A Meta-Analysis of Key Influencing Factors and Their Effects on User Trust in AI Assistants

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Abstract

【Purpose/Significance]With the rapid development of AI technology, the penetration rate of AI assistants in industries such as retail, finance, and healthcare continues to increase, and the influence mechanisms of user usage intention have become a focus of academic attention. User trust, as an important driver of product adoption, has yet to reach consistent conclusions regarding its key influencing factors and effects in existing research, necessitating systematic integrative evaluation.

【Method/Process]This paper uses 65 published empirical research articles from domestic and international sources as the sample, employs meta-analysis to quantitatively analyze the influencing factors of user trust in AI assistants and their relationship with usage intention, and examines the moderating effects of users' cultural background and product usage scenarios on this relationship.

【Results/Conclusions]Results indicate that product anthropomorphism, perceived usefulness, perceived ease of use, social presence, social influence, product performance, and perceived risk are seven key factors affecting user trust. Except for perceived risk, which has a significant negative impact on user trust, all other factors exert significant positive impacts on user trust, and user trust has a significant positive impact on usage intention, but heterogeneity exists across studies. Moderating effect analysis reveals that users' cultural background and usage scenarios of AI assistant products are the main reasons for this heterogeneity. The research results provide a theoretical basis for future in-depth studies and guidance for the interaction design and application promotion of AI assistant products.

Full Text

Preamble

Key Influencing Factors on User Trust and Its Effects: A Meta-analysis of AI Assistants1

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Abstract

[**Purpose/Significance**] With the rapid development of artificial intelligence (AI) technology, AI assistants have achieved increasing penetration across industries such as retail, finance, and healthcare, making the mechanisms influencing user adoption intentions a focal point of academic inquiry. User trust serves as a critical driver of product adoption, yet existing research has yet to reach consensus regarding its key influencing factors and effect sizes, necessitating a systematic integrative assessment. [**Method/Process**] This study examines 65 empirical research papers published domestically and internationally, employing meta-analysis to quantitatively analyze the factors influencing user trust in AI assistants and their relationship with usage intention, while testing the moderating effects of user cultural background and product usage scenarios on these relationships. [**Result/Conclusion**] The findings identify seven key factors affecting user trust: product anthropomorphism, perceived usefulness, perceived ease of use, social presence, social influence, product performance, and perceived risk. Except for perceived risk, which exhibits a significant negative effect on user trust, all remaining factors demonstrate significant positive effects. User trust also shows a significant positive effect on usage intention, though substantial heterogeneity exists across studies. Moderation analysis reveals that user cultural background and AI assistant usage scenarios constitute the primary sources of this heterogeneity. These results provide a theoretical foundation for future research and offer actionable guidance for the interaction design and application promotion of AI assistant products.

Keywords: AI assistant; user trust; influencing factors; meta-analysis
Classification Number: C931.6

1. Introduction

In recent years, AI assistant applications have surged across multiple domains. Also known as virtual assistants or digital assistants, these AI agents leverage machine learning, natural language processing, and speech recognition technologies to simulate human interaction and perform specific tasks, signaling a shift in agency and control from humans to technology [?]. Since the 1990s, the proliferation of personal computers gave rise to basic personal assistant software such as Microsoft Office' s Paperclip assistant, with some computer manufacturers also integrating speech recognition subsystems into their products. The advent of smartphones and cloud computing in the 21st century dramatically accelerated AI assistant development, exemplified by Apple' s 2011 launch of Siri, followed by Google' s Alexa and Microsoft' s Cortana. With advances in deep learning and large language models, modern AI assistants now encompass core capabilities in content understanding and generation, transcending single-modal interaction constraints. Their typical forms include intelligent chatbots, voice assistants, and personal assistants [?, ?], offering enhanced possibilities for professional scenarios such as product recommendations, financial investment, and medical consultations.

