# FROM BIAS TO BELIEF: A META-ANALYSIS OF USER TRUST IN CHATBOT ADOPTION AND ITS ANTECEDENTS

Fengyang Zhang
School of Management
Shandong University
Jinan, Shandong, China 250100
202100271033@mail.sdu.edu.cn

Yichen Li
School of Information
Renmin University of China
Beijing, China 100872
lyc_flyxwlkq@163.com

Dongfang Sheng[1]
School of Management
Shandong University
Jinan, Shandong, China 250100
dfsheng@sdu.edu.cn

**ABSTRACT**

This study aims to present a comprehensive framework elucidating the trajectory from trust establishment to user adoption intention of chatbots. Through a quantitative analysis of the role of trust in user adoption intention of chatbots, we seek to reconcile and clarify inconsistencies found in previous research and evaluate the robustness of its antecedents. In total, 54 papers comprising 18,707 samples were summarized through the meta-analysis. We categorized trust antecedents based on the Heuristic Systematic Model, subsequently dissecting trust into cognitive and emotional dimensions to scrutinize their impact on user adoption intention. The findings indicate that among systematic factors, chatbot competence and risk exhibit strong correlations with emotional trust, whereas competence and personalization are positively correlated with cognitive trust. All heuristic factors (anthropomorphism, social presence, social influence) demonstrate relatively strong positive correlations with both cognitive and emotional trust. The interaction between emotional and cognitive trust is affirmed, with trust significantly fostering user adoption intention of chatbots. Moreover, this study tests the moderating effect of sample characteristics (culture, IT penetration), chatbot features (text-driven vs. voice-driven, task-oriented vs. conversation-oriented), and usage industry. Theoretical contributions and practical implications are also derived toward the end.

Keywords: Chatbot trust; Chatbot adoption; Meta-analysis; Heuristic systematic model; Trust

## 1. Introduction

Chatbot is a typical form of human-computer interaction service, which originally appeared as a self-service technology, responding to users' needs with predefined content according to predefined rules (Shumanov & Johnson, 2021). With the rapid development of artificial intelligence (AI) technology, chatbots are now regarded as intelligent agent technology, a dialogue system supported by natural language processing, machine learning, and Big Data analytics (Q. Chen et al., 2023).

AI-driven chatbots, empowered by robust computational capabilities, enabling real-time responses and continuous enhancements via the development of sophisticated human-computer interaction technologies, are fundamentally reshaping various industries (B. Li et al., 2023). In the e-commerce industry, chatbots deployed in customer service centers exhibit a capacity for more precise and timely responses to customers' queries (Lin et al.,

---

**Cite**: Zhang, F., Li, Y., & Sheng, D. (2025, July). From bias to belief: A meta-analysis of user trust in chatbot adoption and its antecedents. *Journal of Electronic Commerce Research, 25(3).*

[1] Corresponding author.

2023). Esteemed brands and major platforms such as eBay and Amazon have embraced chatbot-based customer service (X. Cheng, Bao, et al., 2022). Forecasts anticipate retail sales via chatbots to soar to $112 billion by 2023 (X. Wang et al., 2022). In healthcare, as outlined in the Global AI in Healthcare Market Report for 2016-2027, more than 90% of healthcare providers worldwide will have embraced AI cognitive technologies to assist patients by 2025 (Radić et al., 2022). In the educational sphere, leveraging chatbots can assist educators in streamlining their tasks, enhancing efficiency, and providing tailored technical support for personalized education and training (Deng & Yu, 2023). To sum up, an increasing number of companies and organizations are embracing chatbot technology to deliver superior services.

The rapid expansion of the chatbot's application domain has brought forth concerns regarding inaccuracy, privacy, bias, and data security (Bouhia et al., 2022; Hassani & Silva, 2023; Van Dis et al., 2023). In addition, the performance of chatbots falls short of fully meeting human needs, posing a hurdle to widespread user adoption (Mostafa & Kasamani, 2022). Previous studies revealed that users still prefer interacting with human interlocutors, implying that users are not entirely inclined to entrust chatbots with urgent or intricate situations at present (Edwards et al., 2021; Lei et al., 2021; Piçarra et al., 2016). Across various industries such as finance, healthcare, travel, and retail, the adoption of chatbots by users remains lower than industry projections (Prakash et al., 2023). User reluctance towards embracing AI technologies stands as a further impediment to their development. A harmonious amalgamation of human expertise and AI constitutes a pivotal assurance for the advancement of AI technologies (Kreps et al., 2023). Consequently, comprehensive exploration into the mechanisms underlying user adoption intentions toward chatbots can significantly contribute to their widespread acceptance and implementation. This, in turn, holds the potential to bolster productivity, expedite industry-wide digital transformation, and fortify the sustainability of enterprises (Rafiq et al., 2022).

The significance of trust in predicting the utilization of diverse information systems has garnered support from prior research, spanning the adoption of mobile commerce, blockchain technology, and AI technology (Pal et al., 2022). User trust is recognized as a pivotal determinant in the adoption of information systems (Alagarsamy & Mehrolia, 2023). In particular, user trust in chatbots may be more important to their success due to the complex and non-deterministic nature of AI behavior (Jiang et al., 2023; Pantano & Pizzi, 2020). Trust, in this context, is often conceptualized as the degree to which users perceive the reliability and quality of a chatbot system, influencing their willingness to adopt and subsequent behaviors (Hsiao & Chen, 2022; Nguyen et al., 2021). Komiak & Benbasat (2006) proposed a model of cognitive and emotional dimensions, dividing trust into cognitive trust and emotional trust. Cognitive trust involves users' confidence in the reliability and quality of chatbot systems (Q. Chen et al., 2023). In contrast to cognitive trust, emotional trust is shaped by irrational factors and introduces a more subjective element (Gillath et al., 2021). It is based on users' experiences during interactions with service providers and is influenced by subjective emotions (Johnson & Grayson, 2005). Several studies have delved into emotionally driven trust between humans and technology as well, recognizing its significance in enhancing the adoption intention of chatbots (Gkinko & Elbanna, 2023; Hoff & Bashir, 2015; Lappeman et al., 2023).

However, the complexity and unpredictability of AI technology complicate the process of building trust (Schuetz & Venkatesh, 2020). Unlike the establishment of interpersonal relationships in social interactions, users' engagement with chatbots is fundamentally influenced by the distinction between the chatbot itself and living beings, rendering the development of human-AI trust a complex task (Omrani et al., 2022). Consequently, there exists a pressing need for more comprehensive research into the intricacies of building trust within the context of AI technology.

Many scholars have explored the antecedents of user chatbot trust. Nordheim et al. (2019) earlier developed an initial framework of trust antecedents, which categorized the factors associated with user trust in customer service chatbots into three distinct groups: chatbot-related factors, context-related factors, and user-related factors. Subsequent to this foundational work, additional research has enhanced our understanding of the antecedents of trust in chatbots. Some scholars have incorporated more established models into the study of user trust, such as the TAM and TRA models (J. Mou & Benyoucef, 2021). However, there is still a lack of a unified standard in the academic community regarding the specific antecedent factors influencing trust. Variables such as anthropomorphism, social presence, social influence, privacy and security, and system personalization are gradually being included in the research (Hsiao & Chen, 2022; Jiang et al., 2023; Y. Liu et al., 2022; Moussawi et al., 2021). Yet, these complex factors affecting trust still lack support from a theoretical framework.

However, previous research on the role of trust in chatbots and their antecedents has shown many inconsistencies. First, there is a lack of consensus on the classification criteria of trust (unidimensional vs. multidimensional). Specifically, some existing studies consider trust as a unidimensional concept (De Cicco et al., 2021; Shin et al., 2022), while other studies delve into its internal structure and classify trust from different perspectives. For example, some studies classify trust based on its object, distinguishing between trust in technology and trust in service providers (Kuen et al., 2023). Other studies classify trust based on its own characteristics, dividing it into cognitive trust and emotional trust (Lappeman et al., 2023). Second, there are inconsistencies in the causal relationships between trust and other variables across different models. For instance, Tanihatu et al. (2023) considered perceived risk, expected performance, and social influence as factors that, alongside trust, affected user adoption intention, while other studies suggested that these variables were antecedents influencing trust (Alagarsamy & Mehrolia, 2023; Hsiao & Chen, 2022). Third, there is inconsistency in both the magnitude and direction of the correlations between variables found in different studies. For instance, regarding security risk factors, (Patil & Kulkarni (2022) argued that technological security risks did not significantly affect trust beliefs, whereas (Alagarsamy & Mehrolia (2023) asserted that privacy and security issues might have a significant negative impact on trust in chatbots. Besides, given the differences in samples, chatbots, and industries studied, the conclusions in the literature also vary.

Given the extensive body of research investigating the pivotal role of user trust in chatbot adoption intention and its underlying determinants, a systematic review of existing literature becomes imperative. Nonetheless, these existing efforts encounter limitations stemming from three primary areas: First, many studies lack rigorous quantitative reviews (Glikson & Woolley, 2020a; Zierau et al., 2021). A meta-analysis focusing on chatbots and exploring the antecedents and consequences of user trust is missing. Second, there is a lack of a cohesive overall framework that can comprehensively describe the mechanisms influencing trust-building, especially regarding a precise summary of the antecedents of trust formation (Hancock et al., 2021; J. Mou et al., 2017; Sarkar et al., 2020). Specifically, some variables that have been shown to potentially impact the establishment of user trust are absent from meta-analyses. Third, although there are many potential moderating factors that need to be investigated, the existing literature does not comprehensively address the selection of these moderating factors, with some valuable variables for further exploration missing from prior research (Khamitov et al., 2023; Y. Kim & Peterson, 2017; K. Wu et al., 2011). Hence, there is an imperative need to integrate research frameworks concerning the role of trust in users' chatbot adoption intention and its antecedents, as well as to reconcile prior findings. Accordingly, the specific objectives of this study are outlined as follows:

(1) Delineate a holistic and comprehensive framework that elucidates the entire trajectory from the establishment of trust to the user's intention to adopt chatbots, offering valuable insights for future researchers.

(2) Harmonize and clarify inconsistencies found in previous studies by conducting a quantitative analysis of the role of trust in users' chatbot adoption intention and assess the robustness of its antecedents.

(3) Explore potential moderators that may account for variations in the strength of the relationship between trust and user chatbot adoption intention across different studies.

