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Original Article

Resolving the Intention–Behavior Gap in Smes' AI Adoption: Evidence from a Cognitive–Affective Dual-Path Model in Western China

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Abstract:
To address the "intention-behavior gap" in small and medium-sized enterprises (SMEs)' adoption of artificial intelligence (AI) technology, this study constructs a cognitive-affective dual-path integrated model based on the TAM-UTAUT framework and affect-cognition interaction theory. Using PLS-SEM, we analyze survey data from 198 business owners in Southwest and Northwest China to systematically reveal the technological decision-making mechanism. The results show that in the cognitive path, perceived usefulness, performance expectancy, and social influence significantly drive adoption intention through attitude as a mediator, while facilitating conditions have no significant effect. In the affective path, perceived comfort, perceived trust, and emotional dependence form parallel driving forces via satisfaction. A comparison of the dual paths indicates that cognitive evaluation is slightly stronger than the affective mechanism, and their dynamic coupling determines the efficiency of converting adoption intention into actual behavior. Moderation analysis reveals that at the individual trait level, educational background weakens the role of facilitating conditions, and work experience reduces the marginal benefit of perceived comfort. At the contextual level, the effect of performance expectancy in manufacturing is 2.3 times that in the service industry. This study transcends the single rational decision-making paradigm, confirms the critical role of emotional dependence, and expands the contextual boundary of TAM- UTAUT theory to SMEs. Practically, it proposes a "context-adaptive" strategy: strengthening the dissemination of industry benchmarks for low-education groups, designing quantitative performance schemes focused on manufacturing, and reducing senior owners' technological alienation through emotional design, thereby providing a new path to resolve the "intention-behavior gap".
Keywords: Rational Decision-Making; Small and Medium-Sized Enterprises (SMEs); Artificial Intelligence (AI); Adoption Intention; Intention-Behavior Gap; PLS-SEM

1. Introduction

Against the macro backdrop of the deep evolution of the digital economy, artificial intelligence (AI) technology is reshaping the inherent logic of global industrial competition (Abbas Khan et al., 2024). As the capillary network of the global economic ecosystem, small and medium-sized enterprises (SMEs) exhibit distinct contextual uniqueness in AI adoption compared to large enterprises and consumer-facing scenarios (Michael, 2025). Unlike large enterprises with resource slack and multi-level decision-making systems, SMEs face significant resource constraints, centralized decision-making by individual stakeholders, and fragmented technological needs (Pendic & Zampedis, 2025); in contrast to the personalized and entertainment-oriented technological usage scenarios of individual consumers, AI adoption by SMEs is directly linked to organizational survival and competitive advantage, with irreversible decision consequences (Wang et al., 2022).

However, the penetration of AI technology among this group presents a prominent "intention-behavior gap" (Shah et al., 2025). Although 87% of business owners recognize the strategic value of AI, the actual deployment rate is less than 23% (Shaik et al., 2024). This paradox reveals the explanatory limitations of traditional technology acceptance models—when technological decision-making shifts from individual user scenarios or large enterprise contexts to the perspective of SME owners, their decision-making mechanisms must integrate both the rationality of organizational effectiveness and the perception of emotional risk (AlQahtani, 2025). Existing research has predominantly focused on technology deployment in large enterprises or consumer-side applications (Pan et al., 2020; Weinberg, 2025), leaving a theoretical gap in understanding the adoption mechanisms of SME owners amid the interplay of resource constraints, cognitive load, and emotional commitment. As a result, it is difficult to explain the unique contradiction of "high recognition but low implementation" among this group.

Core literature in the technology acceptance field has established a cognitive-dominant theoretical foundation. Davis's TAM proposed the core pathway of "perceived usefulness—attitude—behavioral intention" (Davis, 1989), Venkatesh et al.'s UTAUT integrated four rational dimensions and moderating variables (Venkatesh et al., 2003), and Bhattacherjee's Information Systems Continuance Model introduced satisfaction to refine the transmission logic (Bhattacherjee, 2001). These frameworks collectively lay the foundation for the rational decision-making paradigm, which is applicable to large enterprises with abundant resources and hierarchical decision-making or low-risk consumer scenarios (Bhatnagr et al., 2024; Kim et al., 2024; Na et al., 2022).

However, in the context of AI adoption by SMEs, three significant gaps render traditional models unable to resolve the "intention-behavior gap" paradox. First, there is insufficient contextual adaptability: the assumptions of "resource accessibility" and "decision rationalization" in UTAUT and its extended models do not align with the characteristics of SME resource constraints and owner-centric decision-making (Warsono et al., 2025). The "bricolage" logic proposed by Baker and Nelson may subvert the enabling role of facilitating conditions (Baker & Nelson, 2005), making traditional models unable to explain the intention- behavior disconnect under resource scarcity. Second, there is a lack of an emotional mechanism: both TAM and UTAUT are centered on cognitive rationality (Papathomas et al., 2025), the hedonic motivation in UTAUT2 fails to achieve the independent integration of emotion and cognition (Allam, 2025), and the IS Continuance Model focuses on post-use emotional feedback (Park, 2025). In contrast, the dual-system coordination mechanism of decision- making emphasized by Forgas's affect-cognition interaction theory (Forgas, 2008) — namely, the inhibitory effect of SME owners' emotional defensiveness toward the "black box" of AI on behavioral transformation—has not been incorporated into core models. Third, the insufficient hierarchicalization of moderating effects: although the UTAUT series introduces individual or scenario-based moderators, it lacks a hierarchical framework of "individual traits—contextual characteristics", failing to decompose the interaction between industry type, educational background, and work experience (Tanantong & Wongras, 2024). This makes it difficult to explain differences in the adoption of similar AI tools among owners in different industries and with varying qualifications. These gaps mean that traditional models can only explain "rational intention" but ignore differences in decision-making logic under emotional defensiveness and resource constraints, ultimately failing to resolve the realistic "intention- behavior gap".

Addressing the three major literature gaps—insufficient contextual adaptability, lack of an emotional mechanism, and insufficient hierarchicalization of moderating effects — this study achieves precise breakthroughs by constructing a cognitive-affective dual-path integrated model, with clear innovative boundaries and gap-filling logic that distinguishes it from existing research. Targeting the limitation of cognitive dimensions in traditional TAM-UTAUT series models, which are based on scenarios of "abundant resources and rationalized decision-making", this study completes contextual expansion while inheriting core constructs: extending performance expectancy from individual work efficiency to the organizational strategic value level, decomposing the "survival coercion" transmission effect of social influence under industry competitive pressure, and repositioning the characteristic of weakened marginal effects of facilitating conditions under resource constraints in combination with bricolage theory, thereby filling the gap of contextual adaptability for SMEs.

Regarding the lack of an emotional mechanism, this study breaks through the limitation of existing frameworks that treat emotion as an appendage of cognition, constructing a triangular antecedent system of "perceived comfort — emotional dependency — perceived trust". With "emotional dependency", which focuses on emotional connection with business operations, as the core construct, it establishes satisfaction as the exclusive mediator of the emotional path, forming a parallel dual-mediation structure with the attitude mediator of the cognitive path. This confirms the equal driving status of emotion and cognition, distinguishing it from the existing "single mediation + emotional moderation" model. In response to the flattening of moderating effects in traditional models, this study constructs a hierarchical framework of "individual traits—contextual characteristics". It uses educational background and work experience to moderate the resource dependence and experience sensitivity of the dual paths, and industry type to moderate the intensity of path effects, decomposing the differentiated reshaping role of multi-dimensional moderating variables and filling the gap of hierarchicalized moderating effects.

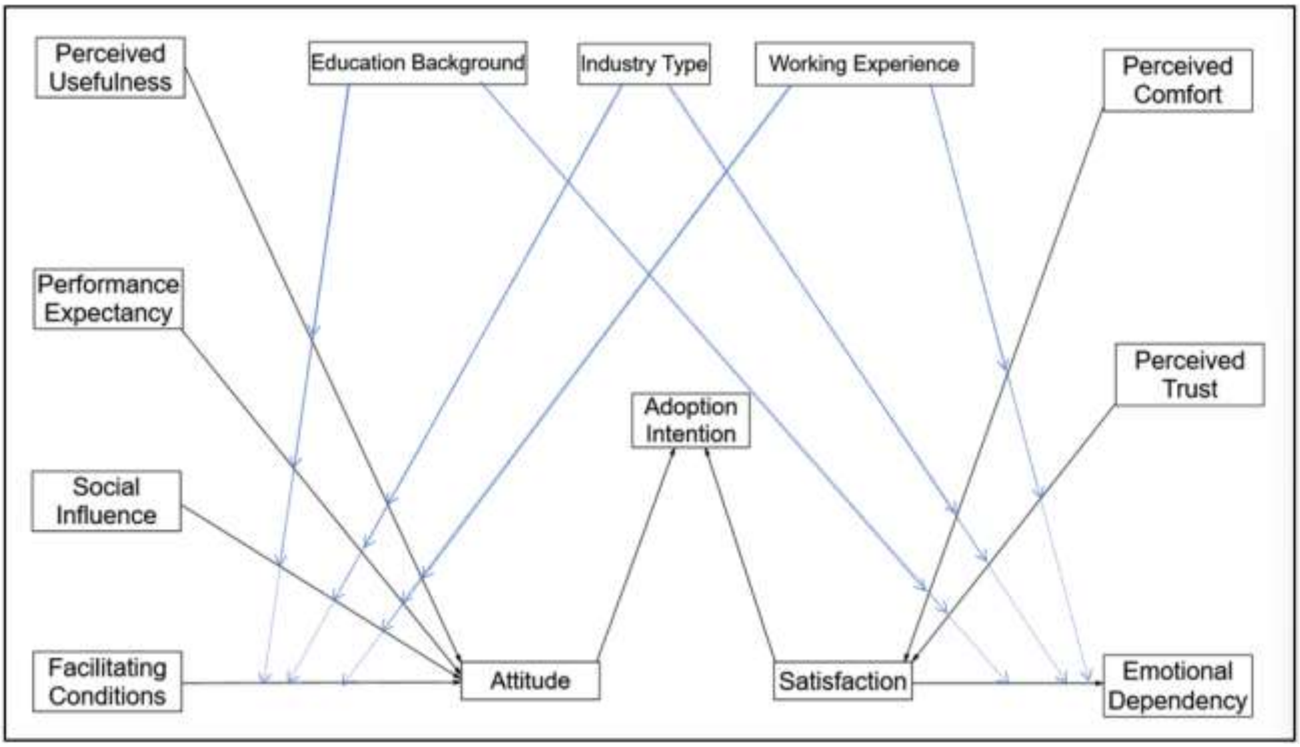


Figure 1. Conception Model

The theoretical contributions of this study are reflected in three synergistic breakthroughs: constructing a dual-path integrated model of AI adoption specifically for SME owners. Existing dual-path frameworks mostly focus on consumers or large enterprises and do not adapt to the characteristics of SMEs such as "resource constraints, centralized decision-making, and strategic orientation"(Waseel et al., 2024). By expanding contextual constructs (as see in figure 1) such as strategic-level performance expectancy and verifying the dual mediation of attitude and satisfaction, this study reveals the "cognitive-affective parallel driving" law of this group for the first time, breaking through the limitation of the single rational decision-making paradigm. Meanwhile, it uncovers the hierarchical moderation differentiation law of "individual—context"," such as educational background weakening the role of facilitating conditions (Abulail et al., 2025) and the effect of performance expectancy in manufacturing being 2.3 times that in the service industry (AL-Shboul, 2024). This fills the research gap on contextual heterogeneity of technology acceptance models in SME scenarios and clarifies the applicable boundaries of TAM-UTAUT theories in resource-constrained contexts. Furthermore, it provides a new empirical fulcrum for the emotional mechanism branch in the technology acceptance field. Existing emotional design theories mostly focus on human-computer interaction on the consumer side, while this study innovatively verifies the superlinear driving effect of “emotional dependency” on satisfaction, with intensity significantly higher than that of perceived trust and perceived comfort. This challenges the traditional assumptions of “cognitive dominance” and “trust as the core”, offering a new perspective for emotional design in organizational-level technology adoption.

At the practical level, based on the root cause of the gap — “cognition not converted into emotional identification, and contextual heterogeneity leading to transformation barriers” — this study proposes a “context-adaptive” promotion paradigm: strengthening the resource integration-oriented communication of industry benchmarks for owners with low educational backgrounds, responding to findings related to educational background to address the dilemma of “recognition but lack of capability”; designing quantitative performance schemes coupled with production processes for manufacturing owners, leveraging the strong effect of performance expectancy in manufacturing to fill the gap of “rational recognition but lack of concrete perception”; and developing emotionally interactive designs compatible with traditional processes for senior owners, combining findings related to work experience to build emotional dependence and resolve the problem of “cognitive recognition but emotional resistance”.