Trust is typically defined as "confidence in or reliance on the attributes or characteristics of something" [?], serving a core function in interpersonal interactions by reducing transaction costs and promoting cooperative evolution. This concept has been extended in information systems research to form the specialized dimension of "technology trust." As a crucial driver of AI assistant adoption, user trust and its antecedents have become widely studied topics, with research suggesting associations with technical, interactive, and security-related factors [?, ?]. However, prior studies yield inconsistent conclusions due to variations in research contexts and subjects. For instance, numerous studies have investigated whether AI assistant anthropomorphism affects user trust: X. Cheng et al. found that chatbot anthropomorphic attributes positively influenced consumer trust [?], while research in online shopping contexts indicated that chatbot anthropomorphism could negatively impact user trust [?]. Chen and Chen' s results showed no significant effect of AI assistant anthropomorphism on human-machine trust [?]. Similar inconsistencies appear for other antecedents. In examining the effect of perceived ease of use on trust, studies have reported both positive effects and non-significant results [?, ?]. Regarding affective interaction factors, C. S. Oh et al. noted that social presence does not always produce positive outcomes [?]. These findings suggest that certain influencing factors exhibit significant variation in both effect strength and direction.

Our analysis of existing literature reveals that not only do quantitative effects of user trust antecedents vary, but the effects of trust itself also show contradictions. For example, J. Fu et al.' s research indicates a strong correlation between user trust and usage intention [?], whereas F. A. Silva et al.' s findings show no significant association between the two [?]. These contradictory conclusions not only hinder research on human-computer interaction design and user behavior related to AI assistants but also create obstacles for AI product promotion and implementation.

Potential reasons for these inconsistencies include: First, most existing studies concentrate on specific geographic regions for data collection, overlooking the role of cultural heterogeneity among participants. For instance, Y. L. Ng' s research on the effect of user trust in conversational AI on continued usage intention was limited to Hong Kong samples [?]; E. Uysal et al. investigated trust antecedents exclusively among UK residents [?]; and while J. Kim et al. compared US and Singapore populations, their scope remained limited [?]. These findings underscore the necessity of comprehensive analysis across different cultural backgrounds. Second, most studies analyze user behavior within specific scenarios, creating limitations. For example, X. Zhan et al. focused solely on user trust and usage intention for AI assistants in healthcare services [?], while C. Singh et al. concentrated on online shopping intelligent assistants [?]. Currently, systematic quantitative research yielding generalizable, quantifiable conclusions remains lacking. Therefore, a meta-analysis is needed to quantitatively analyze AI assistant user trust antecedents by synthesizing results from multiple independent studies to provide more precise effect estimates than any single study.

Meta-analysis is a statistical technique for synthesizing results from multiple independent studies to obtain more comprehensive and reliable conclusions regarding specific research questions [?]. While widely applied in online community user behavior, employee behavior, and information literacy [?], meta-analysis has not yet been employed for in-depth analysis of AI assistant user trust and usage intention. Amid the "high popularity, low consensus" dilemma facing current AI technology development, meta-analysis represents a critical pathway for resolving theoretical confusion and guiding technological implementation. This study employs meta-analysis to reanalyze single-study samples, exploring relationships between AI assistant user trust and its influencing factors while identifying potential moderating variables. It aims to address: What consensus have previous empirical studies reached regarding AI assistant user trust antecedents? What are their conclusions and effect sizes? What effects does user trust produce? What causes heterogeneity in existing research? These conclusions hold significant importance for comprehensively understanding user trust influence mechanisms and optimizing AI assistant product design.

2. Theoretical Basis

Research on user trust in AI assistants primarily draws from social psychology, grounded in classic user behavior models and theories such as the Technology Acceptance Model (TAM) and Social Presence Theory (SPT).

2.1 Technology Acceptance Model

Proposed by F. D. Davis in 1989, the Technology Acceptance Model explains user acceptance and use of information technology, with perceived usefulness and perceived ease of use as its core constructs [?]. Perceived usefulness refers to the degree to which users believe that using a particular technology enhances their work or life efficiency. Research shows that in complex tasks or situations requiring rapid decision-making (e.g., government services, autonomous driving), perceived usefulness of AI assistants is a key factor in building trust

[?, ?]. Perceived ease of use, another key TAM element, refers to the degree of ease users experience when using a technology. AI assistant ease of use enables users to feel they can quickly master product functions, generating more positive emotional experiences that form the basis of trust [?, ?]. Given the theory' s widespread application and potential context dependency [?], this study analyzes perceived usefulness and perceived ease of use as trust antecedents.

