce, aging workers, strong regulatory enforcement)—that can inform UTAUT adaptations in other developing economies.

5.3 Concluding Remarks

This research protocol provides a rigorous theoretical and methodological foundation for investigating the mediating role of behavioral intention in safety mechanism adoption among Guangdong's construction workers. By focusing on the FC→BI→AB pathway, the study addresses a critical gap in UTAUT applications in high-risk industries. The expected findings will not only extend UTAUT theory but also provide evidence-based guidance for policymakers and practitioners seeking to improve occupational safety in one of China's most dynamic and accident-prone sectors. The study ultimately contributes to the broader goal of reducing preventable workplace injuries and fatalities, aligning with China's 14th Five-Year Plan and Sustainable Development Goal 8 (Decent Work and Economic Growth).

CITATION AND REFERENCES

Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211.

Al-Emran, M., Mezhuyev, V., & Kamaludin, A. (2018). Technology acceptance model in M-learning context: A systematic review. Computers & Education, 125, 389–412.

Al-Emran, M., Arpaci, I., & Salloum, S. A. (2021). An empirical examination of continuous intention to use m-learning: An integrated model. Education and Information Technologies, 26(6), 7289–7308.

Alghamdi, A., Al-Hudhaif, S., & Al-Harbi, M. (2021). Wearable safety technologies in construction: A UTAUT-based study. Safety Science, 142, 105387.

Ali, M., Li, S., & Zhang, Y. (2025). Adoption of wearable sensible devices in construction: Extending UTAUT. Automation in Construction, 160, 105289.

American Psychological Association. (2017). Ethical principles of psychologists and code of conduct. APA.

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.

Bandura, A. (1997). Self-efficacy: The exercise of control. Freeman.

Brislin, R. W. (1986). The wording and translation of research instruments. In W. J. Lonner & J. W. Berry (Eds.), Field methods in cross-cultural research (pp. 137–164). Sage.

Chen, Y., & Huang, L. (2022). Challenges of longitudinal research in migrant construction worker populations. Field Methods, 34(2), 145–160.

Chen, Y., & Wang, L. (2023). Factors influencing wearable safety device adoption in Chinese construction sites: A UTAUT perspective. Safety Science, 158, 105991.

Chen, Y., Li, J., & Zhang, W. (2024). Willingness to accept metaverse safety training for construction workers based on extended UTAUT. Frontiers in Public Health, 11, 1294203.

Chin, W. W. (1998). The partial least squares approach to structural equation modeling. In G. A. Marcoulides (Ed.), Modern methods for business research (pp. 295–336). Lawrence Erlbaum.

Chungang, L., Zhuolin, Z., Yee, C. M., & Kharuddin, A. F. (2025). Analysing behaviour of safety technologies in construction: An empirical study using the UTAUT model in Guangdong Province, China. Malque Scientific Journal, 8(6), e2026374.

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. Journal of Applied Social Psychology, 22(14), 1111–1132.

Deci, E. L., & Ryan, R. M. (2000). The “what” and “why” of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268.

Deng, X., Li, S., & Liu, Y. (2021). Sampling strategies for transient construction workers: Lessons from Guangdong. Journal of Construction Engineering and Management, 147(8), 04021067.

Diamantopoulos, A., & Siguaw, J. A. (2006). Formative versus reflective indicators in organizational measure development: A comparison and empirical illustration. British Journal of Management, 17(4), 263–282.

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): A systematic review. Information Systems Frontiers, 21(3), 719–734.

Faul, F., Erdfelder, E., Lang, A. G., & Buchner, A. (2007). GPower 3: A flexible statistical power analysis program. Behavior Research Methods, 39(2), 175–191.

Fishbein, M., & Ajzen, I. (1975). Belief, attitude, intention, and behavior: An introduction to theory and research. Addison-Wesley.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50.

Geisser, S. (1974). A predictive approach to the random effect model. Biometrika, 61(1), 101–107.

Guangdong Bureau of Statistics. (2023). Guangdong statistical yearbook 2023. China Statistics Press.

Guangdong Department of Housing and Urban-Rural Development. (2025a). Notice on promoting the use of “Guidelines for preventing falls from heights in Guangdong’s housing and municipal engineering projects” (Yue Jian Zhi No. 2025-240). Guangdong Provincial Government.

Guangdong Department of Housing and Urban-Rural Development. (2025b). Notice on converting the “Regulations on assigning primary quality and safety responsibility to housing and municipal engineering construction units” from trial implementation to official implementation (Yue Jian Gui Fan No. 2025-3). Guangdong Provincial Government.

Guangdong Department of Housing and Urban-Rural Development. (2025c). Notice on implementing the measures for establishing safety production management institutions and assigning safety management personnel in construction enterprises and projects (Yue Jian Zhi No. 2025-269). Guangdong Provincial Government.

Guangdong Emergency Management Department. (2025). Chart analysis: Overview of production safety accidents in Guangdong Province, January–September 2025. Guangdong Provincial Government.

Guangdong Human Resources Bureau. (2023). Annual report on occupational injuries and economic losses. Guangdong Provincial Government.

Guangdong Provincial Government. (2023). Safety production ordinance of Guangdong Province. Guangdong Provincial Government.

Guangdong Provincial Safety Commission. (2025). Action plan for Guangdong Province’s 2025 “Hidden Hazard Investigation and Governance Year”. Guangdong Provincial Government.

Guangdong SME Bureau. (2023). Safety technology investment survey of small and medium construction enterprises in Guangdong. Guangdong Provincial Government.