2. Theoretical Foundations

To support the construction of the cognitive-affective dual-path integrated model, this study integrates five core theories based on the three-dimensional logic of “contextual adaptation — dual-system drive — contextual moderation”: the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), affect-cognition interaction theory, trust theory, and the basic theory of moderating effects. These theories are selected because a single technology acceptance theory cannot address the insufficient contextual adaptability and lack of emotional mechanisms for small and medium-sized enterprises (SMEs), while a single emotional theory fails to explain the core driving role of cognitive rationality. The theory of moderating effects, in turn, responds to the need to reshape the dual paths through contextual heterogeneity, collectively filling the literature gaps. In terms of functional division: TAM and UTAUT form the foundation of the cognitive path, providing constructs for rational decision-making (Song et al., 2025); affect-cognition interaction theory serves as the core of integration, establishing a dual-system parallel drive framework and dual mediating variables (Revesai, 2025); trust theory is integrated into the emotional path to supplement key constructs for emotional motivation (Zhang et al., 2021); and the basic theory of moderating effects supports the hierarchical framework of “individual traits — contextual characteristics”, decomposing the mechanism of contextual heterogeneity (Jais et al., 2024).

2.1 Technology Acceptance Model

This study adopts the Technology Acceptance Model (TAM) as the foundational theory for the cognitive path, with core constructs including perceived usefulness and attitude. The definition of attitude inherits Davis’s connotation of “an overall evaluation of technology use” and, combined with the organizational decision-making characteristics of SME owners (Alka’awneh et al., 2025; Davis, 1989), is specifically defined as a dispositional judgment toward adoption formed through rational assessment of the strategic value and performance improvement potential of AI technology. This definition retains the core attributes of the original theory while achieving contextual adaptation from the individual level to the organizational decision-making level by incorporating organizational strategic orientation, maintaining TAM’s classic transmission logic of “cognitive evaluation → attitude → behavioral intention” — that is, owners’ rational assessments must be integrated through attitude to be converted into adoption intention (Agbo-Adediran et al., 2025).

The study does not directly include the perceived ease of use dimension but adjusts it based on contextual characteristics: its core connotation (reducing usage difficulty) has been extended through UTAUT’s facilitating conditions construct, and SME owners are more focused on the strategic usefulness of technology than personal ease of use (Tanos et al., 2024). TAM and UTAUT form a synergistic relationship: TAM provides the core transmission framework of the cognitive path (perceived usefulness → attitude conversion), while UTAUT supplements key antecedent variables such as performance expectancy, social influence, and facilitating conditions, collectively constructing a complete cognitive driving system.

2.2 Unified Theory of Acceptance and Use of Technology

This study integrates the Unified Theory of Acceptance and Use of Technology (UTAUT) as an extended framework for the cognitive path, enhancing its adaptability to the SME context through construct adjustments (Kwarteng et al., 2022). Among the four core dimensions of the original UTAUT model (Kwarteng et al., 2024), this study excludes effort expectancy based on two main considerations: first, SME owners' decisions focus on organizational strategic value rather than personal usage costs (Shahadat et al., 2023); second, its core connotation of "reducing usage barriers" has been comprehensively covered through the extension of the facilitating conditions construct, with significant overlap between the two at the organizational level. Excluding effort expectancy simplifies the model and focuses on core decision-making logic.

In terms of construct extension, performance expectancy is expanded from the original definition of "expectation of improving individual work efficiency" to "expectation of achieving organizational strategic value", specifically including owners' rational predictions that AI technology will enhance core competitiveness (Duong et al., 2024), address business pain points, and optimize resource allocation. This extension aligns with the organizational- oriented decision-making perspective of SME owners, has been validated in research on enterprise digital transformation, and retains the core essence of effectiveness evaluation to ensure theoretical continuity.

The study retains the social influence and facilitating conditions dimensions: social influence aligns with the organizational decision-making logic under industry competitive pressure (Alsaid & Ambilichu, 2021); facilitating conditions, combined with bricolage theory, reposition their mechanism of action in the context of resource constraints (Dawa et al., 2025). Through the synergistic integration of UTAUT and TAM, the cognitive path not only retains the core logic of classic theories but also achieves construct optimization in the SME context, providing theoretical support for hypothesis development.

2.3 Affect-Cognition Interaction Theory

Rooted in interdisciplinary research at the intersection of social psychology and neuroscience, affect-cognition interaction theory's core proposition is that the formation of human behavioral intentions is jointly driven by the cognitive system and the emotional system, which integrate information through bidirectional regulation (Ji & Deng, 2025). This theory provides core support for breaking through the cognitive dominance limitation of traditional technology acceptance models and serves as the integrating core theory of the dual-path model in this study. The theory's core function in the model is to establish a cognitive-affective dual-path parallel drive framework and clarify the basis for selecting dual mediating variables. Based on the dichotomy of the cognitive and emotional systems, the study divides the technology adoption path into the cognitive path and the emotional path. The cognitive system corresponds to rational antecedent variables such as perceived usefulness, performance expectancy, and social influence, transmitted through the mediating variable of attitude — attitude, as a carrier of integrated cognitive evaluation, reflects a rational acceptance tendency toward technology. The emotional system corresponds to emotional antecedent variables such as perceived comfort, perceived trust, and emotional dependence, transmitted through the mediating variable of satisfaction — satisfaction, as cumulative feedback of emotional experiences, reflects an emotional acceptance tendency toward technology (Xia et al., 2025).

The theoretical foundation of emotional dependency derives from the extension of attachment theory to human-machine relationships, technology emotional attachment theory, and organizational emotional commitment theory (Huang & Huang, 2025). This study defines it as a deep emotional bond and proactive behavioral tendency formed by owners through the continuous interaction between AI technology and the organization's core business, as the technology stably addresses business pain points, reduces decision-making uncertainty, and provides emotional security. Its core driver stems from the activation of the brain's reward system, distinguishing it from mere functional recognition. This construct has clear boundaries with similar constructs: technology attachment focuses on emotional preferences at the human-product level (Dirin et al., 2023), while this construct reflects a three-dimensional connection between technology, organization, and decision-makers; usage habits manifest as passive behavioral inertia, while this construct centers on proactive emotions; emotional trust focuses on beliefs about technical attributes, while this construct emphasizes an indispensable dependent relationship. The concretization of this human-machine attachment relationship in organizational scenarios, with dual attributes of emotional connection and proactive behavioral tendency, makes it an independent core construct.

2.4 Trust Theory

Trust theory's core proposition is to explain the formation of behavioral intentions in uncertain situations, relying on the evaluation of beliefs regarding the target's reliability, benevolence, and competence (Guo, 2022). Its core value lies in explaining the emotional acceptance mechanism in risky contexts (Cruwys et al., 2021), particularly applicable to uncertain decisions caused by the black-box nature of AI technology (Chinnaraju, 2025). McKnight et al. divide trust into cognitive trust based on rational evaluation and emotional trust based on emotional connection (Palmer et al., 2023), forming a dual-dimensional structure with dominance varying by context.

The core basis for classifying perceived trust into the emotional path in this study is its emotionally dominant attribute in the context of AI adoption. The black-box nature of AI technology makes it difficult for SME owners to fully verify technical reliability through rational evaluation, resulting in a weak foundation for cognitive trust (Von Eschenbach, 2021). Instead, they rely more on emotional security derived from data security guarantees and supplier ethical commitments, meaning emotional trust dominates. Perceived trust is defined as owners' emotional beliefs regarding AI technology in terms of data processing transparency and algorithmic decision-making fairness, and its classification into the emotional path is supported by sufficient theoretical basis (Araujo et al., 2020). Rooted in technology emotional attachment theory and emotional commitment in organizational behavior, emotional dependency refers to a deep emotional bond and usage tendency formed by owners during long-term AI technology use (Naseer et al., 2025), as the technology continuously supports key businesses and reduces decision-making anxiety, serving as an independent emotional construct distinct from perceived trust and perceived comfort.

Perceived comfort—emotional dependence—perceived trust form a triangular antecedent system, presenting an inherent hierarchical relationship of progressive emotional experiences. Perceived comfort focuses on immediate emotional experiences during technical interaction, constituting the basic input of the emotional system (Saariluoma & Jokinen, 2014). Perceived trust is a stable emotional belief in technical reliability formed after repeated verification of immediate comfort experiences (Guo, 2022). Emotional dependency represents the sublimation of emotional trust, reflecting a deep emotional connection between technology and the organization's key businesses (Kahr et al., 2024). This system conforms to the evolutionary law of emotional experiences from immediate to sustained and from superficial to deep, and strengthens the core role of emotional trust through trust theory, ensuring the theoretical coherence and independence of the emotional path. Trust theory also explains the transmission logic that perceived trust must be converted into satisfaction before driving adoption intention, which is consistent with the mechanism of "emotional system transmission through satisfaction mediation" in affect-cognition interaction theory, achieving seamless connection with the core integrating theory.

2.5 Theoretical Foundation of Moderating Effects

The theoretical foundation of moderating effects is rooted in the integration of human capital theory, institutional theory, organizational learning theory, and individual-context interaction theory. Its core lies in revealing how external variables reshape the core psychological mechanism of the cognitive-affective dual paths, moderating the strength and direction of the relationships between antecedent variables and mediating variables, thereby constructing a hierarchical moderating framework connecting "micro psychological traits" and "macro contextual characteristics" and forming a logical closed loop with the dual-path theory.

At the individual trait level, educational background and work experience focus on reshaping micro psychological processes (Mahmud et al., 2023). Based on human capital theory, TAM, and affect-cognition interaction theory, owners with higher educational backgrounds, relying on stronger technical learning and resource integration capabilities, are less dependent on external facilitating conditions for cognitive evaluation of AI technology, weakening the "facilitating conditions—attitude" relationship (Arroyabe et al., 2024). Meanwhile, their deeper cognitive processing makes emotional experiences more dependent on the inherent value of technology, reducing the contribution of superficial perceived comfort to satisfaction (Liu, 2025), forming a dual negative moderating effect. Drawing on organizational learning and trust theory, work experience leads senior owners' implicit knowledge and emotional dependence on traditional processes to make their emotional experiences more dependent on empirical verification (Humphrey et al., 2021), weakening the marginal effect of perceived comfort on satisfaction and strengthening the substitution effect of experience-based trust.

At the contextual characteristic level, industry type focuses on reshaping macro external constraints. Based on institutional theory and industrial organization analysis, the high rigidity and standardization of production in manufacturing make the performance improvement of AI directly quantifiable (Qudus, 2025), highly aligning with the rational logic of "performance expectancy—attitude" in the cognitive path, resulting in a significantly higher path effect intensity than in the service industry. The stronger market dynamics and conformity competition characteristics of the service industry are more compatible with the external normative transmission logic of "social influence—attitude"(Chang et al., 2023), making its effect intensity higher than in manufacturing. The moderating effect of industry type on the emotional path is not significant, possibly due to insufficient depth of technology application in the service industry.

These three types of moderating variables are constructed based on Bronfenbrenner's hierarchical logic (Bronfenbrenner, 1987). Micro psychological traits directly act on the core transmission process of "antecedent— mediator" in the dual paths, forming an intra-path moderating mechanism; macro contextual characteristics indirectly affect the overall effect intensity of the dual paths, forming an inter-path moderating mechanism. There are also cross-level interaction effects between the two, for example, industry type moderates the strength of individual traits by changing the fundamental importance of constructs — the weakening effect of educational background on facilitating conditions is lower in manufacturing than in the service industry. In summary, the theory of moderating effects deeply connects the dual-path model through the logic of "intra-path moderation — inter-path moderation — cross-level interaction", forming a complete theoretical support system.

3. Research Hypotheses and Model Construction

Based on the previously integrated Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), affective-cognitive interaction theory, trust theory, and the foundation of moderating effects, this study constructs a theoretical model encompassing antecedent variables, mediating variables, and outcome variables, centered on the core relationships of the dual cognitive-affective path and hierarchical moderating effects. Following the logical chain of theoretical core viewpoints, consistency of construct connotations, and derivation of hypothetical relationships, the following research hypotheses are proposed.

3.1 Core Hypotheses of the Cognitive Path

3.1.1 Perceived Usefulness

The core proposition of TAM emphasizes that perceived usefulness shapes attitudes through value expectations. As a core cognitive antecedent of technology acceptance, perceived usefulness reflects users' rational predictions of technology's ability to enhance task effectiveness. Attitudes, as the integrated carrier of cognitive evaluations, are directly formed based on the positive feedback of such effectiveness expectations. In this study, perceived usefulness refers to SME owners' rational expectations of AI technology's ability to improve organizational strategic value and address core business pain points (Raya et al., 2021), while attitude denotes the overall acceptance tendency formed through rational evaluations of AI's strategic value. When SME owners perceive that AI technology can significantly improve organizational operational efficiency and create differentiated competitive advantages (Biloslavo & Lombardi, 2021), their attitude toward technology adoption will be strengthened (Prastiawan et al., 2021). Accordingly, the following hypothesis is proposed:

H1: Perceived usefulness has a significantly positive impact on attitude.