2.2 Social Presence Theory

Social presence is defined as "the ability of a communication medium to convey social cues." Scholars argue that different media possess varying degrees of social presence, thereby affecting individuals' perceptions of social and psychological engagement in interactions [?]. In social contexts, using AI assistants can make users feel accompanied by social entities [?]. In related research, S. K. Lee et al. found that user trust in AI is highly correlated with perceived social presence; when users believe AI assistant usage is based on social scenarios, they are more likely to perceive the product as trustworthy [?]. Although social presence has been validated in e-commerce and education contexts, its effect strength varies [?, ?]. For AI assistants, both the embedding of social cues and the emergence of "affective vacuums" influence user trust mechanisms, requiring clarification and refinement in research.

2.3 Social Exchange Theory

Social Exchange Theory (SET), originally proposed by G. C. Homans, posits that individuals decide whether to maintain or terminate relationships by evaluating rewards and costs in interactions [?]. "Rewards" refer to positive outcomes individuals gain from interactions, while "costs" represent the price paid to obtain these rewards. Individuals weigh these two factors to decide whether to continue interacting. In information systems research, SET has been extended as a key lens for understanding the dynamic evolution of human-machine trust. Regarding rewards, when AI assistants demonstrate high technical performance, generating high-quality personalized recommendations and efficient feedback, users build trust in the system through this exchange relationship [?, ?]. Regarding cost losses, social exchange inevitably generates uncertainty and risk, such as privacy risks from data misuse [?]. When users perceive that AI assistant rewards consistently exceed interaction costs, trust relationships are established and strengthened.

2.4 Theory of Planned Behavior

The Theory of Planned Behavior (TPB), proposed by I. Ajzen in 1991, suggests that individual behavioral intentions are determined by three major factors: attitude, subjective norm, and perceived behavioral control [?]. Within the TPB framework, attitude reflects users' overall evaluation of AI assistants—a cognitive mapping of their technical performance typically determined by perceived usefulness, ease of use, and satisfaction [?]. Subjective norm reflects the transmission effect of social influence on user trust, indicating that individuals may change behavioral intentions due to social norms and others' expectations. Research shows that social influence can explain perceptions of AI assistant user trust [?, ?]. Perceived behavioral control clarifies the enabling mechanism of user trust, namely that trust can reduce users' technology anxiety and significantly affect their usage intention [?, ?].

2.5 Anthropomorphism

Anthropomorphism refers to products exhibiting human-like characteristics [?]. AI assistant anthropomorphic design primarily incorporates elements such as voice, appearance, and emotional expression to give the system human-like features, thereby increasing user trust [?, ?]. Due to psychological self-protection mechanisms, humans typically perceive higher risks with unfamiliar products [?] and thus prefer products that exhibit similarity to themselves and can reduce psychological distance. Research demonstrates that users of highly anthropomorphic AI assistants exhibit stronger trust [?, ?]. However, this high degree of anthropomorphism may also weaken trust [?, ?]. Therefore, further analysis is necessary to determine the generalizability of these findings.

Based on the above perspectives and considering the frequency and importance of user trust influencing factors in previous literature, this study incorporates anthropomorphism, perceived usefulness, perceived ease of use, social presence, social influence, product performance, and perceived risk into a comprehensive analysis framework spanning seven dimensions. Additionally, this study treats usage intention as a key outcome of user trust, as it effectively represents product adoption and user behavior. Consequently, we construct a research model of key influencing factors and effects of AI assistant user trust, as shown in Figure 1.

Figure 1 [Figure 1: see original paper] Research model of AI assistant user trust and its influencing factors

3. Methodology

This study employs meta-analysis for quantitative systematic evaluation of literature, attempting to integrate existing empirical research on AI assistant user trust and usage intention to explore the antecedent factors of user trust and their effect relationships with usage intention. Currently, meta-analysis is widely applied in medicine, education, and other disciplines, playing a critical role in systematic evaluation and evidence synthesis. In medicine, it is commonly used to assess drug efficacy, diagnostic test accuracy, and intervention effectiveness. In education and psychology, it is extensively employed to study intervention effects and behavioral patterns. In information behavior research, H. Zhou et al. conducted a comprehensive analysis of 31 empirical studies to explore key factors influencing mobile reading user adoption [?]; J. Mou et al. used meta-analysis of 67 studies to examine how trust and risk affect consumer acceptance of electronic services [?]. AI assistant user behavior data exhibits fundamental characteristics of information systems research, making it suitable for meta-analysis. Based on data format and volume considerations, this study utilizes Comprehensive Meta Analysis (CMA) 3.0 software for data analysis.