Table 1: Review of meta-analyses related to trust in online environments.

| Title | Authors | Object of study | Classification of trust | Moderator |
|---|---|---|---|---|
| Trust in the financial services context: a meta-analysis | (Santini et al., 2023) | Financial services | One dimension | Cultural effects<br>HDI<br>Innovation index<br>Device type |
| Who earns trust in online environments? A meta-analysis of trust in technology and trust in provider for technology acceptance | (Kuen et al., 2023) | Online shopping<br>online banking<br>e-health | Trust in technology,<br>Trust in provider | - |
| Evolving Trust in Robots: Specification Through Sequential and Comparative Meta-Analyses | (Hancock et al., 2021) | Robots | Human factors,<br>Robot factors,<br>Contextual factors | - |
| Trust in Artificial Intelligence: Meta-Analytic Findings | (A. D. Kaplan et al., 2023) | Artificial intelligence | Human, AI, Contextual | - |

| | | | | |
|---|---|---|---|---|
| A Meta-analysis on Children's Trust in Social Robots | (Stower et al., 2021) | Social robots | Social Trust, Competency Trust | Age<br>Interaction Type<br>Interaction Length<br>Robot Type<br>Robot Operation<br>Robot Related Factors<br>Type of Measure |
| Trust and online purchase intention: a systematic literature review through meta-analysis | (Bulsara & Vaghela, 2023) | Online purchase | Trust in website, Trust in e-retailers | - |
| A Meta-analysis of Online Trust Relationships in E-commerce | (Y. Kim & Peterson, 2017) | E-commerce | One dimension | Study design<br>Website type<br>Type of items used to measure the trust Construct |
| A meta-analysis of antecedents and consequences of trust in mobile commerce | (Sarkar et al., 2020) | Mobile commerce | One dimension | Culture |
| Consumer Trust: Meta-Analysis of 50 Years of Empirical Research | (Khamitov et al., 2023) | - | One dimension | Year<br>Target of trust<br>Type of attribute |
| Trust and risk in consumer acceptance of e-services | (J. Mou et al., 2017) | E-services | One dimension | Student sample<br>Culture<br>Type of e-service<br>Year<br>Object of trust |
| A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type | (K. Wu et al., 2011) | Technology | One dimension | Subject type (students or non-students) Context type (commercial or non-commercial) |
| A meta-analysis of trust in mobile banking: the moderating role of cultural dimensions | (Kumar et al., 2023) | Mobile banking | One dimension | Power distance<br>Individualism-collectivism<br>Masculinity-femininity<br>Uncertainty avoidance |
| Trust and Consumers' Purchase Intention in a Social Commerce Platform: A Meta-Analytic Approach | (J. Wang et al., 2022) | Social commerce platform | One dimension | Trust object<br>Website type<br>Social commerce constructs |
| Understanding the effects of trust and risk on individual behavior toward social media platforms: A meta-analysis of the empirical evidence | (Y. Wang et al., 2016) | Social media platforms | One dimension | Culture<br>Trust objects<br>Platform type |
| The Impact of Trust and Recommendation Quality on Adopting Interactive and Non-Interactive Recommendation Agents: A Meta-Analysis | (Ebrahimi et al., 2022) | Recommendation Agents | One dimension | - |
| Consumer trust in e-commerce web sites: A | (Beatty et al., 2011) | E-commerce web sites | One dimension | - |

meta-study

Compared to existing meta-analyses on similar topics, which is presented in Table 1, our paper presents several innovative points: First, we are the first to conduct a meta-analysis in the field of chatbots that distinguishes between emotional trust and cognitive trust to summarize the factors influencing the establishment of user trust and its impact on adoption intention. We firmly believe that a detailed analysis of different types of trust can better elucidate the complex process of trust formation among users. Second, our selection of trust antecedents is unique. We are the first to attempt to summarize trust antecedent variables using the HSM theory in a meta-analysis. This endeavor expands the application of HSM based on previous work and validates the model's effectiveness in the field of user behavior research. Third, our study incorporates moderating variables such as sample characteristics (culture, IT penetration), chatbot features (text-driven vs. voice-driven, task-oriented vs. conversation-oriented), and usage industry. This in-depth exploration provides insights into the sources of heterogeneity in the literature, and the rich array of moderating variables significantly enhances the generalizability of our meta-analysis results, contributing substantial theoretical and practical value to the research findings.

## 2. Theoretical foundation and conceptual framework

### 2.1. User trust in chatbot adoption intention

In the context of user technology adoption, a high level of trust can help users eliminate concerns about the undesirability of the technology, thereby augmenting their inclination to adopt it (Ejdys, 2020). The important role of trust in influencing user adoption intention has been demonstrated in a variety of technological scenarios (Hua et al., 2021; Nguyen et al., 2021). Particularly for AI technologies characterized by elevated uncertainty and risk, the perception of trust assumes even greater importance in the user adoption process (S. Choi et al., 2023). Trust emerges as a crucial mechanism for mitigating complexity and uncertainty (Banerjee & Chua, 2019; Roh et al., 2023), allowing users to establish trust-based relationships with information systems through behaviors such as sharing personal information (Moussawi et al., 2021). The establishment of trust in chatbots is a prerequisite for meaningful interactions to transpire (Glikson & Woolley, 2020b; Simon et al., 2020).

In the research about user chatbot trust, scholars have given multiple definitions of trust depending on the actual context. In alignment with Komiak & Benbasat's (2006) trust-based adoption model, trust can be summarized mainly in terms of cognitive and emotional dimensions respectively. Some scholars posit that trust is rooted in cognitive constructs, grounded in users' rational comprehension and evaluation of the technology's risks and benefits (Gillath et al., 2021). This is consistently understood in research as the level of a user's confidence in the reliability, integrity, and security of the chatbot system (Mohd Rahim et al., 2022; Nguyen et al., 2021; Tanihatu et al., 2023). Several scholars contend that trust is rooted in irrational factors, implying a more subjective element (Gillath et al., 2021). Users typically draw comparisons between technology and humans when deciding whether to accept and use AI. At this juncture, users assess the emotional aspects of technology (Kyung & Kwon, 2022). Emotional trust, in this context, is grounded in the human-like qualities that AI can exhibit (Omrani et al., 2022). When users engage with a chatbot, an emotional bond is established when the chatbot demonstrates responsiveness, care, and concern. This emotional exchange forms a crucial foundation for fostering a trusting relationship (Q. Chen & Park, 2021). X. Cheng, Zhang, et al. (2022) have subdivided chatbot trust into cognitive and emotional dimensions in their study of consumer responses to the chatbot. They argue that, on one hand, the chatbot should adeptly answer complex questions in an intelligent manner to build cognitive trust with consumers. On the other hand, through human-computer dialogues, the chatbot can enhance consumers' perceived enthusiasm for the technology. Drawing on the previous literature, our exploration will delve deeper into understanding the cognitive and emotional dimensions of trust and investigate the interactions between them.

In the realm of user chatbot trust, considerable attention has been devoted to exploring the trust-building path, as evidenced by several studies delving into numerous antecedent variables and applying diverse theories to the research (O. K. D. Lee et al., 2021; Mohd Rahim et al., 2022; Patil & Kulkarni, 2022; Tisland et al., 2022). These studies contribute an abundance of theoretical references and empirical evidence, forming a robust foundation for inductive summaries regarding the antecedents of users' trust in chatbots. In summary, a substantial body of literature has delved into the pivotal role of trust in shaping chatbot adoption intentions and its underlying factors. It allows for the development of a comprehensive path model that traces the evolution of user trust formation to eventual chatbot adoption. Therefore, this study proposes a trust-mediated model to systematically explore the antecedents of chatbot trust and its consequential impact on user adoption intentions. By dissecting the dimensions of trust, we contend that both cognitive trust and emotional trust emerge as critical determinants influencing users' intentions to adopt chatbots. This nuanced approach aims to contribute a deeper understanding of the multifaceted mechanism involved in the interplay between trust and user adoption intentions in the context of chatbot technology.

## 2.2. Heuristic Systematic Model

The Heuristic Systematic Model (HSM) (Chaiken et al., 1989) serves as a primary framework for elucidating the diverse ways in which individuals process information, influenced by various factors. It underscores the dichotomy in information processing, delineating two distinct approaches: the systematic way and the heuristic way (Eagly & Chaiken, 1993). Heuristic processing paths depend on simple decision rules derived from heuristic cues such as surfaces, and intuitive features of information or sources (Petty & Cacioppo, 1986). At this point, individuals allocate diminished cognitive effort, relying more on subjective feelings for information processing (Bohner et al., 1995; Qahri Saremi & Montazemi, 2019). Conversely, the systematic processing pathway involves the meticulous examination of message content (S. Chen et al., 1999). Individuals invest heightened cognitive effort in scrutinizing the message before forming judgments. In this context, systematic cues align more closely with the objective properties of the information content.

The HSM posits that users process information through both systematic and heuristic pathways. In the context of chatbots, on one hand, if users objectively assess that a chatbot is capable, low-risk, and able to provide personalized services, this may increase their trust in the chatbot (Jiang et al., 2023; Y. Liu et al., 2022). On the other hand, if users subjectively judge that the chatbot is friendly, genuinely present, and widely praised by others, this could also enhance their trust (Go & Sundar, 2019; H.-Y. Kim & McGill, 2018). Therefore, we hypothesize that the user's trust in the chatbot is influenced by both systematic factors (competence, personalization, and risk) and heuristic factors (anthropomorphism, social influence, and social presence).

It is significant to note that the HSM has transcended its original boundaries and is now utilized to elucidate a wider array of individual behavioral processes (Chaiken et al., 1989). Firstly, the model has directed focus towards the information processing procedures across diverse platforms, including the review process in e-commerce (K. Z. K. Zhang et al., 2014), the adoption of online product information (Kang et al., 2020), and the dissemination of information on social media platforms (Z. Liu et al., 2012; Yang et al., 2022). Secondly, the HSM has proven invaluable in examining user behavior within a variety of information systems, ranging from the adoption of emerging technologies (Shi et al., 2021) to the management of access rights notifications (James et al., 2021). In the realm of AI technology studies, Shi et al. (2021) suggested that travelers evaluate AI-driven recommender systems by considering both objective characteristics and perceived experiential qualities. They utilize perceived performance and personalization as systematic cues, in contrast to anthropomorphism and social influence as heuristic cues. Y. Liu et al. (2022) explored how the personalization and expertise of chatbot responses affect users' health-related beliefs and their intentions to utilize chatbots. Personalization has emerged as a central concern for users engaging methodically with health issues, while source expertise has been highlighted as a significant heuristic element. Thus, the HSM offers a structured and transparent framework for comprehending the determinant factors, supported by an extensive body of research literature.

## 2.3. Conceptual framework

In this study, we review previous related studies and summarize the variables involved in the studies in Appendix A. Considering the requirements of meta-analysis for sample size and the reliability of conclusions (Ismagilova et al., 2020), we tabulated the number of literature for each variable and determined the final variables to be included by combining them with the HSM model. The competence, risk, and personalization are designated as systematic factors, and the anthropomorphism, social presence, and social influence are designated as heuristic factors. These selections form the basis for constructing a research framework aimed at exploring the antecedents of trust in chatbots and their consequential impact on user adoption intention. Moreover, to delve into the nuanced aspects of trust, this study further divides it into cognitive and emotional dimensions. This subdivision facilitates an exploration of their respective interactions. The resulting framework not only serves as a robust foundation for investigating the role of trust in user adoption intention but also offers a generalized structure for broader research concerning the antecedents of trust. The research model, visually represented in Fig. 1, succinctly illustrates the key components and relationships posited in this study.

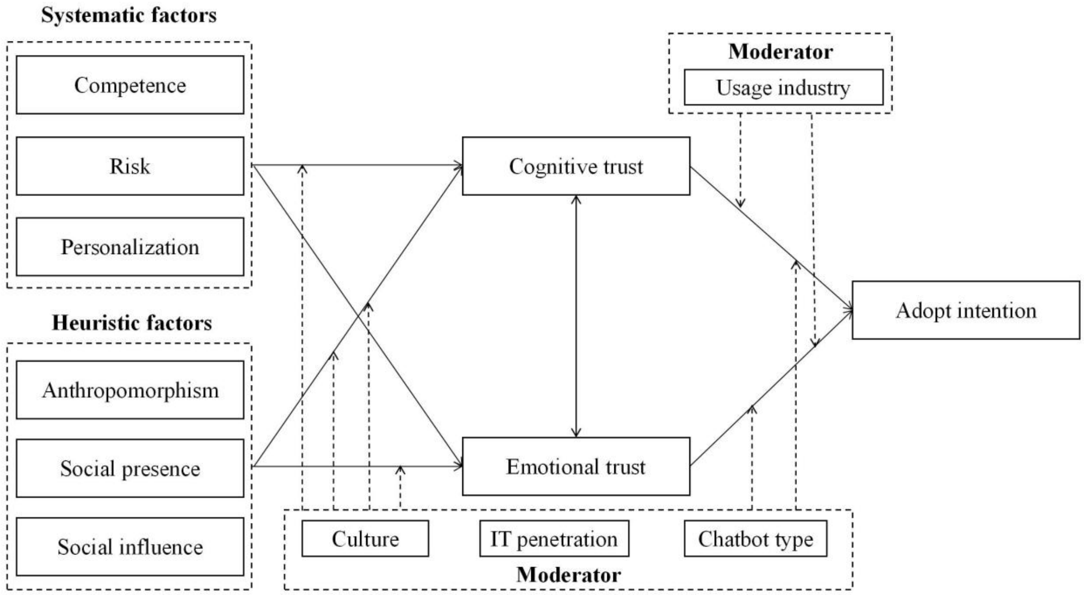


Figure 1. Research model.