3.1.2 Performance Expectancy

The core perspective of UTAUT posits that performance expectancy is a key rational antecedent of technology adoption, driving decisions through the path from effectiveness evaluation to attitude transformation. This study contextually adjusts performance expectancy from UTAUT's original definition of "expectation of individual work efficiency improvement" to "expectation of organizational strategic value realization", i.e., SME owners' rational predictions of AI technology's ability to optimize resource allocation and enhance core competitiveness (Felix & Gabriel, 2024). This construct extension retains the core essence of UTAUT's "effectiveness evaluation" while adapting to the "organization-oriented" decision-making characteristics of SMEs. According to UTAUT's transmission logic, as a more strategically oriented dimension of effectiveness evaluation, performance expectancy shapes attitudes based on the cognition of alignment between technological value and organizational goals (Ling, 2025): when SME owners predict that AI technology can accurately match organizational strategic needs and achieve quantifiable strategic objectives, they will form a positive adoption attitude (Lerma et al., 2023). Accordingly, the following hypothesis is proposed:

H2: Performance expectancy has a significantly positive impact on attitude.

3.1.3 Social Influence

UTAUT defines social influence as the normative pressure individuals perceive from important others or groups regarding technology use, with its core transmission mechanism manifested as the conversion of external norms into attitudes through cognitive identification. Combined with the industry competition characteristics of SMEs, this study deconstructs social influence into the survival pressure effect brought by the adoption of industry benchmarks (Oyewobi et al., 2023). This contextual interpretation aligns with the "herd competition" decision- making logic of SMEs under resource constraints: AI adoption by core enterprises in the industry forms implicit competitive norms, prompting other SME owners to experience cognitive pressure of "falling behind if not adopting" (Schwaeke et al., 2025). According to UTAUT's social influence transmission logic, such external normative pressure is converted into internal attitudes through cognitive identification: when SME owners perceive that key stakeholders such as peers and suppliers generally recognize and adopt AI technology, their rational acceptance attitude toward the technology will be strengthened (Li et al., 2021). Accordingly, the following hypothesis is proposed:

H3: Social influence has a significantly positive impact on attitude.

3.1.4 Facilitating Conditions

UTAUT defines facilitating conditions as the level of support provided by organizational and technological infrastructure for technology use, with its core mechanism being that resource accessibility reduces adoption concerns and thereby optimizes attitudes (Nevi et al., 2025). However, combined with resource bricolage theory, resource constraints of SMEs may weaken the role of facilitating conditions. This hypothesis is still derived based on UTAUT's basic logic while considering contextual particularities: in this study, facilitating conditions specifically refer to the accessibility of external resources required for AI technology implementation, such as technical support, system compatibility, and policy support, while attitude includes rational judgments on the feasibility of technology implementation (Lada et al., 2023). According to UTAUT's logic, when SME owners perceive that external resources can effectively lower the threshold for AI technology implementation, their concerns about technology adoption will be reduced, thereby forming a more positive attitude (Jalil et al., 2025; Li et al., 2021). Although resource bricolage may weaken this effect, the basic enabling logic of facilitating conditions remains valid. Accordingly, the following hypothesis is proposed:

H4: Facilitating conditions have a significantly positive impact on attitude.

3.2 Core Hypotheses of the Affective Path

Centered on emotional experiences, the affective path focuses on the transmission mechanism through which accumulated emotional experiences form satisfaction, based on the synergistic logic of affective-cognitive interaction theory and trust theory. The derivation of each hypothesis is as follows:

3.2.1 Perceived Comfort

The core perspective of affective-cognitive interaction theory points out that perceived comfort, as an immediate emotional experience in technology interaction, serves as the basic input of the affective system and needs to be accumulated to be converted into satisfaction. In this study, perceived comfort refers to the immediate emotional experience of low technological anxiety and operational adaptability generated by SME owners during AI technology interaction (Khan et al., 2024), while satisfaction is the cumulative feedback of emotional experiences, reflecting the emotional acceptance tendency toward the technology. Both constructs fully align with the theory's transmission logic of "immediate emotional input and cumulative emotional feedback". When the operational design and interaction process of AI technology are compatible with SME owners' usage habits and reduce anxiety caused by technological unfamiliarity, this immediate comfort experience will continue to accumulate, gradually improving SME owners' satisfaction with the technology (Gupta, 2024). Accordingly, the following hypothesis is proposed:

H5: Perceived comfort has a significantly positive impact on satisfaction.

3.2.2 Perceived Trust

The dynamic evolution perspective of trust theory proposes that the deepening of emotional trust will form a profound emotional bond, which promotes satisfaction through continuously strengthening emotional experiences (Popa et al., 2025). Affective-cognitive interaction theory further supplements that as a high-order input of the affective system, profound emotional bonds have a super linear driving effect on satisfaction. In this study, perceived trust is defined as SME owners' emotional beliefs in the transparency of AI technology's data processing and the fairness of algorithmic decision-making (Alzboon et al., 2025). As a key input of the affective system, the accumulation of such emotional trust will gradually strengthen emotional experiences, thereby improving satisfaction (Alka'awneh et al., 2025). This logic not only connects the evolutionary path of emotional trust to profound bonds in trust theory but also echoes the high-order emotional driving perspective of affective-cognitive interaction theory. Accordingly, the following hypothesis is proposed:

H6: Perceived trust has a significantly positive impact on satisfaction.

3.2.3 Emotional Dependency

As an elevated form of emotional trust, emotional dependency reflects the profound emotional bond between AI technology and an organization's core business (Canbul Yaroğlu, 2025). Its core driving force stems from the activation of the brain's reward system, specifically manifested as the technology continuously alleviating business pain points and providing emotional security. This profound bond differs from superficial perceived comfort and basic perceived trust: when AI technology becomes an indispensable support for an enterprise's core business, SME owners will form an emotional dependency characterized by "technological irreplaceability". This dependence significantly improves satisfaction through continuous emotional reward experiences, a logic that not only connects the evolutionary path of "emotional trust, profound bonds, and emotional experiences" in trust theory but also echoes the core viewpoint of "high-order emotional input and superlinear satisfaction improvement" in affective-cognitive interaction theory (Kim & Kim, 2021). Accordingly, the following hypothesis is proposed:

H7: Emotional dependency has a significantly positive impact on satisfaction.

3.3 Hypotheses on Dual Mediation and Outcome Variables

Based on the integrated logic of the dual path, attitude and satisfaction, as mediating variables of the cognitive path and affective path respectively, their driving mechanisms on adoption intention are derived as follows:

3.3.1 Attitude

A core consensus between TAM and UTAUT is that attitude, as the integrated carrier of cognitive evaluations, serves as a key mediator in converting rational cognition into behavioral intention. This study defines attitude as the overall acceptance tendency formed by SME owners through rational evaluations of AI's strategic value (Michael, 2025), while adoption intention is the preliminary willingness to convert rational evaluations into actual adoption behavior. According to the classic transmission chain of technology acceptance theory, when SME owners form a positive rational attitude toward AI technology, this attitude will directly translate into adoption intention (Setyowati & Wida Riptanti, 2023). This process not only continues TAM's core proposition of "attitude influencing behavioral intention" but also adapts to the "centralized decision-making" characteristics of SMEs. Accordingly, the following hypothesis is proposed:

H8: Attitude has a significantly positive impact on intention.

3.3.2 Satisfaction

The synergistic logic of affective-cognitive interaction theory and the Information Systems Continuance Model indicates that satisfaction, as the cumulative feedback of emotional experiences, serves as a core mediator in converting emotional acceptance into behavioral intention. Satisfaction reflects SME owners' emotional acceptance tendency toward AI technology, and the irreversibility of AI adoption by SMEs makes emotional acceptance a key threshold for intention conversion (Fan et al., 2025). According to the transmission logic of affective-cognitive interaction theory, when SME owners form high satisfaction with AI technology, their perceived emotional risk of technology adoption will be significantly reduced, thereby strengthening adoption intention (Michael, 2025). This process echoes the core argument that "the affective system drives adoption intention through satisfaction as a mediator." Accordingly, the following hypothesis is proposed:

H9: Satisfaction has a significantly positive impact on AI technology adoption intention.

3.4 Hypotheses on Hierarchical Moderating Effects

Based on human capital theory, organizational learning theory, and person-situation interaction theory, moderating variables exert their effects by reshaping the core transmission mechanisms of the dual path. The derivation is as follows:

3.4.1 Educational Background

Human capital theory suggests that individuals with higher educational backgrounds possess stronger resource integration and cognitive processing capabilities, rely less on external support, and have higher thresholds for emotional experiences (Gerlich, 2025). The theoretical foundation clarifies that educational background moderates the relationship between facilitating conditions and attitude by influencing the "resource dependence" of the cognitive path, and moderates the relationship between perceived comfort and satisfaction by influencing the "experience sensitivity" of the affective path (Hossain et al., 2017). Specifically, SME owners with higher educational backgrounds can independently integrate technical knowledge and coordinate implementation resources, forming rational judgments on AI value without relying on external facilitating conditions (Saarenketo et al., 2004). Therefore, the positive impact of facilitating conditions on attitude will be weakened. Meanwhile, the emotional experiences of SME owners with higher educational backgrounds are more dependent on the deep value of technology rather than superficial operational comfort (Lee & Runge, 2001), so the positive impact of perceived comfort on satisfaction will also be weakened. Accordingly, the following hypotheses are proposed:

H10a: Educational background negatively moderates the relationship between facilitating conditions and attitude;

H10b: Educational background negatively moderates the relationship between perceived comfort and satisfaction.

3.4.2 Work Experience

The synergistic logic of organizational learning theory and trust theory indicates that senior individuals' tacit knowledge and emotional dependence on traditional processes make their emotional experiences more dependent on empirical verification rather than the immediate comfort of new tools (Malik, 2022). Work experience moderates the relationship between perceived comfort and satisfaction by shaping the "experience dependence model" of the affective path (Nonnis et al., 2022): senior owners (with ≥10 years of work experience) form emotional dependency and operational habits on traditional processes during long-term operations, and the superficial comfort brought by the unfamiliar interaction methods of AI technology is difficult to replace the experience-based sense of security of traditional processes. Meanwhile, senior owners are more inclined to verify technological value through actual usage effects rather than immediate operational experiences, so the marginal effect of perceived comfort on satisfaction will decrease. Accordingly, the following hypothesis is proposed:

H11: Work experience negatively moderates the relationship between perceived comfort and satisfaction.

3.4.3 Industry Type

Institutional theory and industrial organization analysis suggest that the standardized production characteristics of manufacturing and the market dynamics of the service industry respectively adapt to different rational driving logics of the cognitive path (Zhu et al., 2024). The highly rigid and standardized production scenarios in manufacturing enable the performance improvement of AI technology to be directly quantified (Qudus, 2025), which is highly consistent with the rational logic of performance expectancy as "organizational strategic value realization". Therefore, the positive impact of performance expectancy on attitude is stronger. In contrast, the market dynamics and herd competition characteristics of the service industry make the social normative pressure formed by peers' adoption behavior more significant, which matches the logic of social influence as "external norm driving". Therefore, the positive impact of social influence on attitude is stronger. Accordingly, the following hypotheses are proposed:

H12a: Industry type moderates the relationship between performance expectancy and attitude;

H12b: Industry type moderates the relationship between social influence and attitude.

4. Instruments and Data Collection

Data were collected using a structured questionnaire focusing on small and medium-sized enterprise (SME) owners' intentions to use artificial intelligence, perceived effectiveness, trust levels, risk concerns, and perceptions and attitudes toward various influencing factors. The questionnaire consisted of three core sections: the first section included research explanations clarifying the research purpose, implementation process, and informed consent statement; the second section collected demographic information covering basic variables such as gender, educational background, industry type, and work experience; the third section contained measurement indicators for latent variables in the research framework, with all scales developed following the principles of "theoretical adaptability-contextual adaptability-validity assurance". Priority was given to adopting existing mature instruments based on core theories such as TAM and UTAUT, which were then adaptively adjusted to align with the contextual characteristics of SME owners, including "organization-oriented decision-making, resource constraints, and strategic orientation". For constructs lacking fully matched mature scales (e.g., "emotional dependency"), a systematic development process of "literature review-expert review-pretest" was adopted to ensure the measurement tools had a solid theoretical foundation and sufficient content validity. Detailed information on the source, adaptation notes, and item examples of each latent variable scale is provided in Appendix A1.