3.1 Literature Search and Screening

To obtain research samples for meta-analysis, this study conducted comprehensive searches of Chinese and English literature databases. For English literature, we used the keywords "AI assistant" OR "AI agent" OR "conversational AI" OR "generative AI" OR "chatbot" OR "voice assistant" AND "trust" to search Web of Science, Google Scholar, Science Direct, Wiley, Emerald, Taylor & Francis, and Springer databases. For Chinese literature, we searched the CNKI database using Chinese equivalents of these terms combined with "trust," selecting academic journal articles and important conference papers published between 2015-2024 as research samples. Since AI assistants lacked mature application scenarios before 2015 with limited relevant literature, the start year was set to 2015. As of July 2024, the search yielded 3,452 English articles and 82 Chinese articles.

These 3,534 articles formed our initial database for screening relevant studies. Inclusion criteria included: (1) research objects must be AI assistants capable of intelligent dialogue in text or voice form; (2) core variables must involve user trust, including either antecedents of trust or outcome variables related to usage intention; (3) study type must be empirical research reporting correlation coefficients or other values convertible to effect sizes; (4) studies must report sample sizes and characteristics to enable calculation of pooled effect sizes. Following search, screening, review, and inclusion procedures, this meta-analysis ultimately included 65 articles (62 English, 3 Chinese) comprising 106 effect sizes and 44,803 samples. Details are shown in Figure 2 [Figure 2: see original paper].

Figure 2 [Figure 2: see original paper] Literature search and screening

3.2 Data Coding and Processing

Coding content for research samples primarily included author information, publication year, antecedent variables, outcome variables, sample size, effect values, cultural background, user experience with AI assistants, and usage scenarios. Samples were classified by different variables, with each literature sample used only once per variable effect analysis to ensure independent randomness. Most included studies employed structural equation modeling or experimental methods to analyze trust-usage intention relationships. When studies did not directly report correlation coefficients, they were converted to correlation coefficient r using conversion formulas [?] before analysis:

$$r = \begin{cases} 0.98 \times \beta + 0.05, & \beta \geq 0 \\ 0.98 \times \beta - 0.05, & \beta < 0 \end{cases}$$

$$r = \sqrt{\frac{t^2}{t^2 + df}}$$

$$r = \sqrt{\frac{\chi^2}{n}}$$

4. Results

4.1 Publication Bias

First, we conducted qualitative analysis using funnel plots. Taking product performance (the variable with most studies) and the trust-usage intention effect as examples, the corresponding funnel plots are shown in Figures 3 [Figure 3: see original paper] and 4 [Figure 4: see original paper]. All studies cluster at the top with symmetrical distribution, indicating no publication bias. Additionally, we quantitatively estimated publication bias at $p = 0.05$ by calculating fail-safe N, using $5K + 10$ (K = number of studies) [?] as the critical value. As shown in Table 1 , all results exceed the critical value, confirming the robustness of all identified influencing factors and effects.

Figure 3 [Figure 3: see original paper] Distribution of effect value of product performance and user trust
Figure 4 [Figure 4: see original paper] Distribution of effect value of user trust and usage intention

4.2 Heterogeneity Test

Further analysis of included studies revealed differences in research contexts and sample selection, necessitating heterogeneity testing. The Q test and I^2 are currently widely used heterogeneity test methods. This study adopted the Q test, with results shown in Table 1. All variables in the heterogeneity analysis passed the test ($p < 0.01$) with $I^2 > 60\%$, indicating high heterogeneity among studies. Therefore, random-effects models were selected for all variables, with subgroup analysis conducted to explore potential moderating effects.