2.3.1. Systematic factors

This study combines the definition of the systematic processing pathway and posits that systematic factors are closely related to the objective characteristics of information system objects (Bohner et al., 1995). We selected competence, risk, and personalization as the systematic factors in this study, for the following reasons: (1) Competence is a systematic and complex process. In previous research, competence has also been widely regarded as one of the systematic factors (Gong, 2021). (2) Risk is an objective characteristic inherent in chatbots, which can only be perceived by users after a certain depth of experience (Patil & Kulkarni, 2022). Therefore, our study considers risk as a systematic factor. (3) User perception of the chatbot's personalization requires a certain level of experience and effort, thus personalization is widely considered a systematic factor (Ait Baha et al., 2023).

2.3.1.1. Competence

Competence reflects a chatbot's ability to perform tasks and provide information accurately and reliably, which includes an evaluation of its objective characteristics such as intelligence, dexterity, and efficiency (Pizzi et al., 2023). Users invest substantial time and effort in engaging with chatbot services to procure accurate, direct, and personalized information for informed decision-making (Nguyen et al., 2021). Consequently, the competence of chatbots emerges as a pivotal factor significantly influencing users' systematic processing behavior. In Gong's research, ability is also considered a systematic factor influencing users' trust in AI-based travel route recommendation systems (Gong, 2021). Previous research has shown that initial trust stems from customers' recognition of technology's prowess in efficiently accomplishing tasks with high quality (G. Kim et al., 2009). Therefore, the competence of chatbots in delivering services and resolving issues positively impacts users' rational cognition, thereby influencing the development of cognitive trust (Jiang et al., 2023). On the one hand, the competence of chatbots to provide services and solve problems has a positive effect on users' rational cognition and thus influences the formation of cognitive trust (Q. Chen et al., 2023). On the other hand, chatbot competence also manifests in its capacity to provide empathetic value by fulfilling users' requirements. Bove (2019) mentions that technologies used in service environments can help identify consumer needs so that the chatbot can respond with empathy. Thus, the AI's adeptness in furnishing precise advice not only allows consumers to perceive the machine's superior computational and service capabilities but also engenders a sense of being understood, creating an impression that the AI chatbot genuinely cares about them. This process fosters both cognitive and emotional trust (Q. Chen et al., 2023; W. B. Kim & Hur, 2023). Thus, chatbot competence emerges as one of the fundamental factors facilitating the establishment of cognitive and emotional trust among users.

2.3.1.2. Risk

Chatbot technology introduces various risks, including technical errors and security breaches, which have the potential to compromise users' rights and interests across financial, psychological, physical, or social dimensions. In this study, risk refers to a type of characteristic element that objectively exists within the chatbot and can only be perceived by users after a certain level of in-depth experience, rather than being something users can perceive in a short period. Therefore, we categorize the variable of risk as a systematic factor (Malodia et al., 2023; Patil & Kulkarni, 2022). Mitigating these risks is essential for maintaining user trust in chatbots (Alagarsamy & Mehrolia, 2023). Firstly, when the technology makes errors and fails to accomplish the user's task, the user may lose confidence and feel frustrated with the technology, which undermines cognitive and emotional trust (Pal et al., 2022). Secondly, if the technology fails to ensure the privacy of users' personal information and the security of their data, users may perceive a vulnerability in safeguarding their rights and interests, thus undermining cognitive trust. Moreover, the insecurity experienced by users when disclosing personal information to chatbots due to potential risks can further erode emotional trust (Lappeman et al., 2023). Based on the above discussion, chatbot risk is one of the key factors hindering user cognitive and emotional trust building.

#### 2.3.1.3. Personalization

Personalized chatbots provide customized services to users and can meet customers' needs more accurately. The continual progress in data mining, machine learning, and other AI technologies has elevated personalization to a pivotal advantage of AI virtual assistants (Chung et al., 2020; W. B. Kim & Hur, 2023; B. Zhang et al., 2023). By publicly or secretly collecting users' personal information, AI systems can provide people with tailored and personalized content that precisely matches the user's characteristics, needs, and interests (Y. Liu et al., 2022), which can promote users' trust in the chatbot and thus significantly increase customer adoption (Komiak & Benbasat, 2006). Users' perception of chatbot personalization requires a certain level of experience and effort, so personalization is widely regarded as a systematic factor (Baha et al., 2023). Y. Liu et al. (2022) treated personalization as a systematic cue in their study on users' willingness to use chatbots in healthcare. In the context of mobile advertising, Shao et al. (2023) posited that personalizing perceived content is fundamental for users to process information effectively. Familiarity with an advertiser's offerings predisposes individuals to systematically review content and instills confidence in the professionalism, trustworthiness, and reliability of advertisements, thereby fostering cognitive trust. Therefore, the personalization of chatbot interactions significantly and positively influences users, facilitating the development of cognitive trust.

### 2.3.2. Heuristic factors

Heuristic factors are intricately connected to individuals' subjective experiences. Elements such as intuitive perceptions and social interaction factors are considered integral components of heuristic cues (Fu et al., 2020). In this study, anthropomorphism, social presence, and social influence are selected as heuristic factors, for the following reasons: (1) Anthropomorphism is closely related to users' intuitive perceptions during human-computer interactions and has been regarded as a heuristic cue in several studies (Shi et al., 2021). (2) Social presence, rooted in communication theory, falls within the category of social interaction factors and can also be considered a heuristic cue (Skalski & Tamborini, 2007). (3) Social influence can shape user behavior through heuristic cues in social interactions and is similarly regarded as a heuristic factor (Zhao, 2023).

#### 2.3.2.1. Anthropomorphism

Anthropomorphism, which can be categorized into linguistic and visual forms, pertains to AI possessing certain human characteristics, such as appearance or speech style. This transformation enables human-computer interaction to resemble human-to-human interaction (Cai et al., 2022; Liang et al., 2021; Lu et al., 2019). Anthropomorphism is closely related to the intuitive perception of the user during human-computer interaction, so this study treats anthropomorphism as a heuristic cue. In recent years, there has been an increasing amount of literature researching non-human products like chatbots, and anthropomorphism is widely regarded as a heuristic factor in the HSM model (Shi et al., 2021; Touré-Tillery & McGill, 2015; Zhao, 2022). The literature suggested that when chatbots exhibit behaviors more akin to humans and provide increased social cues, users' social responses are heightened (Y. Mou & Xu, 2017). This, in turn, mitigates users' concerns about the adoption of new technologies and fosters enhanced trust beliefs (Kim & McGill, 2018). On one hand, linguistic anthropomorphism may imbue clients with the perception that chatbots possess capabilities, benevolence, and honesty through their communication methods and anthropomorphic expressions. On the other hand, visual anthropomorphic designs can cultivate an environment where customers feel as though they are interacting with trustworthy individuals (Klein & Martinez, 2022). Pal et al. (2022) defined users' trust affected by anthropomorphism as emotional trust, arguing that anthropomorphism enables human-machine exchanges with social traits, such as politeness, humor, or empathy, thus facilitating human-machine bonding. Further insights emphasize that anthropomorphism operates by influencing perception across both cognitive and emotional dimensions (Q. Chen & Park, 2021).

#### 2.3.2.2. Social presence

Social presence, rooted in communication theory, denotes the prominence of an individual's existence within social exchanges and the significance of interpersonal connections (Short et al., 1976), falling under the umbrella of social interaction factors. Skalski & Tamborini (2007) have explored social presence as a heuristic cue in investigations concerning the persuasive impact of media messages, asserting that it embodies a condition where a virtual social actor is perceived akin to an actual human counterpart. This conceptualization has been widely used in research on chatbots. Human-robot interactions engender a sense of social presence among users (J. Lee et al., 2022), signifying that chatbots can establish a psychological rapport with users (Yen & Chiang, 2021), a facet known to be pivotal in fostering positive attitudes and behaviors. Strong bonds foster a sense of greater emotional intimacy among users, subsequently enhancing trust (Go & Sundar, 2019; Shumanov & Johnson, 2021). Consequently, technologies that evoke social presence within users are more likely to instill trust (Ogonowski et al., 2014; Yen & Chiang, 2021). Regarding chatbots, social presence can forge an emotional connection between humans and machines, shaping users' perception of the chatbot's proficiency in social interaction, thereby fostering both emotional and cognitive trust. Therefore, social presence significantly and positively influences users to build cognitive trust and emotional trust.

#### 2.3.2.3. Social influence

Social influence encompasses the impact of a user's social environment, including the opinions of their relatives and friends (Mostafa & Kasamani, 2022), and can shape user behavior through heuristic cues in their social interactions. According to the preliminary Unified Theory of Acceptance and Use of Technology (UTAUT), social influence stands out as a core factor predicting behavioral intentions regarding the adoption of specific technologies (Henkel et al., 2023). In the rapidly evolving realm of AI technology, societal acceptance is not universal, with certain AI forms facing resistance from individuals and society at large (F. Kaplan, 2004). Positive social influences at this time help users feel less uncertainty in the face of unknown technologies (Oldeweme et al., 2021). Z. Zhang et al. (2023), in their study of social media relationship strategies, highlighted that the internalization and identification functions of social influence mediate users' information processing. Online pro-social relationship maintenance strategies, characterized by positivity and supportiveness, were found to significantly enhance customers' cognitive and emotional trust. Therefore, the social environment in the context of chatbots similarly influences user trust (M. Cheng, Li, et al., 2022). Positive social influence helps to stimulate congruence and identification between users and chatbots and facilitates users' emotional pleasure when interacting with chatbots, which influences cognitive trust and emotional trust. Therefore, social influence can significantly and positively influence users to build cognitive trust and emotional trust.

### 2.3.3. Cognitive trust and emotional trust

According to Komiak & Benbasat's (2006) trust-based adoption model, emotional trust fundamentally differs from cognitive trust. Whereas, the decision-making process of user adoption often involves the simultaneous establishment of cognitive and emotional trust (Johnson & Grayson, 2005). Therefore, it can be postulated that there is a correlation between cognitive trust and emotional trust. On the one hand, some scholars believe that cognitive trust is the forerunner of emotional trust (Johnson & Grayson, 2005; Zhang et al., 2010). They argue that it is only after establishing cognitive trust that relationships between users and information systems can form, paving the way for emotional connections (Chih et al., 2017). On the other hand, some researchers believe that cognitive trust is influenced by emotional trust. Shi et al. (2021) used HSM to elucidate the relationship between cognitive trust and emotional trust in their study on the use of traveling artificial intelligence agents. The bias effect of HSM implies that heuristics based on people's subjective feelings can influence people's systematic processing by affecting their expectations about the validity of the information. Wan et al. (2020) also argued in their study of online patient counseling that emotional trust enhances the positive effect of cognitive trust on users' willingness to choose a service. Thus, there might be an interactive relationship between users' cognitive trust and emotional trust in the context of chatbot technology adoption. While cognitive trust promotes a stronger emotional connection between humans and computers, emotional trust contributes to the actual development of cognitive trust by increasing users' expectations of chatbot technology performance. Based on the above discussion, there should be a significant correlation between users' cognitive trust and emotional trust.