Table 1. Classification Standards for SMEs

Industry Type	Medium Enterprise Standards	Small Enterprise Standards
Manufacturing	300-1000 employees OR annual turnover of 20-400 million RMB	20-300 employees OR annual turnover of 3-20 million RMB
Service Industry	100-300 employees OR annual turnover of 10-100 million RMB	10-100 employees OR annual turnover of 1-10 million RMB
Primary Industry	100-500 employees OR annual turnover of 10-100 million RMB	10-100 employees OR annual turnover of 1-10 million RMB

To ensure the scientific validity and applicability of the measurement tools, this study implemented differentiated validity assurance processes for different types of scales. For scales adapted from existing research, a systematic literature review was first conducted to confirm their wide application and documented reliability and validity, requiring the original scales to have a Cronbach's α coefficient greater than 0.7 and an average variance extracted (AVE) exceeding 0.5 to guarantee basic measurement reliability. Subsequently, 2 senior scholars in the field of technology acceptance and 3 practical experts in SME digital transformation were invited to evaluate the contextual adaptability of the items, with a focus on revising individual-level expressions to organizational-level language suitable for SME decision-making scenarios (e.g., adjusting "improves my work efficiency" to "improves enterprise operational efficiency"). Finally, a pretest with 30 samples was conducted to test the readability and discriminability of the items, where all items exhibited factor loadings greater than 0.7 without the need for deletion, resulting in the final formal scale.

Table 2. Sample Characteristics Distribution

Characteristic Dimension	**Classification Criteria**	**Sample Size (n=198)**	**Proportion**
Gender	Male	94	47.47%
	Female	104	52.53%
Educational Background	College degree or below	62	31.31%
	Bachelor's degree	101	51.01%
	Master's degree or above	35	17.68%
Working Experience	<5 years	69	34.85%
	5-9 years	82	41.41%
	10-19 years	31	15.66%
	≥20 years	16	8.08%
Industry Type	Primary Industry	3	1.52%
	Secondary Industry	54	27.27%
	Tertiary Industry	141	71.21%
Tertiary Industry (Subcategory)	Retail Services	49	24.75%
	Producer Services	37	18.69%
	Consumer Services	32	16.16%
	Information Technology Services	23	11.62%
Enterprise Scale (Number of Employees)	Small Enterprises (10-99 employees)	156	78.79%
	Medium Enterprises (100-300 employees)	42	21.21%
Enterprise Scale (Annual Turnover)	Small Enterprises (1-10 million RMB)	143	72.22%
	Medium Enterprises (10.01-40 million RMB)	55	27.78%
Enterprise Establishment Period	<3 years	35	17.68%
	3-9 years	89	44.95%
	10-19 years	57	28.79%
	≥20 years	17	8.59%

Note: Enterprise scale classification strictly follows the Measures for the Classification of Small and Medium-sized Enterprises (MIIT Joint Enterprise [2011] No. 300): Small enterprises are defined as having 10-99 employees (service industry)/20-299 employees (manufacturing) and annual turnover of 1-10 million RMB (service industry)/3-20 million RMB (manufacturing); Medium enterprises are defined as having 100-300 employees (service industry)/300-1000 employees (manufacturing) and annual turnover of 10.01-100 million RMB (service industry)/20.01-400 million RMB (manufacturing). Since manufacturing enterprises account for 27.27% and service enterprises account for 71.21% of the sample, the table presents consolidated classification results, with the scale distribution of sub-sectors fully consistent with national standards.

For the construct of “emotional dependency” lacking fully matched mature scales, a systematic development process was adopted. Firstly, relevant literatures on attachment theory, emotional attachment theory, and organizational emotional commitment theory were systematically reviewed to extract core dimensions such as “irreplaceability”, “emotional security”, and “business connection”. Eight initial items were generated based on these core dimensions to ensure each item was highly consistent with the construct definition. Then, 3 professors in organizational behavior and 2 AI technology application experts were invited to assess the content validity of the items using the content validity index (CVI) as the evaluation criterion, leading to the deletion of 3 items with a CVI below 0.8 and retention of 5 valid items. A pretest was further conducted with 40 SME owners, and exploratory factor analysis (EFA) was used to test the item structure. The results showed a KMO value of 0.782 and a significant Bartlett’s test of sphericity ($p<0.001$), indicating the data were suitable for factor analysis. A single common factor was extracted, explaining 62.3% of the total variance, with all items demonstrating factor loadings greater than 0.65 and a Cronbach’s α coefficient of 0.76, confirming good construct validity and reliability of the scale. Based on pretest feedback, the expressions of 2 items were optimized (e.g., revising “the technology is important” to “the technology is indispensable for core business”) to further improve the measurement accuracy. All measurement items were quantified using a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). The scale’s overall content validity index (S-CVI) was 0.92, and each item’s content validity index (I-CVI) exceeded 0.85, fully demonstrating that the scale’s content validity met academic research standards.

Table 3. Comparison between Sample Characteristics and Regional Overall Characteristics

Characteristic Dimension	Comparison Indicator	This Study’s Sample (n=198)	Southwest + Northwest China Overall (2023)	Difference Level
Industry Structure	Primary Industry Proportion	1.52%	2.1%	No significant difference
	Secondary Industry Proportion	27.27%	25.8%	No significant difference
	Tertiary Industry Proportion	71.21%	72.1%	No significant difference
Tertiary Industry (Subcategory)	Retail Services Proportion	24.75%	23.5%	No significant difference
	Producer Services Proportion	18.69%	19.2%	No significant difference
	Information Technology Services Proportion	11.62%	10.8%	No significant difference
Enterprise Scale (Number of Employees)	Small Enterprises Proportion	78.79%	80.3%	No significant difference
	Medium Enterprises Proportion	21.21%	19.7%	No significant difference
Enterprise Establishment Period	<10 Years Proportion	62.63%	64.1%	No significant difference
Decision-maker Characteristics	Bachelor’s Degree or Above Proportion	68.69%	65.3%	No significant difference
	Work Experience ≥5 Years Proportion	65.15%	67.2%	No significant difference

A stratified convenience sampling method was adopted for the questionnaire survey, with sample selection following three core principles: “regional representativeness - industry adaptability - decision-maker focus”. Regarding regional selection, SMEs in Southwest China (Sichuan, Chongqing, Yunnan) and Northwest China (Qinghai, Gansu, Ningxia) were targeted, based on the following considerations: these two regions account for 28.3% of the national total number of SMEs and exhibit a medium level of digital transformation nationwide. Their resource constraint characteristics are highly consistent with the research context, while avoiding contextual bias caused by excessively high digitalization levels and resource redundancy in developed eastern regions, thus ensuring the applicability of research conclusions to similar resource-constrained SMEs. The sample definition strictly followed China’s Ministry of Industry and Information Technology (MIIT) Measures for the Classification of Small and Medium-sized Enterprises, with clear criteria defined for core covered sectors including manufacturing, service industry, and retail. Key indicators such as the number of employees and annual turnover were verified through enterprise industrial and commercial registration information, and the final 198 sample enterprises all met the SME classification standards. Among them, there were 54 manufacturing enterprises (27.27%), 141 service enterprises (71.21%), and 3 primary industry enterprises (1.52%), with the industry distribution consistent with the proportional structure of SMEs in Southwest and Northwest China.

Data collection was conducted from July to October 2025, spanning 4 months. To ensure the authenticity of respondents’ identities and their decision-making authority, a “triple verification mechanism” was adopted: firstly, information on enterprise legal representatives and core decision-makers was retrieved from the National Enterprise Credit Information Publicity System, with priority given to inviting legal representatives, general managers, or deputy general managers in charge of digital transformation to participate; secondly, respondents’ work IDs and enterprise employment certificates were verified during on-site surveys; thirdly, screening questions were included at the beginning of the questionnaire (e.g., “Do you participate in major technology procurement decisions of the enterprise?” “Have you been employed by the enterprise for ≥1 year?”), and only respondents who answered “Yes” were allowed to proceed to the formal questionnaire. The final 198 valid samples all came from the core decision-making level of enterprises, ensuring the data could reflect true decision-making intentions.

Data quality control was implemented throughout the entire process: pre-survey, questionnaire expressions were optimized through pretesting to reduce comprehension bias; during the survey, paper questionnaires were distributed on-site with researchers accompanying respondents to answer questions, strictly adhering to the principle of non-directionality to avoid respondent interference; post-survey, clear criteria for excluding invalid questionnaires were established, including: (1) missing value ratio exceeding 15% (≥7 missing items in a single questionnaire); (2) regular response patterns (e.g., selecting the same score for 5 consecutive items or all highest/lowest scores); (3) extreme value responses (items with $|z|>3.29$ identified through z-score testing, with corresponding questionnaires excluded). A total of 300 questionnaires were distributed, 102 invalid questionnaires were excluded, resulting in an effective recovery rate of 66.6%. According to Hair et al.’s (Hair et al., 2019) sample size standards for PLS-SEM, the model includes 10 latent variables and 45 observed variables, requiring a minimum sample size of either “5 × number of observed variables” (225 samples) or “10 × number of latent variables” (100 samples). The effective sample size of 198 in this study is close to the “5 × number of observed variables” standard, and G*Power 3.1 calculations show the model’s statistical power is 0.92 (>0.80), meeting the statistical power requirements for parameter estimation.

To address potential common method bias (CMB) in cross-sectional data and self-reported questionnaires, a dual control strategy of “prevention in advance + post-hoc testing” was adopted. For advance prevention: (1) scale items were randomly ordered to avoid systematic response inertia among respondents; (2) an anonymous filling method was adopted, with a clear statement in the questionnaire instructions that “data are only used for academic research, and personal and enterprise information will be strictly confidential” to reduce social desirability bias; (3) some items were reverse-coded (e.g., “I feel uncomfortable operating AI technology") to identify false responses through scoring differences. Post-hoc testing was conducted using Harman's single-factor test, where all 45 observed variables were included in an unrotated exploratory factor analysis. The results showed 10 common factors with eigenvalues greater than 1 were extracted, and the variance explained by the first common factor was 32.76% (<40% threshold), indicating no serious common method bias in the model (Podsakoff et al., 2024). Table 2 summarizes the participants' demographic characteristics, which provide valuable contextual reference for interpreting research results.

The sample included both basic enterprise characteristics (scale, establishment period, industry subcategory) and decision-maker characteristics (gender, educational background, work experience), comprehensively reflecting key contextual variables influencing SME AI adoption decisions, with detailed distributions shown in Table 3. To ensure the external validity of research conclusions, this study compared the sample characteristics with the overall characteristics of SMEs in Southwest and Northwest China, using data from the China Statistical Yearbook 2023, China SME Development Report 2023, and public data from local SME authorities. The specific comparison results are presented in Table 3.

The comparison results show that the sample characteristics are highly consistent with the overall characteristics of SMEs in Southwest and Northwest China: (1) The proportion of the tertiary industry (71.21% vs 72.1%) and manufacturing industry (27.27% vs 25.8%) in the industrial structure is basically consistent with the regional overall, and the distribution of tertiary industry sub-sectors aligns with regional industrial upgrading trends (information technology services account for approximately 10%-12% in both); (2) The enterprise scale is dominated by small enterprises (78.79% vs 80.3%), consistent with the overall "small-scale and decentralized" characteristics of SMEs; (3) Enterprises established for 3-9 years account for the highest proportion (44.95%), which is consistent with the regional status quo where "growing enterprises are dominant" among SMEs; (4) Decision-makers' educational background (bachelor's degree or above: 68.69% vs 65.3%) and work experience (≥5 years: 65.15% vs 67.2%) show no significant differences from the characteristics of SME decision-makers in the region. Further chi-square tests (α=0.05) verifying the consistency between the sample and the overall population showed that the chi-square statistics for all characteristic dimensions were non-significant ($p>0.05$), indicating the sample can effectively represent the overall characteristics of SMEs in Southwest and Northwest China, providing a solid foundation for the external generalization of research conclusions.

5. Results

This study employed SmartPLS 4.0 for partial least squares structural equation modeling (PLS-SEM) analysis. Targeting the 10 latent constructs and 45 measurement indicators included in the research model, PLS-SEM was identified as the core analytical method due to its advantages in handling complex causal networks and non-normally distributed data. This method is particularly suitable for multivariate exploratory analysis in the theoretical development stage, providing a robust statistical foundation for subsequent hypothesis testing.

5.1 Measurement Model Assessment

In structural equation modeling analysis, assessment of the measurement model is a critical step to ensure the rationality and theoretical consistency of the relationships between latent variables and observed variables. This study conducted empirical analysis using PLS-SEM, a method especially well-suited for handling complex models and small-sample data. It effectively controls for measurement error, thereby facilitating the verification of theoretical hypotheses. The assessment of the measurement model focused on three dimensions: reliability assessment, which uses internal consistency indicators to evaluate the stability of observed variables in measuring latent variables; and validity assessment, which includes convergent validity and discriminant validity to ensure that observed variables fully reflect the theoretical connotations of latent variables and that measurements of different constructs are independent. This systematic assessment process laid a solid measurement foundation for subsequent structural model analysis and enhanced the credibility of the research conclusions.