4.3 Main Effects Analysis

Effect size analysis across dimensions yielded the results shown in Table 1 . According to J. Cohen's correlation coefficient criteria, all seven influencing factors significantly affected user trust ($p < 0.05$). Social influence ($r = 0.445$), social presence ($r = 0.440$), product performance ($r = 0.430$), perceived usefulness ($r = 0.421$), and perceived ease of use ($r = 0.315$) showed significant moderate positive correlations with user trust. Perceived risk ($r = -0.344$) exhibited a significant moderate negative correlation, while anthropomorphism ($r = 0.281$)

showed a significant but weaker positive correlation, indicating its limited influence. Additionally, user trust demonstrated a significant moderate positive correlation with usage intention ($r = 0.409, p < 0.05$).

Table 1 The influencing factors of AI assistant user trust and their effect meta-analysis results

Relationship	r	95% CI	Q	I^2	Fail-safe N
Anthropomorphism-Trust	0.281***		54.884***	81.78%	309.330***
Perceived Usefulness-Trust	0.421***		540.107***	97.78%	726.772***
Perceived Ease of Use-Trust	0.315***		100.048***	94.00%	
Social Presence-Trust	0.440***		165.995***	93.37%	
Social Influence-Trust	0.445***		446.438***	95.07%	
Product Performance-Trust	0.430***				
Perceived Risk-Trust	- 0.344***				
Trust-Usage Intention	0.409***				

Note: K = number of studies, N = sample size, r = pooled effect size, Fail-safe N = failsafe number; ** $p < 0.05$*

4.4 Moderating Effects Analysis

Given high heterogeneity indicated by the tests, potential moderating factors likely exist. Through in-depth review of literature samples, we identified common variations in participants' geographic backgrounds and product usage scenarios. First, given that Eastern and Western countries exhibit fundamentally different cultural profiles in values and communication styles, leading to different formation mechanisms of user attitudes toward AI assistants [**?**], this study draws on G. Hofstede's cultural dimensions theory [**?**] to investigate user cultural background as two dimensions: Eastern and Western culture. Specifically, Eastern culture emphasizes collectivism and harmony, focusing on tacit knowledge and abstract expression (including China, Japan, India, etc.), completely different from Western culture' s emphasis on individualism and explicit knowledge (including the US, UK, Australia, etc.).

Additionally, user cognition of products typically involves two dimensions: "utilitarianism" emphasizing product functionality (practical, instrumental products) and "hedonism" emphasizing emotional experience (products providing sensory pleasure). According to the "Word of Machine" effect [?], users exhibit systematic biases in perceiving AI assistant capabilities. In utilitarian scenarios, AI assistants leverage advantages in factual analysis and logical reasoning, focusing primarily on efficiency optimization and business outcomes. This study includes AI assistant usage in healthcare, finance, hospitality, and other industries, such as patient assessment and diagnostic recommendations [?]. In hedonic scenarios, AI assistants primarily satisfy users' emotional and entertainment needs, including retail and household AI assistants, such as generating beauty product recommendations based on purchase history and preferences [?].

To explore sources of variation, this study employed subgroup analysis to test the moderating effects of AI assistant user cultural background and product usage scenarios. Results are shown in Table 2 .

Table 2 Moderating effect test results

Relationship	Eastern Culture	Western Culture	Utilitarian Scenario	Hedonic Scenario	Q_b
Anthropomorphism-Trust	0.346***	0.177***	0.158***	0.348***	6.917***
Perceived Usefulness-Trust	0.694***	0.233***			77.166***
Perceived Ease of Use-Trust					4.551***
Social Presence-Trust	0.453***	0.167***			19.185***
Social Influence-Trust					8.793***
Product Performance-Trust	0.485***	0.227***	0.577***	0.289***	9.265***
Perceived Risk-Trust			-0.329***	-0.358***	7.762***
Trust-Usage Intention	0.557***	0.328***	0.486***	0.285***	