### 2.3.4. Trust and chatbot adoption intention

To investigate the pivotal role of trust in fostering user adoption intention of chatbots, this study draws upon the model proposed by Komiak & Benbasat (2006), specifically focusing on the cognitive and emotional dimensions of trust. In various contexts related to the adoption of AI technology, researchers have offered nuanced definitions for cognitive and emotional trust. Furthermore, they have delineated a process through which these two dimensions of trust intricately influence users' adoption intentions. For example, Shi et al. (2021) posited that users expend significant cognitive effort in evaluating the validity and risks associated with recommendations, thereby establishing cognitive trust. This cognitive trust then becomes instrumental in the decision-making process of adopting an AI recommendation system. On the other hand, emotional trust is viewed as relatively irrational, which typically leads to positive attitudes toward the technology, and subsequently impacts adoption behavior (Gursoy et al., 2019). Thus, the establishment of user cognitive and emotional trust can significantly contribute to users' chatbot adoption intention.

2.3.5. Moderator

Currently, many scholars have investigated various moderator variables that could explain heterogeneity between literature in the context of artificial intelligence products such as chatbots, which include sample characteristics (J. Mou et al., 2017; Said et al., 2023) and chatbot features (Y. Cheng et al., 2023), among others. However, despite these investigations, there remain several moderating variables that warrant further exploration and examination (Alsharhan et al., 2023; Ladeira et al., 2023). This study categorizes moderating variables into three main categories: sample characteristics (such as cultural and IT penetration), the usage industry, and the characteristics of the chatbot itself (including conversational dialog systems vs. task-oriented dialog systems, and text-based chatbots vs. voice-based chatbots).

Firstly, prior research highlights that cultural background plays a crucial role in shaping people's attitudes and behavioral responses toward new technologies, including chatbots (Hofstede, 1984). As culture evolves, it profoundly impacts our research samples through factors such as religion, philosophy, social structure, and values (Saaida, 2023). For example, cultural orientations toward individualism and collectivism in Eastern and Western contexts can influence how people perceive chatbots. In Eastern cultures, which emphasize collectivism, chatbots may be more readily accepted as integral parts of society (Lomas et al., 2023). In contrast, Western cultures, with their focus on individualism, may lead to higher expectations for chatbots' independence and autonomy (Belda-Medina & Kokošková, 2023). Shin et al., (2022) indicated that Japanese users prioritize the functional attributes of chatbots, while American users tend to focus on the non-functional aspects of chatbot algorithms.

Apart from cultural factors, the country's information technology (IT) penetration rate may also play a moderating role in the relationships between variables. In countries where IT is relatively widespread, the public's adaptability to and acceptance of new technologies, such as chatbots, may be higher (Zhou et al., 2023). Conversely, in countries where IT is not widely adopted, subjective factors, such as social presence (e.g., evaluations from those around them), might have a greater impact on users' decisions to adopt chatbot services (Lema et al., 2021). In other words, in these countries, the adoption process of chatbots may be more influenced by heuristic factors rather than systematic ones.

Chatbot technology finds applications across various industries, catering to diverse user needs and expectations within distinct environments. Because chatbots have different roles and interact with multiple types of clients in different industries, they often exhibit different characteristics and functionalities. These differing functionalities elicit diverse performance expectations from users, thereby influencing their behavioral patterns (H. Chen et al., 2017). Meng et al. (2022) highlighted that user-specific health anxiety in mHealth contexts augments the significance of cognitive trust while diminishing the impact of emotional trust on sustaining intentions towards conversational robotic services. At the same time, Kyung & Kwon (2022) points out that for services such as travel and education, users tend to rely more on the affective signals of the provider, as there is a lack of objective evidence and the necessary knowledge to evaluate the performance of the service. Thus, the characteristics of user needs in different application industries influence the relationship between user trust and user adoption intention (Gefen et al., 2008). Therefore, our study aims to reveal the differences in the process through which users transition from establishing two types of trust to adopting services across different usage industries.

Finally, the characteristics of the chatbot itself may also play a crucial role. For example, depending on the different application scenarios of AI dialog systems, these systems can be classified into conversational dialog systems and task-oriented dialog systems (McTear, 2021). Task-oriented dialog systems assist with tasks such as product searches and hotel reservations (Z. Zhang et al., 2020), while conversational dialog systems engage in open-domain interactions with humans (Ferreira et al., 2022). Users' perceptions and the process of building trust may vary depending on the specific dialog functionalities of the chatbot. Additionally, chatbots can be categorized as text-based or voice-based (Adamopoulou & Moussiades, 2020; Rajaobelina et al., 2021). The sensory experiences of visual versus auditory inputs differ, which may also influence the complex relationships between variables (Go & Sundar, 2019).

## 3. Method

3.1. Meta-Analysis

In 1976, Glass (1976) defined meta-analysis as “a statistical method that systematically and quantitatively integrates previous research results”. The main advantage of meta-analysis is that it can comprehensively analyze and compare the results of different studies under the same theme. A larger sample can be obtained by meta-analysis, making the conclusions more convincing.

3.2. Search Strategy

Following the PRISMA guidelines (Liberati et al., 2009), we adopted a systematic approach to identify relevant articles for this study. This research delves into the causation and repercussions of people's trust in chatbots, with ("Chatbot" OR "Bot" OR "ChatGPT") AND "trust" AND ("Adoption" OR "Use" OR "Acceptance" OR "Behavioral intention") selected as the search terms. The following databases were used for searching English articles: Web of Science, Wiley, Science Direct, SAGE, Taylor and Francis, and Emerald. As for searching Chinese academic articles, we used the CNKI database, one of the most professional academic databases in China. The initial search resulted in 2210 articles. We executed the subsequent steps to refine the selection of relevant articles.

Initially, 208 duplicate articles were eliminated from the dataset, considering the possibility of articles being duplicated across multiple databases. Subsequently, we scrutinized the titles and abstracts of the remaining papers for further refinement, excluding articles falling into the following categories: (1) Qualitative/review/conceptual articles. (2) Articles relying on secondary data. (3) Articles lacking measurement of the chatbot's credibility. (4) Articles published in languages other than English or Chinese. Following these filtering criteria, 445 articles qualified for the subsequent stage. We examined the full text of each article, ensuring: (1) The article was an empirical study. (2) The article reported the requisite effect size, such as sample size and correlation coefficients. (3) Data from the study were used only once in the meta-analysis. In cases where the same data appeared in both a journal and conference paper simultaneously, we opted for a single inclusion to prevent redundancy.

Our final sample encompasses 54 studies, comprising 48 English articles and 6 Chinese articles. The flow chart in Fig. **2** illustrates the article's identification and selection process. Appendix B provides the profiles and summary of studies used for the analysis.

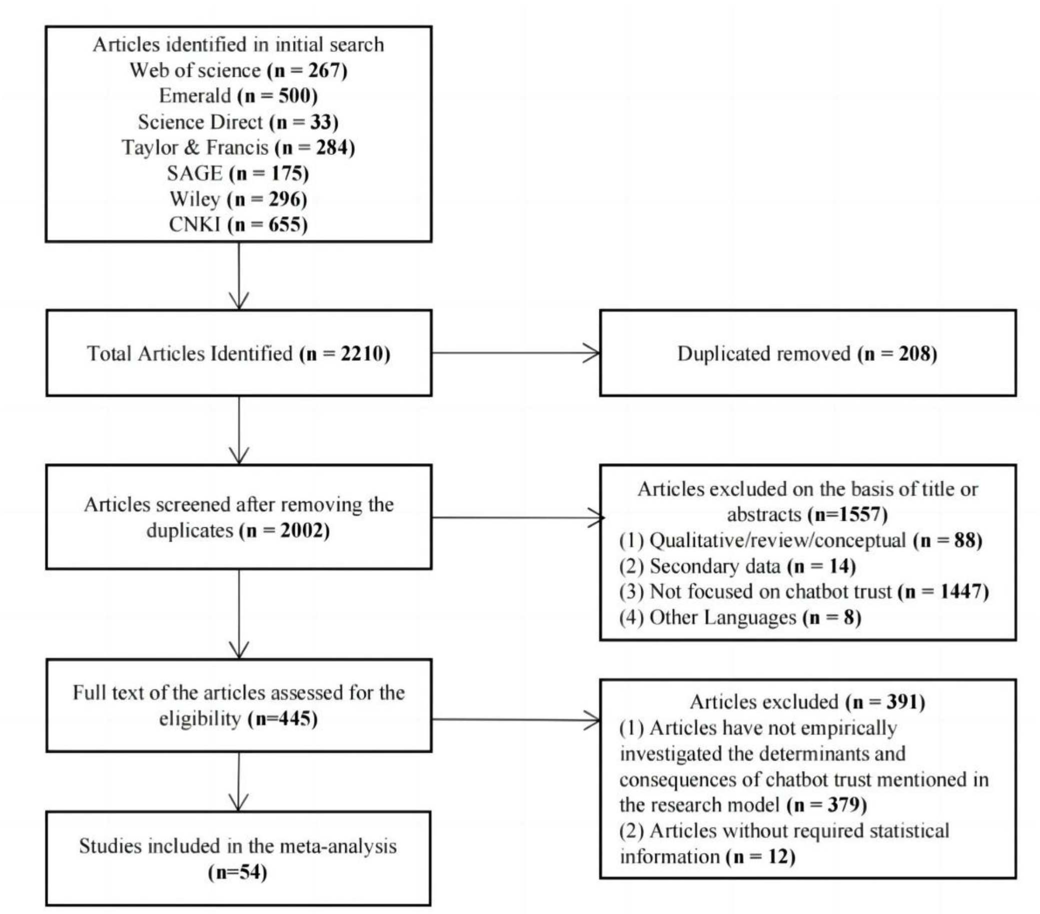


Figure 2. Flow chart for studies identification and selection.

3.3. Coding and effect size integration

As depicted in Appendix B, the 56 sample sets extracted from 54 articles underwent encoding across 7 dimensions: code number, authors and publication date, number of variables, sample size, type of trust, whether it pertains to an e-commerce context, and chatbot usage industry. To articulate the relationship between chatbot trust and other variables, we selected the correlation coefficient (r) as the standardized effect size. Widely endorsed in meta-analysis studies (Lipsey & Wilson, 2001; J. Wu et al., 2023; Yan et al., 2021), the correlation coefficient serves as a robust metric, offering a nuanced measure of the strength of the influence of determinants and facilitating the synthesis of findings.

Additionally, we have followed the recommendation of Jeyaraj & Dwivedi (2020) to try to obtain the original correlation coefficients provided by the study to avoid bias in the conversion of statistics.

Throughout the encoding process, we adhered to the following protocols to uphold the independence of the literature samples: (1) In cases where an article presented multiple independent samples to derive effect values, we coded each independently. (2) If an article subdivided a variable to furnish multiple effect sizes or if variables were categorized into distinct dimensions for discussion, we included the effect size post-averaging (Jeyaraj & Dwivedi, 2020).