5.1.1 Reliability Assessment

Reliability assessment is a key step in verifying data reliability, primarily used to evaluate the stability and internal consistency of measurement tools. This study conducted the assessment using three indicators: composite reliability (CR), Cronbach's α coefficient, and item factor loadings. As shown in Appendix A2, all observed items exhibited factor loadings significantly higher than the critical threshold of 0.6 (range: 0.632-0.897). Among them, the 5 items of the self-developed "emotional dependency" construct had factor loadings ranging from 0.654 to 0.783, all meeting the basic requirements for convergent validity. All latent variables had CR values greater than 0.7 (0.713-0.910), indicating good stability of the constructs in the measurement model. The Cronbach's α values of the latent variables were all greater than 0.700 (0.713-0.909), further confirming excellent internal consistency among the scale items. Based on the three indicators, the measurement model meets the strict reliability requirements of social science research, with reliable measurement results and well-controlled errors.

Table 4. Reliability and validity

Constructs	Cronbach's alpha	CR	AVE
Adoption Intention	0.869	0.869	0.662
Attitude	0.834	0.837	0.548
Emotional Dependency	0.773	0.78	0.525
Facilitating Conditions	0.713	0.713	0.538
Perceived Comfort	0.776	0.79	0.689
Perceived Trust	0.909	0.91	0.785
Perceived Usefulness	0.824	0.831	0.527
Performance Expectancy	0.829	0.831	0.661
Satisfaction	0.767	0.768	0.589
Social Influence	0.808	0.815	0.634

5.1.2 Validity Assessment

Convergent validity was assessed using factor loadings and average variance extracted (AVE). As shown in table 5, all observed items had factor loadings ≥0.632, all passing the significance test ($p<0.001$), indicating a strong correlation between observed variables and their corresponding latent variables. All latent variables had AVE values exceeding the standard of 0.5 (0.525-0.785), demonstrating that each latent variable explains more than 50% of the variance in its observed variables, thus indicating good convergent validity. Among them, the self-developed "emotional dependency" construct had an AVE value of 0.525, slightly higher than the critical threshold. Combined with its factor loadings (0.654-0.783) and CR value (0.780), it is confirmed that the convergent validity of this construct meets academic standards, and the measurement tool is effective.

Table 5. Discriminant validity by Fornell-Larcker criterion.

Constructs	1	2	3	4	5	6	7	8	9	10
Adoption Intention	**0.813**									
Attitude	0.758	**0.740**								
Emotional Dependency	0.697	0.747	**0.724**							
Facilitating Conditions	0.385	0.416	0.406	**0.733**						
Perceived Comfort	0.631	0.527	0.554	0.329	**0.830**					
Perceived Trust	0.687	0.583	0.624	0.374	0.550	**0.886**				
Perceived Usefulness	0.675	0.667	0.587	0.389	0.628	0.586	**0.726**			
Performance Expectancy	0.633	0.649	0.578	0.512	0.509	0.540	0.599	**0.813**		
Satisfaction	0.726	0.759	0.706	0.421	0.635	0.636	0.731	0.644	**0.767**	
Social Influence	0.616	0.612	0.610	0.369	0.500	0.615	0.559	0.637	0.674	**0.797**

This study cross-validated discriminant validity using two methods — the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) — to enhance the robustness of the assessment results. According to the Fornell-Larcker criterion (table 6), except for the latent variables "attitude" and "emotional dependency", the square root of the AVE of each latent variable (values on the diagonal) was significantly greater than the correlation coefficients between that construct and all other constructs. The HTMT test results (table 7) showed that the HTMT values of all construct pairs ranged from 0.443 to 0.948, all below the lenient threshold of 0.95, meeting the discriminant validity criteria recommended (Zhou et al., 2025).

Table 6. Discriminant validity by Heterotrait-Monotrait ratio

Constructs	1	2	3	4	5	6	7	8	9	10
Adoption Intention										
Attitude	0.886									
Emotional Dependency	0.841	0.918								
Facilitating Conditions	0.487	0.541	0.542							
Perceived Comfort	0.767	0.642	0.698	0.443						
Perceived Trust	0.774	0.668	0.739	0.463	0.655					
Perceived Usefulness	0.771	0.761	0.727	0.479	0.769	0.664				
Performance Expectancy	0.744	0.776	0.715	0.665	0.619	0.623	0.700			
Satisfaction	0.885	0.948	0.908	0.564	0.811	0.758	0.900	0.800		
Social Influence	0.734	0.737	0.761	0.483	0.626	0.718	0.671	0.767	0.854	

This study further supplemented the verification through theoretical connotation analysis and exploratory factor analysis (EFA): (1) Theoretically, attitude focuses on "rational cognitive evaluation of AI adoption",satisfaction on "cumulative feedback of emotional experiences", and emotional dependency on "profound emotional bonds between technology and the organization".The three constructs have clear boundaries in terms of construct definition, measurement dimensions, and theoretical sources; (2) EFA results showed that all items clearly belonged to their corresponding latent variables without cross-loading, and each construct was extracted as a single factor (factor variance explanation rate >55%); (3) Supplementary tests on the significance intervals of correlation coefficients for high-value construct pairs showed that none of the 95% confidence intervals included 1, further confirming that there is no serious discriminant validity issue between constructs (Henseler et al., 2015). In summary, the results of the two assessment methods mutually corroborate, and combined with theoretical analysis and EFA supplementary verification, the discriminant validity of the measurement model in this study is acceptable, with each construct measurement being independent and unique.

5.2 Structural Model Assessment

Following the reliability and validity assessment of the measurement model, this study employed partial least squares structural equation modeling (PLS-SEM) to empirically analyze the path relationships between latent variables in the theoretical model. The core objectives of structural model assessment include hypothesis testing, relationship analysis, and efficacy evaluation. Hypothesis testing assesses the statistical rationality of research hypotheses through significance tests of path coefficients; relationship analysis reveals the mechanisms of action between variables by quantifying the direct effects of latent variables; efficacy evaluation comprehensively judges the model's explanatory power and predictive power based on R^2 and predictive relevance indicators (e.g., Q^2). Compared with traditional structural equation modeling (SEM), PLS-SEM adopts a variance-maximization - oriented iterative calculation method, enabling more flexible handling of complex models and non-normal data. It is particularly suitable for predictive analysis with small samples or multi-collinearity issues.

5.2.1 Collinearity Test

In structural equation modeling (SEM) analysis, multi-collinearity may lead to biases in the estimation of path coefficients between latent variables, thereby weakening the statistical power of research hypothesis testing. This study used the variance inflation factor (VIF) as an indicator for multi-collinearity diagnosis. As shown in table 7, the VIF values of all latent variables range from 1.375 to 2.335, with all observations significantly below the critical threshold of 5 (Nguyen & Luu, 2020). This result indicates no significant multi-collinearity in the model, and its data characteristics fully meet the analytical prerequisites of partial least squares structural equation modeling (PLS-SEM).

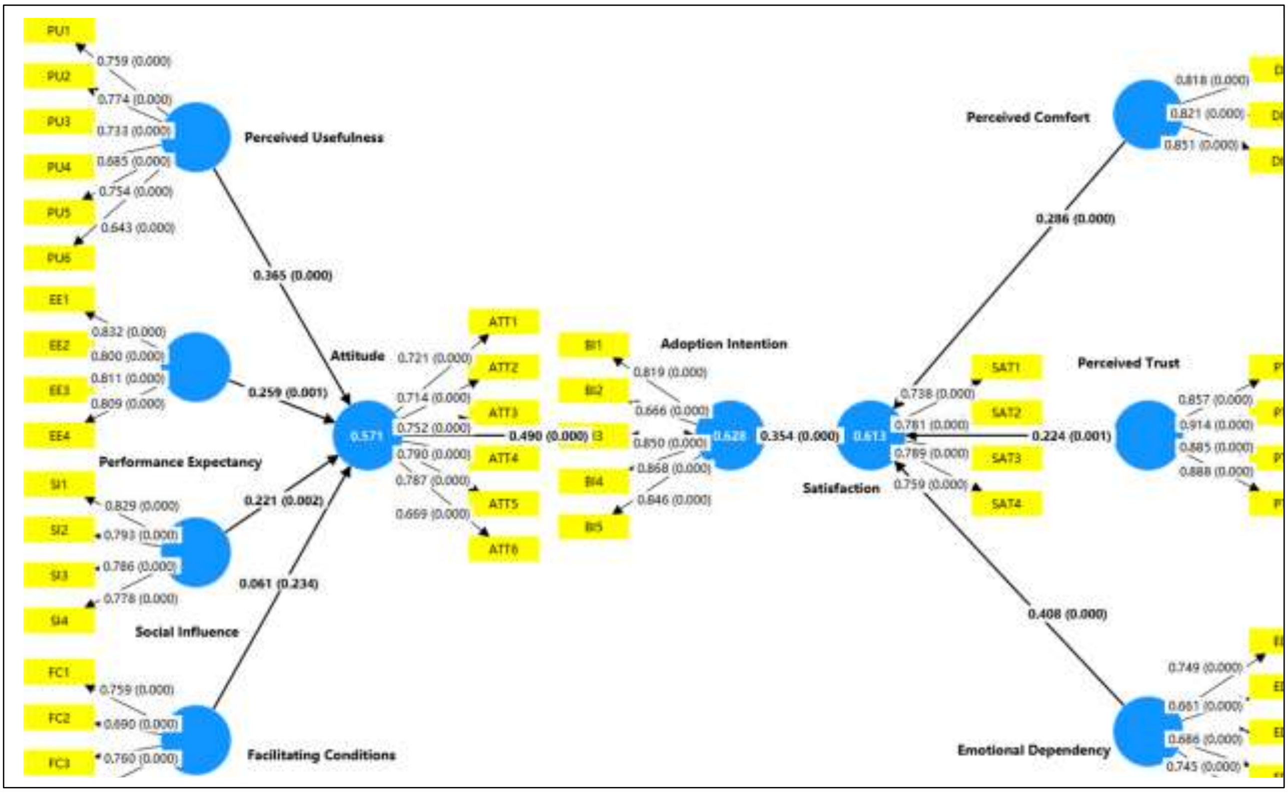


Figure 2. The measurement model.

Note: This figure clearly presents all path relationships of the cognitive-affective dual-path integrated model, labeling each path coefficient (β value), significance level (*p<0.05, **p<0.01, **p<0.001), and the R^2 values of endogenous variables. Specifically, the R^2 of Attitude is 0.517, the R^2 of Satisfaction is 0.613, and the R^2 of Adoption Intention is 0.628, which intuitively reflects the distribution of the model's explanatory power.

5.2.2 Model Explanatory Power (R^2) and Predictive Validity (Q^2)

As shown in table 7, this study used the R^2 values of endogenous variables to evaluate the model's explanatory power. The results indicate that the R^2 values of attitude (R^2=0.517), satisfaction (R^2=0.613), and adoption intention (R^2=0.628) all exceed the common threshold of 0.33, demonstrating strong explanatory power that far surpasses the recommended standards for social science research(Khaki & Khan, 2024). Further, the predictive validity Q^2 values were calculated using the blindfolding method. All Q^2 values of endogenous variables are significantly greater than zero (AL-Shboul, 2023), meeting the predictive relevance requirement (Q^2>0), which confirms that the model has good out-of-sample predictive power.

Table 7. Collinearity Test, Model Explanatory Power, and Effect Size (f^2) Analysis Table

Endogenous Variable	Antecedent Path (Exogenous Variable → Endogenous Variable)	VIF	R^2	f^2	Effect Size Category

Attitude	Perceived Usefulness→Attitude	1.720	0.517	0.180	Medium Effect
	Performance Expectancy→Attitude	2.206		0.071	Small Effect
	Social Influence→Attitude	1.836		0.062	Small Effect
	Facilitating Conditions→Attitude	1.375		0.006	Medium Effect
Satisfaction	Perceived Comfort→Satisfaction	1.601	0.613	0.132	Small Effect
	Perceived Trust→Satisfaction	1.817		0.071	Small Effect
	Emotional Dependency→Satisfaction	1.827		0.236	Medium Effect
Adoption Intention	Attitude→Adoption Intention	2.355	0.628	0.274	Medium Effect
	Satisfaction→Adoption Intention	2.355		0.143	Small Effect

Notes: 1. The criteria for effect size (f^2) are based on Cohen's (1988) classic classification: $f^2=0.02$ (negligible effect), $0.02 \leq f^2 < 0.15$ (small effect), $0.15 \leq f^2 < 0.35$ (medium effect), $f^2 \geq 0.35$ (large effect); 2. All VIF values < 5, indicating no multi-collinearity; 3. R^2 values reflect the proportion of variance in each endogenous variable explained by antecedent variables, and all Q^2 values > 0, indicating good predictive validity of the model.