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2021). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage Publications.

Hayes, A. F. (2018). Introduction to mediation, moderation, and conditional process analysis (2nd ed.). Guilford Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis. Structural Equation Modeling, 6(1), 1–55.

Huang, X., Liu, Y., & Chen, Z. (2023). Facilitating conditions and PPE compliance in Shenzhen construction projects. Journal of Safety Research, 85, 201–213.

Kish, L. (2020). Survey sampling. Wiley (Classic reprint).

Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). Guilford Press.

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1–10.

Kummer, T. F., Schäfer, K., & Todorova, N. (2013). Acceptance of hospital information systems: A study of the UTAUT model. Health Policy and Technology, 2(3), 134–142.

Li, J., Zhang, C., & Wang, H. (2024). Construction workers’ behavioral intention toward a passive back-support exoskeleton: Application and extension of UTAUT model. In Construction Research Congress 2024 (pp. 738–747). American Society of Civil Engineers.

Li, S., & Zhang, Y. (2023). Social influence and safety technology adoption among migrant construction workers in Guangdong. Journal of Construction Engineering and Management, 149(4), 04023012.

Li, X., Wang, L., & Liu, Y. (2023). The role of facilitating conditions in construction safety technology adoption: Direct and indirect effects. Accident Analysis & Prevention, 183, 106982.

Lin, X., & Sun, J. (2021). Voluntariness of use and social influence in construction safety app adoption. Journal of Civil Engineering and Management, 27(6), 412–425.

Little, R. J. A. (1988). A test of missing completely at random for multivariate data with missing values. Journal of the American Statistical Association, 83(404), 1198–1202.

Liu, X., Wang, L., & Chen, Y. (2023). The intention-behavior gap in construction safety technology adoption: A longitudinal study. Safety Science, 162, 106089.

Ministry of Emergency Management. (2024). National construction safety statistics 2023. China Emergency Press.

Ministry of Housing and Urban-Rural Development. (2024). China construction safety report 2023. MOHURD.

National Development and Reform Commission. (2021). The 14th Five-Year Plan for national economic and social development of the People's Republic of China. NDRC.

Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric theory (3rd ed.). McGraw-Hill.

Oliveira, T., Faria, M., Thomas, M. A., & Popovič, A. (2014). Extending the understanding of mobile banking adoption: When UTAUT meets TTF and ITM. International Journal of Information Management, 34(5), 689–703.

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. Annual Review of Psychology, 63, 539–569.

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behavior Research Methods, 40(3), 879–891.

Ringle, C. M., Wende, S., & Becker, J. M. (2022). SmartPLS 4. SmartPLS GmbH.

Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

Schafer, J. L., & Graham, J. W. (2002). Missing data: Our view of the state of the art. Psychological Methods, 7(2), 147–177.

Sheeran, P., & Webb, T. L. (2016). The intention–behavior gap. Social and Personality Psychology Compass, 10(9), 503–518.

Shen, L., Zhang, Z., & Long, R. (2023). UTAUT applications in developing economies: A systematic review. Technology in Society, 72, 102187.

Shin, J., Kim, S., & Lee, J. (2024). Unlocking determinants of smart construction: An integrated model of UTAUT2, TTF, and perceived risk for IoT acceptance in AEC industry. Journal of Building Engineering, 85, 108632.

State Council of China. (2021). National work safety rectification plan (2021–2025). State Council Document No. 23.

Stone, M. (1974). Cross-validatory choice and assessment of statistical predictions. Journal of the Royal Statistical Society: Series B, 36(2), 111–133.

Tang, L., & Zhou, Q. (2024). Age-related barriers to digital safety technology adoption in

China's construction industry. Journal of Safety Research, 88, 245–258.

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144–176.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. MIS Quarterly, 15(1), 125–143.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178.

Wang, L., Liu, X., & Chen, Y. (2021). Job characteristics and safety technology adoption: A moderation analysis. Journal of Safety Research, 79, 212–223.

Williams, M. D., Rana, N. P., & Dwivedi, Y. K. (2015). The unified theory of acceptance and use of technology (UTAUT): A systematic review. Journal of Enterprise Information Management, 28(3), 443–488.

Wu, X., Zhang, L., & Li, H. (2020). Social influence and mobile safety app adoption among Chinese construction workers. Safety and Health at Work, 11(3), 312–319.

Wu, X., Zhang, L., & Li, H. (2023). Voice-command interfaces for low-literacy construction workers: A UTAUT study. Automation in Construction, 145, 104635.

Xu, J., Wang, L., & Li, S. (2021). Understanding the intention-behavior gap in construction safety: A situational perspective. Accident Analysis & Prevention, 156, 106118.

Yin, S., Li, H., & Wang, X. (2021). Collectivist culture and safety compliance in Chinese construction teams. Journal of Construction Engineering and Management, 147(5), 04021034.

Zhang, F., & Cheng, L. (2024). Intersectional analysis of safety technology adoption among construction workers in Guangdong. Safety Science, 170, 106359.

Zhang, Y., Liu, X., & Chen, W. (2022). User-centered design for older construction workers: A UTAUT study. Gerontechnology, 21(2), 145–158.

Zhang, Y., Liu, X., & Chen, W. (2024). Digital transformation of China's construction industry: A systematic review. Automation in Construction, 158, 105215.

Zhou, Q., & Tang, L. (2022). Extending UTAUT for construction safety technology adoption: A research agenda. Journal of Civil Engineering and Management, 28(5), 341–355.