Besides, different studies may have different conceptualizations of determinants and causal variables, and meta-analysis requires mapping different forms of conceptualization to the construct variable framework (Li, 2023). After a collective discussion among the three researchers, this paper integrates and categorizes the literature based on a unified standard coding scheme for variable definitions, and the results of research constructs categorization are shown in Appendix C.

3.4. Moderator coding

As previously mentioned, we selected three categories of moderating variables: sample characteristics, usage industry, and chatbot features. In this study, we used subgroup analysis to examine categorical variables and meta-regression to analyze continuous variables.

Firstly, we compiled the sample countries from each study and categorized them into Eastern cultures (e.g., China, India, Korea) or Western cultures (e.g., the United States, Canada, Italy). Additionally, we obtained the percentage of internet users in various countries for 2022 from the *International Telecommunication Union (ITU) World Telecommunication/ICT Indicators Database*, using this as an indicator of IT penetration. Detailed data can be found in Appendix B.

Secondly, we chose the usage industry of chatbots as the moderating variable. Specifically, our investigation initially delved into determining whether the chatbot's usage industries were within the realm of e-commerce. After excluding some categories with insufficient sample sizes (k<2), we further categorized these industries into 8 distinct categories. Table 2 furnishes a comprehensive description along with an illustrative example of the moderator variables.

Table 2: Moderator coding.

| Moderator | Name | Description | Example |
|---|---|---|---|
| Is (not) an e-commerce situation | In e-commerce situation | Electronic commerce (e-commerce) refers to companies and individuals that buy and sell goods and services over the Internet (Bloomenthal, 2023). | Customer service chatbot in Amazonas |
| | Not in an e-commerce situation | Industries that do not belong to e-commerce situations. | Offline supermarket waiter chatbot |
| Chatbot Usage Industries | Online Retailing | It is an electronic form of shopping for goods from online stores where buyers and sellers meet virtually and create a marketplace (e.g. jd.com).<br>Note: In this article, online retailing does not include service transactions (such as ordering hotel rooms). | Marketing chatbot in JD |
| | Hotels & Tourism | It includes online travel agencies (OTA) (e.g. hotels.ctrip.com), travel route planning systems (e.g. Google Trips), and hotel and catering industries. | Hotel service chatbot |
| | Financial Industry | It refers to the special industries dealing in financial commodities, including banking, insurance, trust, securities, and leasing industries. | Chatbot in online banking |
| | Media | It includes print media (newspapers, magazines, periodicals, etc.) and electronic media (radio, television, news websites, etc.). | Chatbot for searching news |
| | Education | It refers to the collection of educational products and organizations that provide educational services. | Teaching chatbot |

| Moderator | Name | Description | Example |
|---|---|---|---|
| | Medical and Health | It provides the public with a collection of products (goods and services) directly or closely related to health. | Chatbot for answering medical questions |
| | Personal Assistant | It is an intelligent system developed based on artificial intelligence technology that can help users complete various tasks and provide various services. | Siri |
| | Inside the Enterprise | Chatbot used by employees within the enterprise. | Office assistant chatbot |

Finally, we classified the chatbots in the literature into conversational dialog systems versus task-oriented dialog systems, and text-based chatbots versus voice-based chatbots. Detailed data on these classifications can also be found in Appendix B.

3.5. Meta-analysis procedures

We chose to conduct the meta-analysis through CMA software, which is one of the most widely used software for conducting meta-analysis of business management studies (Brüggemann & Rajguru, 2022). This analytical approach offers the flexibility of employing either a fixed-effect or random-effect model. The fixed-effect model presupposes a uniform effect size across all studies included in the analysis, whereas the random-effect model allows for variability in the true effect size from one study to another (Borenstein et al., 2010). Given our assumption that differences in sample characteristics, types of chatbots, and usage industries may lead to significant variations in effect sizes between articles, we opted for a random effects model to evaluate the correlation coefficients among the variables. Considering the substantial differences in sample sizes (N) across different studies, our research utilized a weighted average of correlations (Hunter & Schmidt, 2004; J. Mou et al., 2017). The purpose of the weighted average correlation is to correct sampling errors in order to obtain more accurate estimates. This method weights the correlation for each study according to the following formula:

$$\mathrm{r}_{+} = \frac{\sum \mathrm{N_i r_i}}{\sum \mathrm{N_i}} \tag{1}$$

where $\mathrm{N_i}$ is the sample size of each study and $\mathrm{r_i}$ is the observed correlation value of each study. In addition, we calculated the confidence intervals. Significant correlation means that the confidence interval does not include 0. We used the Q-test and $\mathrm{I}^2$ test to determine whether the studies included were homogeneous (Huedo-Medina et al., 2006; Jackson et al., 2012). To conduct a homogeneity test, the Fisher Z transformation was applied using the formula:

$$z_{r_i} = 0.5 \times \ln\left(\frac{1 + r_i}{1 - r_i}\right) \tag{2}$$

Then, Homogeneity Q was calculated using the formula:

$$Q = \sum_{i=1}^{k} (w_i)(z_r')^2 \tag{3}$$

$$z_r' = \frac{\sum_{i=1}^{k} w_i z_{r_i}}{\sum_{i=1}^{k} w_i} = \frac{\sum_{i=1}^{k} (\mathrm{N_i} - 3) z_{r_i}}{\sum_{i=1}^{k} (\mathrm{N_i} - 3)} \tag{4}$$

Finally, we used Egger regression to assess the publication bias of the included articles and performed additional robustness analyses on the results (Egger et al., 1997).

## 4. Results

4.1. Heterogeneity and publication bias

The heterogeneity test is an essential part of a meta-analysis. Heterogeneity is the fact of consisting of parts or things that are very different from each other, which refers to the intergroup variance between different studies (Ryan, 2014). As stated above, we used the Q-test and $\mathrm{I}^2$ test to determine whether the studies included were homogeneous. The results of the heterogeneity test are given in Table 3. Consistent with our expectations, except for COM-ET ($p=0.192$, $\mathrm{I}^2=34.34$) and SI-CT ($p=0.217$, $\mathrm{I}^2=34.52$), all relationships among variables exhibited significant heterogeneity ($p<0.05$, $\mathrm{I}^2>75$). This shows the presence of heterogeneity between the studies. Furthermore, the results of the heterogeneity test affirm the appropriateness of applying the random-effects model.

Table 3: Results of heterogeneity test.

| Assumption | K | N | Q-test | | | | Tau-squared | | | | Egger regression | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Q-value | df (Q) | P-value | I-squared | Tau-Squared | SE | Variance | Tau | Intercept | P-value |
| COM - CT | 11 | 2790 | 93.692 | 10.000 | <0.001 | 89.327 | 0.035 | 0.020 | <0.001 | 0.186 | 4.999 | 0.096 |
| COM - ET | 5 | 1466 | 6.092 | 4.000 | 0.192 | 34.342 | 0.002 | 0.004 | <0.001 | 0.044 | 2.868 | 0.242 |
| PR - CT | 6 | 1868 | 77.407 | 5.000 | <0.001 | 93.541 | 0.049 | 0.036 | 0.001 | 0.221 | 7.967 | 0.196 |
| PR - ET | 2 | 700 | 4.551 | 1.000 | 0.033 | 78.025 | 0.011 | 0.020 | <0.001 | 0.104 | - | - |
| PE - CT | 3 | 923 | 10.654 | 2.000 | 0.005 | 81.228 | 0.014 | 0.018 | <0.001 | 0.120 | 16.362 | 0.488 |
| ANT - CT | 4 | 778 | 15.542 | 3.000 | 0.001 | 80.698 | 0.022 | 0.023 | 0.001 | 0.150 | 8.455 | 0.358 |
| ANT - ET | 7 | 2282 | 187.540 | 6.000 | <0.001 | 96.801 | 0.095 | 0.059 | 0.003 | 0.308 | -4.427 | 0.782 |
| SP - CT | 5 | 1590 | 40.658 | 4.000 | <0.001 | 90.162 | 0.031 | 0.026 | 0.001 | 0.177 | 4.980 | 0.479 |
| SP - ET | 4 | 1356 | 38.442 | 3.000 | <0.001 | 92.196 | 0.039 | 0.037 | 0.001 | 0.197 | 6.608 | 0.444 |
| SI - CT | 3 | 848 | 3.054 | 2.000 | 0.217 | 34.519 | 0.002 | 0.006 | <0.001 | 0.045 | -2.253 | 0.770 |
| SI - ET | 3 | 813 | 7.359 | 2.000 | 0.025 | 72.823 | 0.010 | 0.014 | <0.001 | 0.102 | 11.218 | 0.087 |
| ET - CT | 3 | 1026 | 51.504 | 2.000 | <0.001 | 96.117 | 0.074 | 0.078 | 0.006 | 0.272 | 39.495 | 0.373 |
| CT - AI | 44 | 14920 | 1288.000 | 43.000 | <0.001 | 96.661 | 0.087 | 0.024 | 0.001 | 0.296 | 8.971 | <0.001 |
| ET - AI | 24 | 6916 | 723.130 | 23.000 | <0.001 | 96.819 | 0.108 | 0.035 | 0.001 | 0.328 | -2.728 | 0.611 |

*Note: k:* number of studies; *N:* sample size; SE: standard error; COM: Competence; RI: Risk; ANT: Anthropomorphism; SP: Social presence; SI: Social influence; ET: Emotional trust; CT: Cognitive trust; AI: Adopt intention.

Publication bias occurs when research studies are selectively published based on their results rather than their intrinsic merits or other factors. It involves the tendency for studies to be published in peer-reviewed journals depending on the direction and strength of their results (Nikolopoulou, 2022). This bias can potentially compromise the accuracy and persuasiveness of the research findings. To scrutinize the presence of publication bias, we employed Egger's test, which utilizes linear regression with an intercept to quantify the extent of systematic differences among studies (Egger et al., 1997). The results of this test are detailed in Table 3, with RI-ET excluded from analysis due to sample size limitations. A classic fail-safe N test was conducted specifically for CT-AI, revealing a failure safety factor of 49249—far exceeding 5K+10 (where K represents the number of independent samples in a variable). This outcome implies that, while some degree of publication bias may exist, its impact on the meta-analysis results is notably limited. Consequently, the analytical outcomes are less susceptible to distortion arising from publication bias (Peng et al., 2022; Yan et al., 2021).

### 4.2. Main results

In the context of the random effects model, the outcomes of the meta-analysis concerning the primary variables are presented in Table 4. Broadly, all antecedents, except risk, exert influence on the development of user cognitive and emotional trust. Moreover, the correlation between cognitive and emotional trust is substantiated. Additionally, both user cognitive and emotional trust exhibit a positive influence on the user's intention to adopt chatbots.