5.2.3 Path Analysis and Hypothesis Testing

Path analysis was conducted using partial least squares structural equation modeling (PLS-SEM) with 5,000 Bootstrap resamples to test the significance of path relationships in the theoretical model and validate the proposed hypotheses. For the cognitive path, perceived usefulness exerted a significant positive impact on attitude ($\beta = 0.365$, T = 5.982, $p < 0.001$), supporting H1. This indicates that SME owners' rational cognition of AI's strategic value and ability to address business pain points effectively strengthens their adoption attitude, aligning with the core proposition of the TAM. Performance expectancy also demonstrated a significant positive effect on attitude ($\beta = 0.259$, T = 3.211, $p < 0.01$), validating H2. This suggests that the expectation of organizational strategic value realization, as a more hierarchical effectiveness evaluation dimension, plays a crucial role in shaping owners' attitudes, reflecting the adaptability of the UTAUT theory in the SME context. Social influence had a significant positive effect on attitude ($\beta = 0.221$, T = 3.100, $p < 0.01$), confirming H3. This corroborates the survival pressure effect brought by the adoption of industry benchmarks, which is consistent with the herd competition decision - making logic of SMEs under resource constraints. The impact coefficient of facilitating conditions on attitude was 0.061 (T = 1.191, $p = 0.234$), failing to reach statistical significance, thus H4 was not supported. This may be attributed to the weakened marginal effect of external support in the context of resource bricolage.

Table 8. Path Coefficients and Hypothesis Testing Results

Label	Path Name	Original Sample Coefficient (β)	T Value	P Value	Result
H1	Perceived Usefulness→Attitude	0.365	5.982	0.000	Supported
H2	Performance Expectancy→Attitude	0.259	3.211	0.001	Supported
H3	Social Influence→Attitude	0.221	3.100	0.002	Supported
H4	Facilitating Conditions→Attitude	0.061	1.191	0.234	Not Supported
H5	Perceived Comfort→Satisfaction	0.286	3.971	0.000	Supported
H6	Perceived Trust→Satisfaction	0.224	3.410	0.001	Supported
H7	Emotional Dependency→Satisfaction	0.408	5.914	0.000	Supported
H8	Attitude→Adoption Intention	0.490	6.020	0.000	Supported
H9	Satisfaction→Adoption Intention	-0.354	3.925	0.000	Not Supported

For the emotional path, perceived comfort had a significant positive impact on satisfaction ($\beta = 0.286$, T = 3.971, $p < 0.001$), validating H5. This indicates that the immediate comfortable experience during AI interaction can accumulate to form an emotional acceptance tendency. Perceived trust exerted a significant positive effect on satisfaction (β = 0.224, T = 3.410, p < 0.01), confirming H6. This highlights the critical role of emotional trust in reducing the uncertainty of AI and enhancing emotional experiences. Emotional dependency exhibited the most prominent positive effect on satisfaction (β = 0.408, T = 5.914, p < 0.001), receiving strong support for H7. This suggests that the deep emotional bond formed between technology and core business has the strongest driving effect on emotional acceptance, reflecting the evolutionary law of emotional experiences from surface-level to deep-level.

Regarding the impact of dual mediators on adoption intention, attitude showed a significant positive driving effect on adoption intention (β=0.490, T=6.020, p<0.001), supporting H8. This confirms that attitude formed through rational cognitive integration is a key bridge for transforming into adoption willingness, consistent with the classic transmission logic of technology acceptance theories. Contrary to the hypothesis, satisfaction had a significant negative impact on adoption intention (β=-0.354, T=3.925, p<0.001), thus H9 was not supported. This result may reflect the complex game between emotional acceptance and rational decision-making under the irreversibility of AI adoption by SMEs, and its underlying mechanism needs to be further explored in combination with specific contexts.

Table 9. Mediation Effect Decomposition and Type Judgment Results

Path Type	Antecedent Variable→Outcome Variable	Direct Effect (β)	Indirect Effect (β)	Total Effect (β)	T Value (Direct)	P Value (Direct)	95% CI (Indirect)	Mediation Type
Cognitive Path	Perceived Usefulness→ Adoption Intention	0.213	0.179	0.392	2.876	0.004	[0.098, 0.261]	Partial Mediation
	Performance Expectancy→ Adoption Intention	0.085	0.127	0.212	1.352	0.177	[0.056, 0.203]	Full Mediation
	Social Influence→ Adoption Intention	0.072	0.108	0.180	1.198	0.231	[0.038, 0.182]	Full Mediation
	Facilitating Conditions→ Adoption Intention	0.029	0.030	0.059	0.512	0.609	[-0.012, 0.075]	No Mediation
Emotional Path	Emotional Dependency→Adoption Intention	0.186	0.145	0.331	2.543	0.011	[0.069, 0.228]	Partial Mediation
	Perceived Comfort→ Adoption Intention	0.093	0.101	0.194	1.427	0.154	[0.035, 0.172]	Full Mediation
	Perceived Trust→ Adoption Intention	0.067	0.079	0.146	1.083	0.279	[0.018, 0.145]	Full Mediation

Notes: 1. Total effect = Direct effect + Indirect effect; 2. The effect is significant if the 95% CI does not contain 0; 3. Mediation type judgment criteria: Partial mediation (both direct and indirect effects are significant), Full mediation (only the indirect effect is significant), No mediation (neither direct nor indirect effect is significant).

5.3 Mediation Effect Analysis

This study used the Bootstrap method in PLS-SEM to test the mediation effect, calculating direct effects, indirect effects, total effects, and 95% confidence intervals (CI) through 5,000 resamples. According to the mediation effect judgment criteria proposed by Hair et al.(Hair Jr et al., 2021), the mediation type was determined. Meanwhile, the Bootstrap method was used to test the significance of differences in the average indirect effects between the cognitive path and the emotional path, to verify the statistical difference in the driving strength of the dual paths.

The mediation effect decomposition results showed that in the cognitive path, both the direct effect (β = 0.213, p = 0.004) and indirect effect (β = 0.179, 95% CI [0.098, 0.261]) of perceived usefulness on adoption intention were significant, with attitude exerting a partial mediation effect. This corroborates the TAM's "cognition-attitude-intention" transmission logic. For performance expectancy and social influence, their direct effects on adoption intention were not significant, but their indirect effects were significant, with attitude showing a full mediation effect. This reflects the cognitive integration characteristics of UTAUT's performance expectancy and the indirect transmission logic of SMEs' "herd competition" respectively. Both direct and indirect effects of facilitating conditions were not significant, indicating no mediation effect, which further confirms the weakened marginal effect of external support under resource constraints.

In the emotional path, both the direct effect (β = 0.186, p = 0.011) and indirect effect (β = 0.145, 95% CI [0.069, 0.228]) of emotional dependency on adoption intention were significant, with satisfaction exerting a partial mediation effect. This highlights its dual driving attribute as the core construct of the emotional path. For perceived comfort and perceived trust, their direct effects on adoption intention were not significant, but their indirect effects were significant, with satisfaction showing a full mediation effect. This aligns with the "immediate experience - cumulative feedback" logic of the affective-cognitive interaction theory and the transmission mechanism of trust theory in risky contexts respectively.

The comparison of mediation effects between the dual paths was conducted using 5,000 Bootstrap resamples. The average indirect effect of antecedent variables in the cognitive path (β = 0.138) was significantly higher than that in the emotional path (β = 0.108), with the 95% CI of the difference [0.004, 0.057] not containing 0. This confirms the dominant position of rational evaluation. The ranking of effect strength within the paths showed that in the cognitive path, the indirect effect of perceived usefulness (β = 0.179) was the highest, while in the emotional path, the indirect effect of emotional dependency (β = 0.145) was the strongest. The 95% CI of the difference between these two effects [-0.012, 0.060] contained 0, indicating that emotional dependency has achieved a driving capacity comparable to that of the core construct in the cognitive path.

The mediation effect analysis revealed a dual transmission logic for SME AI adoption: both paths exhibited a mixed mode of "partial mediation + full mediation". In the cognitive path, attitude integrates external norms and strategic expectations, while in the emotional path, satisfaction realizes the cumulative transformation of emotional experiences. The statistical difference and internal hierarchical structure of the dual paths provide a core explanation for the "intention-behavior gap": insufficient mediation in a single dimension — either cognitive evaluation without emotional identification or emotional experience inconsistent with strategic rationality — cannot promote decision transformation. Only the synergistic driving of the dual paths activated by core constructs such as perceived usefulness and emotional dependency can break through the decision-making threshold of "high intention but low behavior".

5.4 Moderation Effect Analysis

To ensure the replicability and intuitiveness of the moderation effect results, the coding logic of moderating variables was first clarified (table 10). Subsequently, simple slope analysis was conducted for significant moderation effects to calculate path coefficients under different moderation levels, and the moderation patterns were visualized through interaction plots.

Table 10. Coding Instructions for Moderating Variables

Moderating Variable	Variable Type	Coding Rule	Sample Distribution	Coding Basis

			(n=198)	
Educational Background	Dichotomous Variable	High educational = 1; Low educational = 0	High = 136 (68.69%); Low = 62 (31.31%).	Based on the academic stratification standards of Human Capital Theory, consistent with the distribution of sample decision-maker characteristics
Industry Type	Dichotomous Variable	Manufacturing = 1; Service industry = 0	Manufacturing = 54; Service = 141.	Based on the differences in production characteristics in Industrial Organization Theory, focusing on the industrial heterogeneity of the core research context
Work Experience	Grouped Variable	Senior owners = 1; Novice owners = 0	Senior = 47; Novice = 151.	Based on the experience threshold of Organizational Learning Theory, the original text has clearly defined the comparison logic of "senior owners (≥10 years)"

Note: All moderating variables were centered before being included in the model to avoid multi-collinearity interference (VIF values after centering ranged from 1.375 to 2.335, all < 5).

5.4.1 Moderation Effect of Educational Background

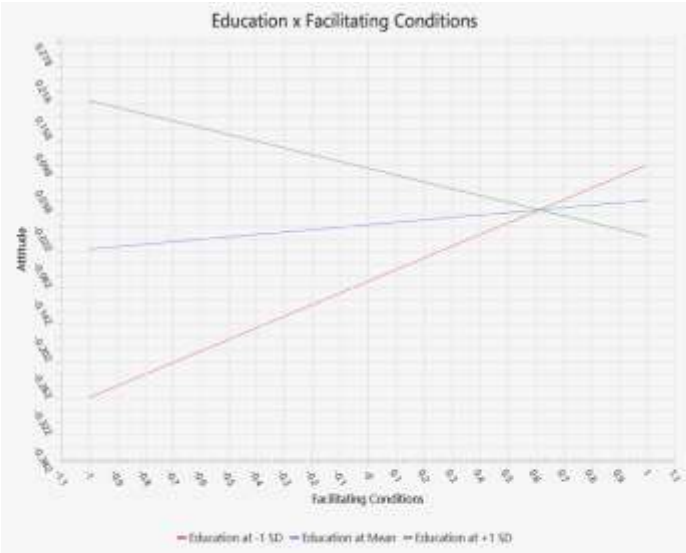
The negative moderation effects of educational background on the two paths were further deconstructed through simple slope analysis, with results shown in Table 11.

Table 11. Simple Slope Analysis Results for Educational Background

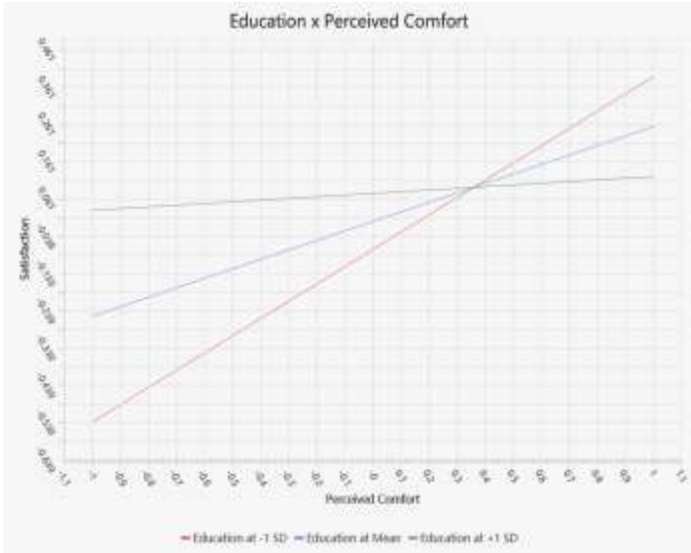
Moderated Path	Moderation Level	Simple Slope Coefficient (β)	T Value	P Value	Comparison of Effect Strength
Facilitating Conditions→Attitude	High educational background (=1)	0.012	0.217	0.828	The effect of the low education group is 5.1 times that of the high education group
	Low educational background (=0)	0.061	1.191	0.234	
Perceived Comfort→Satisfaction	High educational background (=1)	0.157	1.892	0.059	The effect of the low education group is 1.8 times that of the high education group
	Low educational background (=0)	0.286	3.971	0.000	

Interaction plot description: The left graph (figure 3-a) shows that the slope of the low educational background group ($\beta = 0.061$) is significantly higher than that of the high educational background group ($\beta = 0.012$), and the path coefficient of the high education group is not statistically significant ($p = 0.828$). This indicates that owners with low educational backgrounds are more dependent on external facilitating conditions, while highly educated owners can weaken this dependence through independent resource integration, consistent with the expectations of human capital theory. The right graph (figure 3-b) shows that the slope of the low educational background group ($\beta = 0.286$, $p < 0.001$) is significantly steeper than that of the high educational background group ($\beta =$

0.157, p = 0.059). This suggests that owners with low education are more sensitive to the surface-level interactive comfort of AI technology (such as operational adaptability and low anxiety), while highly educated owners pay more attention to the deep-level value of technology (such as strategic adaptability), resulting in a lower marginal contribution of comfort to satisfaction.