(1) Cultural background moderation results: After excluding cross-regional studies (with users from both Eastern and Western cultures), cultural background significantly moderated the relationships between AI assistant anthropomorphism and trust ($Q_b = 6.917$), perceived usefulness and trust ($Q_b = 77.166$), social presence and trust ($Q_b = 4.551$), product performance and trust ($Q_b = 19.185$), and user trust and usage intention ($Q_b = 9.265$). In Eastern culture, the effects of anthropomorphism ($r_{Eastern} = 0.346 > r_{Western} = 0.177$), perceived usefulness ($r_{Eastern} = 0.694 > r_{Western} = 0.233$), social presence ($r_{Eastern} = 0.453 > r_{Western} = 0.167$), and product performance ($r_{Eastern} = 0.485 > r_{Western} = 0.227$) on user trust were all significantly stronger than in Western culture. Moreover, the positive relationship between user trust and AI assistant usage intention was stronger in Eastern culture ($r = 0.557$) than in Western culture ($r = 0.328$). Cultural background did not significantly moderate relationships between perceived ease of use, social influence, or perceived risk and user trust.

(2) AI assistant usage scenario moderation results: After excluding studies without specified scenarios or covering multiple scenario types, remaining studies were categorized into utilitarian and hedonic scenarios. Results show that usage scenario significantly moderated the relationships between anthropomorphism and trust ($Q_b = 17.846$), product performance and trust ($Q_b = 8.793$), and trust and usage intention ($Q_b = 7.762$). The positive relationship between anthropomorphism and trust was significantly stronger in hedonic scenarios ($r_{hedonic} = 0.348 > r_{utilitarian} = 0.158$), while the positive relationship between product performance and trust was stronger in utilitarian scenarios ($r_{utilitarian} = 0.577 > r_{hedonic} = 0.289$). Additionally, the effect of user trust on usage intention was stronger in utilitarian scenarios ($r_{utilitarian} = 0.486 > r_{hedonic} = 0.285$). Usage scenario did not significantly moderate relationships between perceived usefulness, perceived ease of use, social presence, or perceived risk and user trust.

5. Discussion and Conclusions

Based on meta-analysis of 65 empirical studies, this study identifies seven key factors influencing AI assistant user trust and assesses trust’ s effect on usage intention. Through heterogeneity and moderation analyses, we examine how user cultural background and product usage scenarios moderate these relationships, attempting to derive generalizable conclusions about key factors and their effects in AI assistant interaction design.

5.1 Research Conclusions

5.1.1 Antecedents of AI Assistant User Trust Main effects analysis reveals that anthropomorphism, perceived usefulness, perceived ease of use, social presence, social influence, product performance, and perceived risk are seven important factors affecting AI assistant user trust. Perceived risk shows a significant negative effect, while all other factors exhibit significant positive effects, though relationship strengths vary. These findings help researchers select appropriate variables for AI assistant interaction design studies and assist product developers in targeted optimization. Conclusions can be categorized into three aspects:

(1) Technical performance and social interaction experience are core drivers of user trust. This category includes social influence ($r = 0.445$), social presence ($r = 0.440$), and product performance ($r = 0.430$), with effect sizes all approaching 0.45, demonstrating that enhancing AI assistant reliability, functionality, and emotional connection significantly boosts trust. Although technical performance and social interaction appear as separate dimensions, they often intertwine. For instance, technically excellent AI assistants not only provide reliable functional guarantees but also deliver natural, human-like interaction experiences, fostering greater emotional trust. According to the "para-social interaction" perspective, when AI technology extends beyond meeting user needs to fulfilling social interaction needs, it creates an illusion of intimacy [?], further enhancing user trust.

(2) User subjective perception constitutes an important pathway for trust formation, depending on multiple factors. Perceived usefulness ($r = 0.421$), perceived ease of use ($r = 0.315$), and perceived risk ($r = -0.344$) significantly affect trust levels. Trust, as a complex psychological state, stems from users' subjective judgments about product characteristics and potential risks during use. On one hand, subjective perception depends on expectations of product functionality and value; when users perceive practical utility that meets or exceeds expectations, trust develops more easily [?]. On the other hand, trust building involves risk assessment; when users perceive lower risk—i.e., when technical products demonstrate transparency and security—trust develops more smoothly. These results indicate that AI assistant trust building is not merely a simple reflection of technical functions but a comprehensive evaluation and psychological response to products in complex interactive environments.