Table 4: Results of the meta-analysis.

| Assumption | K | N | Effect size and 95% CI | | | Two-tailed test | |
|---|---|---|---|---|---|---|---|
| | | | Point estimate | Lower limit | Upper limit | Z-value | P-value |
| COM - CT | 11 | 2790 | 0.664 | 0.592 | 0.725 | 13.158 | <0.001 |
| COM - ET | 5 | 1466 | 0.597 | 0.552 | 0.638 | 20.297 | <0.001 |
| PR - CT | 6 | 1868 | -0.062 | -0.243 | 0.124 | -0.653 | 0.514 |
| PR - ET | 2 | 700 | -0.311 | -0.451 | -0.157 | -3.863 | <0.001 |
| PE - CT | 3 | 923 | 0.528 | 0.411 | 0.628 | 7.643 | <0.001 |
| ANT - CT | 4 | 778 | 0.544 | 0.419 | 0.650 | 7.283 | <0.001 |
| ANT - ET | 7 | 2282 | 0.513 | 0.323 | 0.664 | 4.781 | <0.001 |
| SP - CT | 5 | 1590 | 0.559 | 0.436 | 0.662 | 7.544 | <0.001 |
| SP - ET | 4 | 1356 | 0.581 | 0.431 | 0.699 | 6.427 | <0.001 |
| SI - CT | 3 | 848 | 0.589 | 0.530 | 0.642 | 15.512 | <0.001 |
| SI - ET | 3 | 813 | 0.520 | 0.415 | 0.612 | 8.340 | <0.001 |
| ET - CT | 3 | 1026 | 0.433 | 0.148 | 0.651 | 2.890 | 0.004 |
| CT - AI | 44 | 14920 | 0.541 | 0.475 | 0.601 | 13.270 | <0.001 |
| ET - AI | 24 | 6916 | 0.598 | 0.505 | 0.677 | 10.104 | <0.001 |

Firstly, among the systematic factors analyzed, competence exhibited the highest correlation with cognitive trust (r=0.664, p<0.001) and emotional trust (r=0.597, p<0.001). This significant relationship suggests that users' perceptions of competence may play a pivotal role in building trust, aligning with trust-building theories that emphasize the importance of perceived ability and reliability. Additionally, personalization shows a significant positive correlation with cognitive trust (r=0.528, p<0.001), indicating that customized experiences can enhance users' sense of trust. Personalization may make users feel more valued and understood, thereby fostering a stronger cognitive connection. Conversely, risk exhibited a noteworthy medium-strength negative impact on emotional trust (r=-0.311, p<0.001), suggesting that perceived risks diminish users' emotional connections. Interestingly, risk did not significantly affect cognitive trust (r=-0.062, p=0.514). This discrepancy raises questions about the nature of emotional versus cognitive trust and how different factors might interact to influence each type. Secondly, as shown in Table 4, significant positive correlations were observed between the heuristic factors and both forms of trust. The correlation coefficients, all exceeding 0.5, suggest that the heuristic variables collectively exert a strong influence on both cognitive and emotional trust. Among these, social influence (r=0.589, p<0.001) exhibited the strongest correlation with cognitive trust, while anthropomorphism (r=0.544, p<0.001) and social presence (r=0.559, p<0.001) demonstrated a relatively weaker impact on cognitive trust. Social presence emerged as the factor with the highest correlation with emotional trust (r=0.581, p<0.001), while anthropomorphism (r=0.513, p<0.001) and social influence (r=0.520, p<0.001) displayed a comparatively lower impact on emotional trust. Thirdly, our findings revealed a significant correlation between emotional trust and cognitive trust (r=0.433, p=0.004). Furthermore, as anticipated, both cognitive (r=0.541, p<0.001) and emotional trust (r=0.598, p<0.001) significantly and positively influence users' adoption intention of chatbots, while emotional trust has a slightly higher influence on it.

## 4.3. Moderator analyses

### 4.3.1. Results of subgroup analysis

Table 5 reports the results of the subgroup analysis. To ensure sufficient statistical power in our study, we excluded results with K<2 from the moderator analysis, which are represented by a "-" in the table. The moderating effect of cultural background differences is not significant. However, it is interesting to note that the relationships between variables in Western culture are slightly higher than in Eastern culture. Specifically, the impact of competence on cognitive trust is more pronounced (r=0.801*** vs. r=0.635***), and the correlation between the two types of trust and adoption is also greater (CT-AI: r=0.581*** vs. r=0.522***; ET-AI: r=0.678*** vs. r=545). Additionally, different types of chatbots have a significant moderating effect on relationships. In task-driven conversational environments, the correlations are stronger, particularly the impact of competence on cognitive trust (r=0.633*** vs. r=0.562***) and social presence on emotional trust (r=0.590*** vs. r=0.433***). Text-based chatbots show a significantly greater impact on cognitive trust through anthropomorphism than voice-based chatbots (r=0.790*** vs. r=0.561). The correlations between the two types of trust established by users and their adoption intention differ under the influence of chatbot types. Emotional trust is more readily converted into adoption intention when using voice-based chatbots (r=0.583 vs. r=0.659), whereas cognitive trust is more easily converted into adoption intention when using text-based chatbots (r=0.537*** vs. r=0.518***)

Table 5: Result of Subgroup Analyses (a).

| Relationship | E-commerce situation | Non-e-commerce environment | Z | Western | Eastern | Z | Task-oriented | Conversational-oriented | Z | Textual | Voice | Z |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| COM - CT | 0.700 (900) | 0.648 (1275) | 0.587 | 0.801 (233) | 0.635 (2557) | 1.277 | 0.680 (1912) | 0.598 (878) | 2.121 | 0.667 (2527) | 0.617 (463) | 1.082 |
| COM - ET | 0.654 (388) | 0.566 (463) | 4.151 | - | 0.579 (1282) | 3.455 | 0.633 (588) | 0.562 (878) | 4.188 | 0.609 (1203) | 0.566 (463) | 1.162 |
| RI - CT | - | -0.062 (1868) | - | 0.338 (479) | -0.224 (1389) | 3.023 | 0.017 (1313) | -0.179 (555) | 1.592 | -0.041 (1578) | - | 0.471 |
| RI - ET | - | -0.311 (700) | - | - | -0.311 (700) | - | - | - | - | -0.311 (700) | - | - |
| PE - CT | - | 0.528 (923) | - | - | 0.506 (680) | 0.568 | 0.506 (680) | - | 0.568 | 0.506 (680) | - | 0.568 |
| ANT - CT | 0.641 (315) | 0.439 (463) | 15.483 | - | 0.544 (778) | - | 0.581 (515) | - | 3.101 | 0.790 (515) | 0.561 (463) | 4.648 |
| ANT - ET | 0.733 (605) | 0.398 (1677) | 7.492 | - | 0.442 (1881) | 47.076 | 0.539 (2019) | - | 2.999 | 0.539 (2019) | 0.390 (463) | 1.658 |
| SP - CT | 0.622 (774) | - | - | - | 0.576 (1397) | 1.029 | 0.590 (975) | 0.443 (816) | 4.779 | 0.559 (1590) | - | 0.980 |
| SP - ET | 0.628 (741) | - | - | - | 0.604 (1196) | 0.954 | 0.628 (714) | 8.362 | - | 0.581 (1356) | - | - |
| SI - CT | - | 0.580 (664) | 0.141 | - | 0.580 (664) | 0.141 | 0.616 (583) | - | 2.973 | 0.589 (848) | - | - |
| SI - ET | - | 0.479 (629) | 3.329 | - | 0.479 (629) | 3.329 | 0.519 (548) | - | 0.012 | 0.520 (813) | - | - |
| ET - CT | - | 0.433 (1026) | - | - | 0.433 (1026) | - | 0.334 (763) | - | 3.130 | 0.334 (763) | - | 3.130 |
| CT - AI | 0.647 (1842) | 0.528 (11551) | 4.142 | 0.581 (3896) | 0.522 (11415) | 1.068 | 0.542 (12741) | 0.521 (2839) | 0.158 | 0.537 (13775) | 0.518 (5730) | 0.089 |
| ET - AI | 0.686 (1875) | 0.547 (4015) | 2.139 | 0.678 (1980) | 0.545 (4936) | 2.690 | 0.609 (5863) | 0.539 (1512) | 1.094 | 0.583 (6310) | 0.659 (1265) | 0.787 |

Note: Z: Z-value COM: Competence; RI: Risk; ANT: Anthropomorphism; SP: Social presence; SI: Social influence; ET: Emotional trust; CT: Cognitive trust; AI: Adopt intention.

We observed that the moderating effect of the usage industry is quite significant. Initially, we categorized the service scenarios into e-commerce and non-e-commerce sectors and found that the correlations between variables are notably stronger in the e-commerce sector. Specifically, in e-commerce contexts, chatbot competence more effectively translates into users' emotional trust (r=0.654*** vs. r=0.566***), and the impact of anthropomorphism is markedly more pronounced (ANT-CT: r=0.641*** vs. r=0.439***; ANT-ET: r=0.733*** vs. r=0.398***). Furthermore, the association between cognitive trust and users' adoption intention is considerably greater (r=0.647*** vs. r=0.528***).

Table 6: Result of Subgroup Analyses (b).

| Relationship | Usage industry | K | N | Effect size and 95% CI | | | Two-tailed test | | Q-test | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Point estimate | Lower | Upper | Z-value | P-value | Q-value | df (Q) | P-value |
| CT - AI | Retailing | 8 | 1731 | 0.647 | 0.550 | 0.727 | 9.948 | 0.000 | 24.631 | 7.000 | 0.001 |
| | Hotels & -Tourism | 6 | 3061 | 0.570 | 0.310 | 0.751 | 3.877 | 0.000 | | | |
| | Finance | 11 | 3582 | 0.578 | 0.447 | 0.685 | 7.209 | 0.000 | | | |
| | Education | 3 | 1644 | 0.480 | 0.074 | 0.749 | 2.283 | 0.022 | | | |
| | Medical and Health | 2 | 590 | 0.540 | 0.159 | 0.781 | 2.670 | 0.008 | | | |
| | Media | 2 | 690 | 0.327 | 0.214 | 0.432 | 5.461 | 0.000 | | | |
| | Inside the Enterprise | 2 | 656 | 0.271 | -0.188 | 0.632 | 1.164 | 0.244 | | | |
| | Personal Assistant | 3 | 924 | 0.565 | 0.484 | 0.636 | 11.298 | 0.000 | | | |
| ET - AI | Retailing | 8 | 1875 | 0.686 | 0.548 | 0.787 | 7.337 | 0.000 | 4.991 | 3.000 | 0.172 |
| | Hotels & -Tourism | 3 | 1130 | 0.635 | 0.339 | 0.816 | 3.702 | 0.000 | | | |
| | Finance | 6 | 1458 | 0.461 | 0.282 | 0.609 | 4.689 | 0.000 | | | |
| | Medical and Health | 2 | 650 | 0.628 | 0.031 | 0.895 | 2.047 | 0.041 | | | |

Note: k: number of studies; N: sample size; ET: Emotional trust; CT: Cognitive trust; AI: Adopt intention.

Next, we categorized users by the industry in which they use chatbots, with detailed results presented in Table 6. Due to the limited research and variability across industries for some variables, our analysis focused on how specific industries moderate the relationship between the two types of trust and adoption intention. We discovered that the industry of chatbot use significantly influences the relationship between cognitive trust and adoption intention. Specifically, in the online retail sector, the correlation between cognitive trust and adoption intention is exceptionally high (r=0.647***). In contrast, in education and internal company contexts, this correlation is weak (r=0.480**; r=0.271 n.s.). Notably, we found differences in the impact of the two types of trust across industries. For instance, in the banking sector, cognitive trust has a strong correlation with adoption intention (r=0.578***), whereas emotional trust exhibits a weaker correlation compared to other industries (r=0.461***). Conversely, in several other sectors, emotional trust has a stronger correlation with adoption intention than cognitive trust.