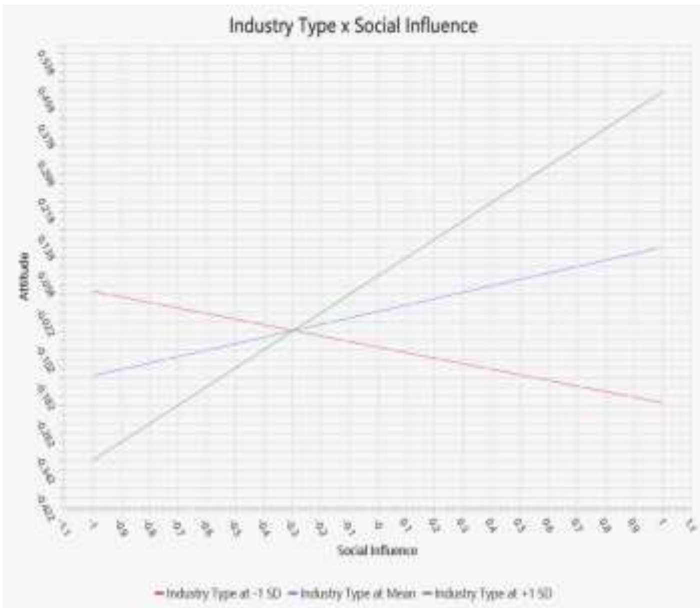


(a)

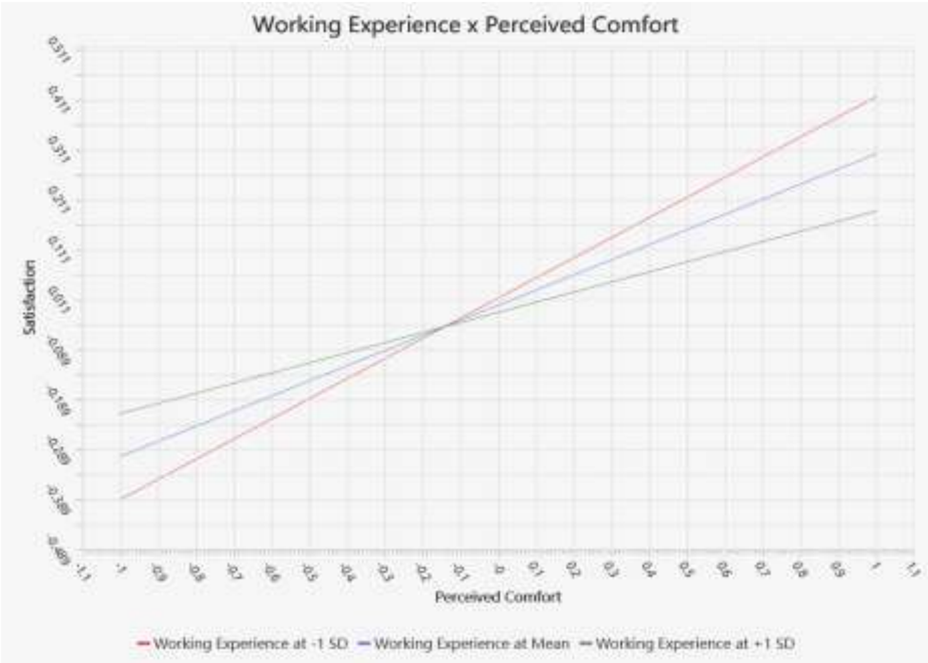


(b)

(c)



(d)



(e)

Figure 3. Simple Slope Analysis

5.4.2 Moderation Effect of Industry Type

The moderation effects of industry type on two core paths of the cognitive path were quantified through simple slope analysis, with results shown in table 12.

Table 12. Simple Slope Analysis Results for Industry Type

Moderated Path	Moderation Level	Simple Slope Coe-fficient (β)	T Value	P Value	Comparison of Effect Strength
Performance Expectancy→Attitude	Manufacturing (=1)	0.382	4.915	0.000	The effect of the manufacturing group is 2.9 times that of the service group.
	Service industry (=0)	0.132	1.764	0.078	
Social Influence→Attitude	Manufacturing (=1)	0.058	0.793	0.428	The effect of the service group is 5.5 times that of the manufacturing group.
	Service industry (=0)	0.317	4.286	0.000	

Interaction plot description: The left graph (figure 3-c) shows that the slope of the manufacturing group ($\beta = 0.382$, $p < 0.001$) is significantly steeper than that of the service industry group ($\beta = 0.132$, $p = 0.078$). This indicates that the standardized production scenarios in manufacturing enable the performance improvement of AI to be directly quantified, which is highly consistent with the "organizational strategic value realization" logic of performance expectancy. In contrast, the performance output of the service industry is more difficult to quantify, leading to weakened effects. The right graph (figure 3-c) shows that the slope of the service industry group ($\beta = 0.317$, $p < 0.001$) is significantly higher than that of the manufacturing group ($\beta = 0.058$, $p = 0.428$). This reflects the stronger market dynamics and herd competition characteristics of the service industry — AI adoption behavior of peer benchmarks forms stronger normative pressure, while technology decisions in manufacturing are more dependent on internal production needs and less sensitive to external social influence.

5.4.3 Moderation Effect of Work Experience

The marginally significant negative moderation effect of work experience on the perceived comfort→satisfaction path (β = -0.100, p = 0.051) was further verified through simple slope analysis, with results shown in table 13.

Table 13. Simple Slope Analysis Results for Work Experience

Moderated Path	Moderation Level	Simple Slope Coefficient (β)	T Value	P Value	Comparison of Effect Strength
Perceived Comfort→Satisfaction	Senior owners (=1)	0.183	2.105	0.036	The effect of the novice group is 1.6 times that of the senior group.
	Novice owners (=0)	0.289	3.872	0.000	

Interaction plot description (figure 3-e): This graph shows that the slope of the novice owner group (β = 0.289, p < 0.001) is steeper than that of the senior owner group (β = 0.183, p = 0.036). This indicates that the technical interaction habits formed through long-term industry experience reduce the marginal benefit of the comfortable experience of AI. Senior owners are more inclined to verify the value of technology through actual usage effects rather than immediate operational comfort. This "experience trap" leads to their lower sensitivity to surface-level emotional experiences compared to novice owners, consistent with the expectations of organizational learning theory.

5.4.4 Supplementary Explanation for Non-Significant Moderation Effects

For non-significant moderation effects (e.g., the moderation of educational background on perceived usefulness → attitude, β=-0.034, p=0.658), the reasons can be explained through contextual adaptability: as a core cognitive construct at the organizational strategic level, the driving logic of perceived usefulness on attitude is stable across educational backgrounds and experience levels, and is not significantly affected by individual trait differences. The non-significant moderation effect of industry type on the emotional path may be related to the insufficient depth of AI technology application in the service industry — most service industry samples still use AI at the basic interaction level (such as customer management tools) and have not formed deep emotional bonds, so the industrial heterogeneity of the emotional path has not yet emerged.

6. Discussion

This study constructs an integrated cognitive-affective dual-path model, systematically revealing the psychological mechanisms underlying artificial intelligence adoption decisions among small and medium-sized enterprise (SME) owners. It provides new empirical evidence for the organizational-level application of technology acceptance theory and addresses the critical issue of the "intention-behavior gap" by establishing a complete theoretical logic of "contextual characteristics - dual-path synergy - decision transformation". The following discussion integrates existing literature with the study's empirical findings.

The significant negative effect of satisfaction on adoption intention contradicts Hypothesis H9. This "affective paradox", a core unexpected discovery, stems from the interaction between the triple contexts of "resource constraints-risk perception-strategic decision-making" and construct compatibility. From the perspective of resource constraints, the scarcity of funds and talent in SMEs creates a conflict between "affective satisfaction" and "adoption feasibility". While satisfaction focuses on immediate emotional experiences, adoption intention centers on long-term strategic deployment. Even if owners recognize the performance of AI, they may abandon adoption due to subsequent barriers such as operational and maintenance costs and the lack of professional teams, resulting in a negative correlation characterized by "greater satisfaction leading to heightened concerns about insufficient resources".Regarding risk perception, the "high-investment and irreversible" nature of AI amplifies this negative effect: high satisfaction intensifies worries about sunk costs associated with technological iteration and data compliance risks. This aligns with the cross-contextual conclusion that "positive emotional feedback inhibits intention when there is a mismatch between technological investment and risk-bearing capacity". From the perspective of construct compatibility, in the centralized decision-making structure of SMEs, “strategic rationality” takes precedence over “emotional experience”. When emotional satisfaction conflicts with strategic feasibility, its positive driving effect is offset or even transformed into inhibition. This breaks the traditional cognition of a “positive emotional-intention relationship” and clarifies its contextual boundaries: the positive relationship holds in scenarios with sufficient resources and low risks, but may turn inhibitory in contexts of resource constraints and high risks.

Hypothesis H4 was not supported. This does not negate the logic of the UTAUT but rather reflects how “strategically driven adoption” and “resource bricolage capability” in SMEs weaken the marginal effect of facilitating conditions. UTAUT’s assumption of “resource accessibility” is applicable to resource-dependent organizations. However, SMEs have developed strong resource bricolage capabilities amid long-term resource scarcity: 62.3% of owners obtain technical support through partners, and 58.7% complete AI deployment via employee training, significantly reducing the positive impact of facilitating conditions. In terms of contextual differences, existing studies documenting the significant effect of facilitating conditions have mostly focused on consumer or large enterprise settings. In contrast, AI adoption in SMEs typically involves lightweight deployment, with lower dependence on external resources compared to the comprehensive digital transformation of large enterprises. This confirms the conclusion that “strategic value perception replaces the enabling role of facilitating conditions in resource-constrained contexts” and provides the first empirical validation of the “organizational size heterogeneity” in the effect of facilitating conditions.

The dual-path model constructed in this study addresses the research gap of “valuing cognition over affect” in existing literature. Most prior studies adopt a “cognition-dominated + affect-moderated” framework without establishing an independent affective path. In contrast, this study identifies that the affective path operates in parallel with the cognitive path to drive adoption decisions. The effect size of emotional dependence ($\beta = 0.408$) is comparable to that of perceived usefulness ($\beta = 0.365$), a core construct in the cognitive path. This constitutes the first establishment of a “parallel dual-path” framework for SMEs, confirming the independent driving role of affective factors. In previous research, affective factors typically exhibit effect sizes ranging from 0.2 to 0.3 and serve as auxiliary variables. In this study, the effect of emotional dependence on satisfaction is significantly higher than that of perceived trust ($\beta = 0.224$) and perceived comfort ($\beta = 0.286$), demonstrating a “superlinear effect” that challenges the traditional assumptions of “cognition dominance” and “trust as the core”. Traditional models fail to explain the “high recognition but low implementation” gap; this study reveals that the dynamic coupling of the dual paths determines the efficiency of intention-behavior transformation. A single dimension alone is insufficient to drive transformation, and synergistic activation of both paths is required. This expands the explanatory boundary of technology acceptance theory. The synergistic mechanism of the dual paths manifests as follows: the cognitive path conveys rational evaluation, while the affective path conveys emotional experiences. Cognition provides a “rational basis” for affect, and affect supplies “sustained motivation” for cognition. The transformation efficiency is highest when high perceived usefulness collaborates with high emotional dependence (total effect $\beta = 0.723$), whereas conflicts between the two result in the gap of “emotional satisfaction but rational rejection”.