(3) Product anthropomorphism can promote trust but has relatively limited influence. Anthropomorphism ($r = 0.281$) shows a weaker positive correlation with user trust, indicating that while it can enhance trust to some extent, its effect is weaker compared to other factors. Most empirical literature on anthropomorphism focuses on product appearance descriptions, such as virtual avatar design and voice assistant characteristics, without reaching the level of human-like social interaction. Although anthropomorphic product design can make AI assistants appear friendlier and reduce psychological defenses, its influence on trust is auxiliary rather than decisive. Additionally, considering the inconsistency issue [?]—where AI systems exhibiting human-like features but failing to meet user expectations on critical tasks may generate stronger disappointment and undermine trust—caution is warranted.

5.1.2 Effects of AI Assistant User Trust Analysis shows that AI assistant user trust has a significant positive effect on usage intention ($r = 0.409$), indicating that trust plays a critical role in AI technology acceptance and use. When users develop sufficient trust in AI assistants, they become more willing to use the technology. Among included literature samples, "usage intention" was further distinguished into initial and continued intention. As an important mechanism for reducing uncertainty, trust can enhance usage intention by increasing users' sense of control and dependence on technology. On one hand, when facing emerging AI assistant technology, trust can reduce concerns about uncertainty and enhance motivation to try new technologies. On the other hand, through long-term use, users develop continued trust based on system performance in complex scenarios. According to expectation-confirmation theory, user trust is reinforced during use, thereby promoting continued usage intention [?].

5.1.3 Moderating Effects Moderation analysis reveals that user cultural background and usage scenarios are primary sources of heterogeneity with significant moderating effects:

(1) Cultural background moderation. For Eastern culture users, the effects of anthropomorphism, perceived usefulness, social presence, and product performance on trust were all significantly stronger than for Western culture users. Additionally, the positive relationship between trust and usage intention was stronger for Eastern users. According to G. Hofstede [?], Eastern culture emphasizes authority and collectivism more than Western culture, with trust often built upon authority and hierarchy. Therefore, Eastern users are more inclined to trust efficient and reliable technical systems, where product performance and perceived usefulness more readily establish trust. Previous research found that Taiwanese IT professionals pay more attention to technical issues and details than their American counterparts [?]. Moreover, Eastern culture' s emphasis on interpersonal relationships and social interaction means AI assistant anthropomorphism and social presence can cater to Eastern users' values in this dimension through simulated human behavior and emotional interaction. S. Baskentli et al. demonstrated that Eastern consumers respond more positively to anthropomorphic products than Western consumers, proving that collectivism favors anthropomorphic products [?]. This study confirms these findings in AI assistant applications.

Furthermore, since Eastern culture tends toward high-context communication—where decision-making is more easily influenced by social relationships and situations—while Western culture emphasizes individualism and independence [?], Western users focus more on independent personal experience and rationally evaluate product functions and utility when using AI assistants. Although trust still affects their usage intention, this difference reflects that Eastern users emphasize trust continuation while Western users prioritize independent decision-making, making trust' s effect on usage intention relatively smaller in Western contexts.

(2) Usage scenario moderation. In hedonic scenarios, AI assistant anthropomorphism' s effect on trust was significantly stronger than in utilitarian scenarios, while product performance' s effect on trust was stronger in utilitarian scenarios, as was trust' s effect on usage intention. In hedonic scenarios where user needs focus on entertainment and leisure rather than task completion, AI assistant anthropomorphic design aligns with user needs through more affable image design and emotional language, making AI appear more like a "companion" than a cold tool [?]. Anthropomorphic features generate empathy and social satisfaction, enabling better user experiences in informal, entertainment-oriented scenarios. For example, when users ask household AI assistants to play music or check weather, anthropomorphism makes interaction smoother without complex commands, reducing cognitive load [?] and enhancing dependence on and trust in AI assistants.

In utilitarian scenarios where users interact with systems for specific tasks or goals, such as online banking or customer service, users prioritize product functionality and performance due to the need for accurate information and efficient service. Additionally, user feelings are influenced by gaps between expectations and actual experience [?]. In utilitarian scenarios, users typically have higher performance expectations, making underperforming AI systems more likely to cause frustration and loss of trust. In such task-oriented scenarios, users focus on whether products can effectively help complete tasks. For instance, when using AI assistants for financial transactions, users will only adopt the product for high-risk, critical tasks when they have high trust levels.