4.3.2. Results of meta-regression analysis

This study performed a meta-regression analysis to investigate IT penetration as a quantitative moderating variable, with results detailed in Table 7. The analysis indicates that IT penetration significantly moderates only the relationship between emotional trust and adoption intention. Specifically, higher IT penetration in a given country or region facilitates the conversion of emotional trust into adoption intention for chatbots (β=1.034, p=0.015). However, IT penetration does not universally enhance all variable relationships. For example, it may diminish the impact of social presence on both types of trust (SP - CT: β=-1.928; SP - ET: β=-1.605). Notably, IT penetration might reduce the influence of anthropomorphism on cognitive trust (β=-0.842), while potentially strengthening its effect on emotional trust (β=1.465).

Table 7: Results of Meta-regression Analyses

| Relationship | β | Standard error | 95% lower | 95% upper | z | p value |
|---|---|---|---|---|---|---|
| COM - CT | 0.914 | 0.857 | -0.765 | 2.593 | 1.070 | 0.286 |
| COM - ET | 0.262 | 0.461 | -0.641 | 1.164 | 0.570 | 0.570 |
| RI - CT | 0.299 | 0.331 | -0.350 | 0.947 | 0.900 | 0.367 |
| ANT - CT | -0.842 | 1.059 | -2.918 | 1.234 | -0.800 | 0.427 |
| ANT - ET | 1.465 | 1.267 | -1.018 | 3.948 | 1.160 | 0.248 |
| SP - CT | -1.928 | 2.101 | -6.045 | 2.190 | -0.920 | 0.359 |
| SP - ET | -1.605 | 2.880 | -7.249 | 4.040 | -0.560 | 0.577 |
| CT - AI | 0.341 | 0.255 | -0.159 | 0.840 | 1.340 | 0.181 |

| | | | | | | |
|---|---|---|---|---|---|---|
| ET - AI | 1.034 | 0.423 | 0.205 | 1.863 | 2.45 | 0.015 |

Note: Z: Z-value COM: Competence; RI: Risk; ANT: Anthropomorphism; SP: Social presence; ET: Emotional trust; CT: Cognitive trust; AI: Adopt intention.

4.4. Robustness analyses

According to the MOOSE guidelines (Stroup, 2000), the results of the meta-analysis were analyzed for robustness by meticulously reviewing the literature for high-quality sample surveys. The assessment of survey quality in a study involved considering various criteria, such as response rate, sample representativeness, pre-testing of questionnaires, and non-response follow-up (Rao et al., 2008). Studies were classified as high quality if they adequately addressed survey respondent coverage or implemented measures against non-response bias (Li, 2023). After the exclusion of low-quality studies, our study conducted analyses on the remaining 11 variable relationships to gauge the robustness of the primary findings. Appendix E shows the results of the robustness analysis. Notably, the main variable relationships exhibited no significant deviations after the removal of low-quality sample studies and remained consistent with the earlier findings. This consistency underscores the robust nature of the analytical findings in this study.

## 5. Discussion and implications

Our study explores the role of trust in users' chatbot adoption intentions and its antecedents. We categorize the antecedents of trust using the Heuristic Systematic Model and further dissect trust into its cognitive and emotional dimensions to examine their effects on user adoption intention. The findings reveal that, among systematic factors, chatbot competence and risk are strongly correlated with emotional trust, while competence and personalization positively correlate with cognitive trust. All heuristic factors show relatively strong positive correlations with both cognitive and emotional trust.

Although we attempted to distinguish between the cognitive and emotional dimensions of trust, the results indicate that, in most cases, they are highly correlated and have similar positive effects on adoption intention. However, we found that in certain specific contexts, the role of emotional trust is more significant. This finding suggests that, from an overall perspective, trust can be considered as a unidimensional variable. However, this conclusion may not apply to all chatbot application scenarios. We discovered that in some contexts, the role of emotional trust is significantly greater than that of cognitive trust. For instance, when using voice-based chatbots, the correlation between emotional trust and adoption intention is much higher than that of cognitive trust (in contrast, when using text-based chatbots, the effects of emotional trust and cognitive trust are quite similar). In these cases, we should treat trust as two distinct dimensions for separate study. Our finding helps to address the inconsistencies regarding trust dimensions in previous research to some extent.

In addition, our study innovatively uses sample characteristics, chatbot features, and usage industries as moderating variables to explore the effects of a range of moderating factors, thereby enhancing the theoretical and practical value of our research.

5.1. Principal findings

5.1.1. Main effect analysis

First, certain scholars in previous research posited that systematic factors exert a greater influence on cognitive trust, whereas heuristic factors are more inclined to impact emotional trust (Gong, 2021). However, our study did not align with this perspective. For instance, risks associated with systematic factors were observed to exert a more pronounced impact on emotional trust compared to cognitive trust. Similarly, the anthropomorphic and social influences stemming from heuristic factors exhibited a slightly stronger positive effect on cognitive trust. This observation suggests that the influence of systematic and heuristic factors on trust may be intricate and multifaceted.

Second, within the realm of systemic factors, the association between chatbot competence, risk, and emotional trust is noteworthy, as is the relationship between competence, personalization, and cognitive trust. Regarding chatbot competence, we found that the effect of chatbot competence was significant for both forms of trust, aligning with the consensus in most prior studies. Some scholars even posit that competence is an integral component of the trust definition (Mayer et al., 1995). Notably, competence exerts a more substantial influence on trust compared to other factors, emphasizing the pivotal role of chatbot competence in the decision-making process of trust endorsement. In the context of chatbot risk, our study synthesizes previous research, revealing that risk significantly influences emotional trust while exhibiting no notable effect on cognitive trust. On one hand, risks associated with chatbots, such as user privacy and data security concerns, induce insecurity among users, impeding the establishment of emotional trust (Lappeman et al., 2023). On the other hand, the inconsequential impact of risk on cognitive trust may be attributed to two factors: (1) Bouhia et al. (2022) argued in their study that privacy concerns remain prominent regardless of users' familiarity with chatbots. This implies that users' perceived trust does not realize a significant enhancement due to the reduction of privacy risk. (2) When deciding whether to adopt a chatbot, a significant number of customers exhibit risk preference. This means they can cognitively accept the risks associated with using the chatbot, and these risks do not significantly impede the development of cognitive trust in the chatbot (Dekkal et al., 2023). Our study underscores that personalization indeed exerts a significant positive impact on individuals' cognitive trust. When users are presented with a service tailored to their needs, they are more inclined to engage with it systematically and trust that the chatbot is reliable.

Third, all heuristic factors were found to be significantly correlated with both cognitive and emotional trust. Regarding anthropomorphism, a high degree of anthropomorphic characteristics leads individuals to perceive a chatbot as possessing human abilities, fostering a sense of benevolence (Klein & Martinez, 2022). Furthermore, we observed that the impact of anthropomorphism on trust varied significantly across different fields. In the e-commerce sector, there exists a notably high correlation between anthropomorphic interaction and trust, whereas in non-e-commerce domains such as the hotel and tourism industry, this effect is comparatively less pronounced. The reason for this difference may be attributed to the potential terror valley effect in these areas, where excessive personification could have a negative impact on trust (Cui, 2023). Social presence is the factor with the strongest correlation with emotional trust. The social presence experienced by users from human-computer interactions contributes to the linking of human-computer emotional bonds and also enhances user trust by facilitating users' perceptions of chatbot interaction capabilities. Social influence is the factor with the strongest correlation with cognitive trust, which primarily enhances user trust by reducing user uncertainty about chatbot technology. Notably, when customers initially interact with a chatbot, they are inclined to rely more heavily on social influences. This implies that consumers take into account the opinions of those around them, such as peers and family members, which subsequently impacts their trust and decision-making in the context of chatbots (Mostafa & Kasamani, 2022).

Fourth, previous studies have presented diverse perspectives on the interplay between cognitive trust and emotional trust, and this study verified the correlation between the two. On one hand, when individuals cultivate emotional trust in chatbots—such as perceiving interactions with chatbots as easy, pleasant, and warm—they may concurrently develop heightened cognitive biases, encompassing perceptions of robot ability, integrity, and kindness (Liao & Zheng, 2018). On the other hand, the establishment of cognitive trust also serves to facilitate the development of an interactive relationship between the user and the chatbot, thereby fostering the augmentation of emotional trust (Chih et al., 2017).

Fifth, our study shows that both cognitive and emotional trust have a significant positive impact on chatbot adoption intention. This finding aligns with numerous empirical studies in the field (Pal et al., 2022; Shi et al., 2021). When users place trust in chatbots, they exhibit a greater likelihood of accepting and endorsing the chatbot service.

5.1.2. Moderator effect analysis

As previously discussed, we aim to elucidate the high heterogeneity in the literature through three lenses: sample characteristics, chatbot features, and usage industries. Our findings indicate that all three types of moderating variables exert some degree of influence. Firstly, trust is more likely to translate into user adoption intention in Western cultural contexts. This phenomenon may stem from the Western emphasis on personal freedom and independence, which encourages individuals to rely more on personal judgment and trust when making decisions (Gazi et al., 2024). Furthermore, Western societies highly value the establishment of contracts and credit systems, making trust a crucial factor in reducing transaction costs and enhancing efficiency in commercial and everyday transactions (Den Butter & Mosch, 2003).

This study also reveals that the IT penetration rate in a country facilitates the conversion of affective trust into adoption intention. In countries with high IT penetration, consumers are likely more familiar with product technologies, which helps in adopting chatbots once affective trust is established. Surprisingly, IT penetration does not positively impact all relationships. In regions with lower IT penetration, users may lack familiarity and experience with AI products like chatbots. If they perceive chatbots as genuinely present in society, it could significantly enhance their cognitive and affective trust. Additionally, it is intriguing that IT penetration affects anthropomorphism differently. High IT penetration implies users are more accustomed to using chatbots. When interacting with anthropomorphic chatbots, users might more easily attribute human traits to the robots, thus establishing trust on an emotional level. However, IT penetration might diminish anthropomorphism's effect on cognitive trust, as cognitive trust is based on performance and reliability assessments. In environments with widespread IT, users may focus more on systemic factors affecting the actual functionality and efficiency of chatbots rather than heuristic features like anthropomorphism (Roy & Naidoo, 2021).

Secondly, the features of chatbots are also a significant moderating variable. Current literature predominantly focuses on task-driven dialogue systems, where the establishment of trust and adoption intentions is closely related to both systemic and heuristic factors we investigate. This might be because users tend to have higher attention and expectations when using chatbots for specific purposes, whereas conversational systems are often used more for pleasure (Adam et al., 2021; J. Zhang et al., 2024). Additionally, we found that text-based chatbots tend to facilitate trust more effectively than voice-based ones. This could be because visual cues provide more information than auditory ones, allowing users to better experience the chatbot's features (Föcker et al., 2022).

Thirdly, our study reveals the moderating role of the industry in which chatbots are used. In various domains, the work content, form, and expression of chatbots exhibit substantial differences. Specifically, the correlation between variables was notably more robust in the e-commerce context. This discrepancy might be attributed to the fact that the e-commerce domain represents an earlier and more widely embraced arena for chatbot technology. Individuals in this domain are more acquainted with the utilization of chatbots and the intricacies of trust-building processes, rendering them more attuned to the objective attributes of chatbots and their emotional nuances in human-computer interactions.

When examining specific industries, familiarity and attention towards online retail may be one reason why both cognitive and emotional trust is highly correlated with adoption intention. In contrast, in sectors such as education or within companies, the adoption of chatbot services by employees or users may be influenced by other factors, such as mandatory regulations from the organization. This could lead to scenarios where users must adopt chatbot services even if they do not trust them. Additionally, the significance of cognitive versus emotional trust varies across industries; for example, in the financial and banking sectors, where precision is crucial, cognitive trust tends to be more important than emotional trust.