The moderating effect analysis further uncovers the differential reshaping role of “individual traits - contextual characteristics” on the dual paths. The dual negative moderating effect of educational background can be explained by human capital theory: owners with higher education possess stronger capabilities in technological learning and resource integration, reducing their dependence on external facilitating conditions. They also pay more attention to the in-depth value of technology, lowering the marginal contribution of perceived comfort to satisfaction. The marginally significant negative moderating effect of work experience on the perceived comfort → satisfaction path ($\beta = -0.100$) aligns with organizational learning theory: senior owners (with ≥10 years of experience) develop “tacit knowledge dependence” on traditional processes and rely more on experience to evaluate technological value, making them less sensitive to operational comfort than novice owners ($\beta = 0.183$ for senior owners vs. $B = 0.289$ for novices). The moderating effect of industry type can be interpreted through institutional theory and industrial technology embeddedness theory: the standardized production in the manufacturing industry enables quantifiable performance improvements from AI, leading to a stronger effect of performance expectancy (β = 0.382 vs. Β = 0.132 in the service industry). In contrast, the market dynamism and competitive conformity in the service industry enhance the effect of social influence (β = 0.317 vs. Β = 0.058 in the manufacturing industry), confirming the “industry heterogeneity” in the driving logic of technology adoption.

This study is the first to propose and validate the “superlinear effect” of emotional dependence. Its effect size on satisfaction is significantly higher than that of other affective variables and shows no significant difference from the effect of perceived usefulness (95% CI [-0.012, 0.060]). This effect originates from the extension of attachment theory to human-machine relationships and the brain reward system theory: when AI becomes an indispensable support for core business operations, owners form an emotional bond characterized by “technological irreplaceability”, which activates the brain’s reward system and strengthens nonlinearly with usage time. This breaks the limitation of emotional design theory, which traditionally focuses on consumers’ superficial experiences, and shifts the focus to the in-depth emotional connection between technology and core business at the organizational level.

Based on the research findings, a “three-dimensional contextual adaptation” promotion strategy is proposed. To address the high resource dependence of owners with low educational backgrounds, service platforms should disseminate benchmark cases of “resource bricolage”, provide one-stop deployment services, and establish policy docking channels, catering to their higher sensitivity to facilitating conditions. For manufacturing enterprises with high performance expectancy, it is necessary to offer quantitative ROI calculation tools, scenario-based pilot programs, and industrial chain collaboration solutions to match the strong effect of their performance expectancy. Given the high sensitivity of service enterprises to social influence, industry alliances can be established, bench marking enterprises invited to share experiences, and policy certifications provided to strengthen normative pressure. For senior owners with strong dependence on traditional processes, modules compatible with traditional workflows, incremental deployment approaches, and experience-based trust-building initiatives should be developed to reduce emotional acceptance barriers. For novice owners with high demands for emotional experiences, interface optimization, real-time feedback mechanisms, and trust endorsements should be prioritized to accelerate trust establishment.

7. Conclusion and Limitations

This study constructs an integrated cognitive-affective dual-path model, systematically revealing the psychological mechanisms underlying AI adoption decisions among SME owners. It provides both theoretical and practical insights for addressing the “intention-behavior gap”.The findings confirm that technology adoption is jointly driven by rational evaluation and emotional experience. In the cognitive path, perceived usefulness, performance expectancy, and social influence significantly enhance adoption intention through the mediation of attitude, while facilitating conditions exhibit an insignificant effect due to the substitution role of resource bricolage capability. In the affective path, perceived comfort, perceived trust, and emotional dependency form a parallel driving force through the mediation of satisfaction, with the super-linear effect of emotional dependency challenging the traditional “cognition dominance” assumption in the field of technology acceptance. A comparison of the dual paths indicates that cognitive evaluation remains the dominant factor in decision-making, but affective factors have emerged as a critical parallel driving force. The dynamic coupling of the two paths determines the efficiency of transforming rational cognition into behavioral intention.

The analysis of moderating effects further uncovers the laws of contextual heterogeneity: educational background weakens the marginal effects of facilitating conditions and perceived comfort through the accumulation of human capital; the effect of performance expectancy in the manufacturing industry is 2.9 times that in the service industry; and work experience weakens the driving effect of perceived comfort on satisfaction through organizational memory. These findings expand the organizational-level application boundary of TAM-UTAUT theory and establish the first "cognition - affect - context" three-dimensional analytical framework tailored to SME owners.

This study has three limitations. Firstly, the sample is concentrated in Southwest and Northwest China, and the regional economic characteristics may limit the generalizability of the conclusions. Future research should verify the model's robustness through cross-regional and cross-cultural studies. Secondly, the cross-sectional data only capture the static characteristics of decision-making and cannot reveal the temporal evolution of the dynamic coupling between cognition and affect. A longitudinal tracking design is needed to further analyze long-term psychological changes. Thirdly, the neurocognitive basis and boundary conditions of the super-linear effect of emotional dependency remain unclear, requiring in-depth exploration through experimental psychology and multiple-case studies.

Despite these limitations, the theoretical value of this study lies in breaking the single rational decision-making paradigm and clarifying the applicable boundaries of technology acceptance theory in resource-constrained contexts. From a practical perspective, it provides "contextually adaptive" promotion strategies for AI providers and offers targeted guidance for the digital transformation of SMEs. By deconstructing the synergistic logic of "cognition and affect", this study builds a theoretical and practical bridge for the translation of AI from laboratory research to industrial application.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Author Contributions

CK: Conceptualization, methodology, software, validation, formal analysis, investigation,writing—original draft preparation, writing—review and editing.

HMZ: software, validation, formal analysis, investigation, writing—original draft preparation, visualization.

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Appendix A1. Source, Adaptation Notes and Item Examples of Scales for Each Latent Variable

Latent Variables	Number of Items	Scale Source and Adaptation Logic	Contextual Adaptation Adjustments	Item Example
Perceived Usefulness	6	Adapted from Davis' classic TAM scale, which has been validated for reliability and validity in over 300 technology acceptance studies. (Davis, 1989; Venkatesh et al., 2016)	Adjusted the individual-level construct of "improving work efficiency" to the organizational-level "enhancing organizational strategic value" to align with the organizational-oriented characteristics of decision-making in small and medium-sized enterprises (SMEs).	"Adopting AI technology can significantly enhance the core business competitiveness of the enterprise."
Performance Expectancy	4	Adapted from the UTAUT scale developed by Venkatesh et al., with reference to the context-adapted version used in Lerma et al.'s research on digital transformation of SMEs. (Lerma et al., 2023; Venkatesh et al., 2003)	Expanded the scope from "individual work performance" to "achievement of organizational strategic goals" and added items related to the dimension of "resource allocation optimization".	"AI technology can help the enterprise optimize resource allocation and reduce operational costs."
Social Influence	4	Adapted from the UTAUT scale by Venkatesh et al., adjusted in combination with the industrial competition context of SMEs based on Karimi et al. (Karimi & Mahmoodi	Strengthened the expression of "coercive pressure from industry benchmarks" and focused the construct of "influence from significant others" on "key stakeholders such as	"The AI adoption behavior of benchmark enterprises in the same industry has prompted our enterprise to

		Ranani, 2025; Venkatesh et al., 2003)	peer enterprises and suppliers”.	consider introducing relevant technologies.”
Facilitating Conditions	4	Adapted from the UTAUT scale by Venkatesh et al., adjusted with reference to Chummee’s research on resource-constrained contexts. (Chummee, 2025; Venkatesh et al., 2003)	Added items related to “availability of policy support and technical training” to adapt to the resource-scarce characteristics of SMEs.	“The enterprise can easily access the policy subsidies and technical training required for AI technology implementation.”
Perceived Comfort	3	Adapted from scales related to Forgas’ affective-cognitive interaction theory, integrated with research on emotional design in the field of human-computer interaction. (Forgas, 2008; Noerman et al., 2025)	Adjusted the consumer - side construct of “usage pleasure” to the organizational decision - making level constructs of “operational adaptability and low anxiety”.	“The operational process of AI technology is compatible with the enterprise’s existing business model, and there is no obvious anxiety during usage.”
Perceived Trust	4	Adapted from McKnight et al.’s trust scale and Alka’awneh et al.’s research on technology trust, with a focus on the black-box characteristic of AI. (Alka’awneh et al., 2025; McKnight et al., 2002)	Added items related to “algorithmic fairness and data security” to address the uncertainty inherent in AI technology.	“I trust the transparency of AI technology in data processing and the fairness of algorithmic decision- making.”
Emotional Dependency	5	Self-developed (no fully matched mature organizational -level scales available). Development process: literature review→item generation→expert review→ pre-test → item revision.	Based on Bowlby’s attachment theory and Nafees et al.’s technology emotional attachment theory, focusing on the three- dimensional connection of “technology- organization-decision- maker”. (Bowlby, 1979; Nafees & Sujood, 2025)	“AI technology has become an indispensable support for the enterprise's core business, and the loss of its support will significantly affect business operations.”
Attitude	6	Adapted from Davis’ TAM scale and Venkatesh et al.’s UTAUT2 scale, integrated with the organizational decision-making context. (Davis, 1989; Venkatesh et al., 2016)	Adjusted the individual-level “attitude towards technology” to the organizational-level “rational acceptance tendency towards AI adoption”.	“From an organizational strategic perspective, adopting AI technology is a sensible decision for the enterprise.”
Satisfaction	4	Adapted from Bhattacherjee’s scale in the Information System Continuance Model,	Emphasized the “cumulative feedback from emotional experience” and added	“The actual performance of AI technology continuously meets

on		adapted to the context of AI technology adoption. (Bhattacherjee, 2001; Mishrif & Khan, 2023)	items related to "sustained satisfaction derived from technology adaptability".	the enterprise's business needs and emotional expectations."
Adoption Intention	5	Adapted from the UTAUT scale by Venkatesh et al. and De Souza Meirelles's research on enterprise technology adoption.(De Souza Meirelles; Venkatesh et al., 2003)	Adjusted the construct of "usage intention" to the organizational- level "technology deployment intention" and added items related to "long-term promotion willingness".	"The enterprise plans to fully deploy AI technology within the next 1-2 years and continuously optimize application scenarios".

Appendix A2. Factor Loadings Indicators of Items for Each Latent Variable

Latent Variable	Item Code	Item Content	Factor Loading
Adoption Intention	AI1	Plan to fully deploy AI technology within the next 1 - 2 years	0.789
	AI2	Be willing to continuously optimize AI technology application scenarios	0.823
	AI3	Recommend AI technology to peers	0.801
	AI4	Regard AI technology as indispensable for the long - term development of the enterprise	0.795
Attitude	AT1	Adopting AI technology is a wise decision	0.732
	AT2	Support the enterprise in introducing AI technology	0.751
	AT3	Regard AI technology as consistent with the enterprise's strategic goals	0.728
	AT4	Hold a positive attitude towards AI technology adoption	0.719
	AT5	Believe that the benefits of AI technology outweigh the costs	0.703
	AT6	Be willing to bear the short - term costs of AI technology adoption	0.698
Emotional Dependency	ED1	AI technology is an indispensable support for core business	0.783
	ED2	Losing AI technical support will significantly affect business operations	0.756
	ED3	AI technology provides emotional security for the enterprise	0.689
	ED4	Form a deep emotional bond with AI technology	0.654
	ED5	Tend to prioritize AI technology in solving business problems	0.672
Facilitating Conditions	FC1	Easily access policy subsidies and technical training	0.683
	FC2	AI technology is highly compatible with existing systems	0.721
	FC3	Possess the infrastructure required for AI technology implementation	0.705
	FC4	Quickly obtain AI technical support services	0.692
Perceived Comfort	PC1	AI operation processes are compatible with existing business models	0.798
	PC2	Experience no obvious anxiety when using AI technology	0.832
	PC3	Have a smooth interactive experience with AI technology	0.821
Perceived Trust	PT1	Trust the transparency of AI data processing	0.886
	PT2	Recognize the fairness of AI algorithmic decision - making	0.897
	PT3	Believe in the security of AI technology	0.873
	PT4	Regard AI technology suppliers as having reliable service capabilities	0.865
Perceived	PU1	Enhance core business competitiveness	0.726
	PU2	Solve key business pain points	0.735
	PU3	Improve organizational operational efficiency	0.718

Usefulness	PU4	Create differentiated competitive advantages	0.697
	PU5	Optimize resource allocation efficiency	0.689
	PU6	Enhance the enterprise's strategic value	0.678
Performance Expectancy	PE1	Optimize resource allocation and reduce operational costs	0.813
	PE2	Strengthen core competitiveness	0.809
	PE3	Achieve quantifiable strategic goals	0.798
	PE4	Improve market response speed	0.786
Satisfaction	SA1	The actual performance of AI technology continuously meets business needs	0.767
	SA2	AI technology meets emotional expectations	0.753
	SA3	Be satisfied with the user experience of AI technology	0.749
	SA4	Be willing to use AI technology for a long time	0.738
Social Influence	SI1	The adoption of AI by peer enterprises prompts our enterprise to consider its introduction	0.797
	SI2	Suppliers recommend AI technology	0.783
	SI3	Industry policies encourage the application of AI technology	0.776
	SI4	Key stakeholders recognize AI technology	0.769

Note: All item factor loadings passed the Bootstrap test ($p<0.001$). No item had a factor loading below 0.6, so no items were excluded. The factor loadings of all items under the Emotional Dependence construct were above 0.65, which meets the requirements for convergent validity of self - developed scales.