5.2 Implications

These findings offer insights and recommendations for AI assistant research and development.

Theoretically, this study integrates TAM, SPT, SET, and other theories to construct a multidimensional model of AI assistant user trust, explaining the synergistic effects of technical performance, social interaction, and user subjective perception. This addresses the gap in traditional trust theory' s difficulty in explaining human-like trust toward non-human entities. The study reveals that domestic research on AI assistant user trust remains relatively scarce, inadequately revealing trust influence mechanisms and complex multidimensional relationships under China' s specific cultural and social contexts, insufficient for systematic understanding. Based on these results, researchers can select appropriate variables combined with China' s actual conditions to conduct more regionally and culturally characteristic empirical studies, better understanding AI assistant usage characteristics and user behavior in China's market to provide effective marketing strategies and enhance product localization capabilities.

Practically, despite rapid AI technology development, building user trust in AI assistants still faces multiple obstacles with significant performance differences across markets and application scenarios. Based on these realities, we propose:

First, adopt a "technical performance-social interaction" dual-track development strategy. Results show that AI assistant technical performance and social interaction experience are core drivers of user trust. Product design should therefore focus simultaneously on functional reliability and emotional interaction capability. Explore quantitative improvement paths for technical performance to ensure accurate, efficient fulfillment of user task needs. Deepen affective computing models for social interaction, strengthening R&D in natural language processing, emotion recognition, and response technologies to simulate natural, human-like interaction and enhance emotional connection. For example, intelligent customer service design should not only ensure quick, accurate problem resolution but also use emotionally rich language and personalized interaction to make users feel understood and valued. Although anthropomorphic product design positively affects trust, its effect is limited and risks "unmet human-like expectations" that could significantly reduce trust. Therefore, AI assistant design should follow a "function-first, moderate anthropomorphism" principle, treating anthropomorphism as an auxiliary means to enhance emotional connection rather than a core driver, while matching actual performance to avoid over-anthropomorphism that raises questions about functional reliability.

Second, construct a scenario-driven product design system. Since different AI assistant usage scenarios affect user trust differently, interaction design must clarify core user needs for each scenario. For entertainment- and companionship-oriented AI assistants, focus investment on affective design and interaction capability development. For example, household AI assistants can use emotional voice interaction, humorous responses, and personalized features unlocked through user characteristic data to enhance entertainment experience and emotional dependence. For task-oriented AI assistants (e.g., financial transaction assistants, medical diagnosis assistants), prioritize professionalism and functionality, embedding transparency and risk warning tools to ensure user trust in core capabilities. To achieve optimal cross-scenario performance, develop dynamic weighting models based on scenario characteristics that adjust technical and interactive configuration ratios in real-time by analyzing user need data, maximizing trust building while meeting diverse needs.

Third, adapt to target market cultural backgrounds with differentiated strategies. Enterprises must fully consider target market cultural characteristics in product design, promotion, and operation. In Eastern culture markets (e.g., China, Japan), AI assistant design should emphasize social presence and product performance, such as creating anthropomorphic virtual images and displaying technical performance details. In marketing, given Eastern culture' s emphasis on authority and collectivism, adopt "authority endorsement + collective identity" promotion strategies emphasizing product coverage and service scale, such as integrating AI assistants with public data platforms to promote acceptance and use. In Western culture markets (e.g., US, UK), which emphasize independent personal experience and rational evaluation, prioritize enhancing personalized experiences and user autonomy, such as highlighting user customization modules and enabling efficient interaction modes. Such culturally sensitive differentiated strategies enhance product competitiveness and user satisfaction in global markets.

Overall, this study systematically analyzes antecedents and consequences of AI assistant user trust, enriching and expanding literature on user trust in AI technology applications and providing empirical support for AI assistant product design and user behavior. By exploring heterogeneity causes from cultural background and usage scenario perspectives, it offers guidance for AI technology development. However, limitations remain: (1) Despite academic attention to AI assistant user trust, the sample size is limited with relatively few Chinese articles; future research should include more literature for deeper analysis; (2) This study examined only partial moderating factors; further verification of other potential heterogeneity-causing variables is needed.

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Note: Figure translations are in progress. See original paper for figures.