### 5.2. Theoretical implications

First, this study compiles chatbot antecedents derived from prior research based on the HSM and examines the strength of the effects of various user chatbot trust antecedents along with the influence of trust on adoption intentions. Diverging from conventional review articles or meta-analyses, this study introduces an innovative categorization of trust-influencing factors into systemic and heuristic categories. Moreover, it classifies trust into cognitive and emotional dimensions, exploring their interactions. This endeavor establishes a foundational research framework with broad applicability to related fields and extends the utility of HSM, offering valuable insights for studies on user chatbot trust and adoption intention.

Second, this study explains the existing inconsistent conclusions by summarizing and coordinating related literature. To tackle the issue of disparate research frameworks, this study constructs a generalizable framework utilizing two trust dimensions as mediating variables. The rationality of this framework is substantiated through theoretical modeling and meta-analysis. Additionally, in response to the inconsistent strength attributed to trust antecedents, the study presents consistent quantitative results accompanied by reasoned explanations.

Finally, this study examines the variances in the establishment and conversion of user trust, considering factors such as the cultural context of the sample location (Eastern vs. Western), the penetration rate of IT, the type of chatbots (task-driven vs. conversational; text vs. voice), and the service industry as moderating variables. This provides numerous new research perspectives in this field.

### 5.3. Practical implications

This study provides valuable insights into effectively managing intelligent transformation within organizations in the AI era. On one hand, our findings underscore several factors for chatbot designers to consider in future development processes. On the other hand, we present a framework aimed at enhancing the decision-making ability of managers across various industries when deploying chatbots.

For chatbot designers, it is crucial to consider optimizing the design scheme of chatbots from both systematic and heuristic perspectives. Designers must explore methods to enhance chatbot performance, augment their problem-solving abilities, tailor personalized chatbot services for users, and minimize design risk vulnerabilities. Furthermore, our study demonstrates that heuristic factors such as anthropomorphism can positively influence user trust, a consideration often overlooked by many chatbot designers. In the future, designers could try to add more anthropomorphic elements to chatbots to make them more lifelike and could even try to set different types of faces and voice tones to different customers according to their preferences.

For managers currently utilizing or considering the implementation of chatbots, our research offers a decision-making framework. Managers must meticulously assess whether the chatbot employed by the enterprise can effectively meet customer demands. A chatbot's poor performance, coupled with inherent risks, can hinder customer trust, resulting in customers abandoning chatbot services and potentially causing adverse effects on the enterprise's revenue. Furthermore, our research underscores the popularity of personalized chatbot services among users. In the era of big data, personalized services are increasingly prioritized across industries, particularly in the service sector. Thus, managers should prioritize the evaluation of chatbots with personalized service capabilities.

Simultaneously, enterprise managers should recognize the influence of heuristic factors on user trust. Incorporating anthropomorphic elements into chatbots, such as human-like embodiment, natural-sounding speech, and colloquial expressions, can bridge the gap between chatbot language and human communication. Social presence in chatbot interactions is another crucial consideration. Realistic service simulations can diminish perceived distance in virtual interactions and boost user engagement. Moreover, given the substantial impact of social influence on trust, it is recommended that enterprises bolster their publicity efforts. Leveraging multimedia channels and diverse perspectives can effectively promote chatbot services, thereby expanding their social influence and fostering broader acceptance of chatbots.

It merits emphasis that, despite the prevailing belief among academics and industry professionals in the inherent cognitive aspects of trust, our research underscores the pivotal role of cultivating emotional trust among end-users. Notably, the influence of emotional trust on users' intentions to adopt is found to be even more substantial than that of cognitive trust. Consequently, strategic leaders are encouraged to prioritize the development of emotional trust as a key component in fostering user engagement and adoption.

Finally, we recommend that enterprises serving Western customers and those providing task-driven chatbot services pay particular attention to the process of building user trust. Additionally, chatbot designers should consider enhancing the visual elements of chatbots, rather than relying solely on voice features to convey information to customers. Furthermore, businesses across various industries must recognize the unique priorities within their respective sectors. Users in different industries exhibit distinct needs, leading to varying impacts of trust-building factors on them. Managers should assign chatbots based on their specific industry rather than simply copying successful models from other sectors. For example, in the financial industry, practitioners should prioritize cognitive trust over emotional trust compared to other industries. Service providers deploying chatbots in different sectors must understand their users and thoroughly consider their needs and psychology. Tailoring adjustments to all aspects of chatbot performance is crucial for effectively delivering accurate services that align with user needs and enhancing overall production and service efficiency.

### 5.4. Limitations and future research

There are some limitations in our study. First, the inclusion of literature was constrained by specific screening criteria. For instance, certain articles lacked appropriate effect sizes, presenting only regression coefficients. These articles were consequently excluded, potentially introducing a degree of incompleteness to the study results. Additionally, some literature did not provide sufficient evidence for assessing trust classification, leading to its exclusion. Second, numerous variables affect trust, but due to limited literature and sample sizes, it is challenging and easy to lead to errors to include all variables in the analysis. However, certain models and variables, such as perceived warmth and user interface, hold research value as well. All of these related variables from previous research are listed in Appendix A. Future research can further explore the influence of these variables on trust. Third, our study distinguishes between cognitive trust and emotional trust, but the results show a strong positive correlation between them. Overall, there is no significant difference in their positive effects on adoption intention. Therefore, we suggest that future research may consider combining both dimensions into a single 'trust' dimension to simplify the model structure and more directly analyze the overall impact of trust on adoption intention. However, it is worth noting that our study also found that emotional trust plays a significantly greater role than cognitive trust in certain specific contexts. As a result, we suggest that research in certain scenarios should still treat trust as two distinct dimensions, such as studies focused solely on voice-based chatbots. Finally, we have found that the factors influencing trust are intricate, and the relationships between variables can be complex. Due to the nature of meta-analysis, it is not well-suited for analyzing the complex causal relationships between variables (Gurevitch et al., 2018). Our research did not consider the interaction of trust antecedents, nor their direct impact on adoption intention. Unfortunately, due to the limited number of available studies, our data does not support conducting SEM analysis. Therefore, there may still be some potential research space in the interpretation of user adoption mechanisms. However, we believe that future research on chatbot trust issues will continue to grow, and subsequent meta-analyses may incorporate additional articles published later to explore this topic in greater depth using SEM.

**Acknowledgment**

This study was supported by The National Social Science Fund of China under Grant No. 23BTQ086.

## REFERENCES

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, *31*(2), 427–445. https://doi.org/10.1007/s12525-020-00414-7

Adamopoulou, E., & Moussiades, L. (2020). Chatbots: History, technology, and applications. *Machine Learning with Applications*, *2*, 100006. https://doi.org/10.1016/j.mlwa.2020.100006

Ait Baha, T., El Hajji, M., Es-Saady, Y., & Fadili, H. (2023). The Power of Personalization: A Systematic Review of Personality-Adaptive Chatbots. *SN Computer Science*, *4*(5), 661. https://doi.org/10.1007/s42979-023-02092-6

Alagarsamy, S., & Mehrolia, S. (2023). Exploring chatbot trust: Antecedents and behavioural outcomes. *Heliyon*, *9*(5), e16074. https://doi.org/10.1016/j.heliyon.2023.e16074

Albayrak, T., Rosario González-Rodríguez, M., Caber, M., & Karasakal, S. (2023). The Use of Mobile Applications for Travel Booking: Impacts of Application Quality and Brand Trust. *Journal of Vacation Marketing*, *29*(1), 3–21. https://doi.org/10.1177/13567667211066544

Alimamy, S. (2023). I will be with you Alexa! The impact of intelligent virtual assistant's authenticity and personalization on user reusage intentions. *Computers in Human Behavior*, 143(1),107711.

Alsharhan, A., Al-Emran, M., & Shaalan, K. (2023). Chatbot Adoption: A Multiperspective Systematic Review and Future Research Agenda. *IEEE Transactions on Engineering Management*, 1–13. IEEE Transactions on Engineering Management. *71*, 10232–10244. https://doi.org/10.1109/TEM.2023.3298360

Balakrishnan, J., & Dwivedi, Y. K. (2021). Role of cognitive absorption in building user trust and experience. *Psychology & Marketing*, *38*(4), 643–668. https://doi.org/10.1002/mar.21462

Banerjee, S., & Chua, A. Y. K. (2019). Trust in online hotel reviews across review polarity and hotel category. *Computers in Human Behavior*, *90*, 265–275. https://doi.org/10.1016/j.chb.2018.09.010

Beatty, P., Reay, I., Dick, S., & Miller, J. (2011). Consumer trust in e-commerce web sites: A meta-study. *ACM Comput. Surv.*, *43*(3), 14:1-14:46. https://doi.org/10.1145/1922649.1922651

Behera, R. K., Bala, P. K., Rana, N. P., & Dwivedi, Y. K. (2022). Assessing the influence of COVID-19 protocol on online health information seeking intention of athletes in India. *Benchmarking: An International Journal*. *30*(8), 2670–2704. https://doi.org/10.1108/BIJ-11-2021-0718

Behera, R. K., Bala, P. K., & Ray, A. (2021). Cognitive Chatbot for Personalised Contextual Customer Service: Behind the Scene and beyond the Hype. *Information Systems Frontiers*. *26*(3), 899–919. https://doi.org/10.1007/s10796-021-10168-y

Belda-Medina, J., & Kokošková, V. (2023). Integrating chatbots in education: Insights from the Chatbot-Human Interaction Satisfaction Model (CHISM). *International Journal of Educational Technology in Higher Education*, *20*(1), 62. https://doi.org/10.1186/s41239-023-00432-3

Bloomenthal, A. (2023). *E-commerce Defined: Types, History, and Examples*. Investopedia. https://www.investopedia.com/terms/e/ecommerce.asp

Bohner, G., Moskowitz, G. B., & Chaiken, S. (1995). The Interplay of Heuristic and Systematic Processing of Social Information. *European Review of Social Psychology*, *6*(1), 33–68. https://doi.org/10.1080/14792779443000003

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2010). A basic introduction to fixed-effect and random-effects models for meta-analysis. *Research Synthesis Methods*, *1*(2), 97–111. https://doi.org/10.1002/jrsm.12

Bouhia, M., Rajaobelina, L., PromTep, S., Arcand, M., & Ricard, L. (2022). Drivers of privacy concerns when interacting with a chatbot in a customer service encounter. *International Journal of Bank Marketing*, *40*(6), 1159–1181. https://doi.org/10.1108/IJBM-09-2021-0442

Bove, L. L. (2019). Empathy for service: Benefits, unintended consequences, and future research agenda. *Journal of Services Marketing*, *33*(1), 31–43. https://doi.org/10.1108/JSM-10-2018-0289

Brüggemann, P., & Rajguru, K. (2022). Comprehensive Meta-Analysis (CMA) 3.0: A software review. *Journal of Marketing Analytics*, *10*(4), 425–429. https://doi.org/10.1057/s41270-022-00184-5

Bulsara, H. P., & Vaghela, P. S. (2023). Trust and online purchase intention: A systematic literature review through meta-analysis. *International Journal of Electronic Business*. 1*8*(2), 148–164. .https://www.inderscienceonline.com/doi/10.1504/IJEB.2023.130155

Cai, D., Li, H., & Law, R. (2022). Anthropomorphism and OTA chatbot adoption: A mixed methods study. *Journal of Travel & Tourism Marketing*, *39*(2), 228–255. https://doi.org/10.1080/10548408.2022.2061672

Chaiken, S., Liberman, A. M., & Eagly, A. H. (1989). *Heuristic and systematic information processing within and beyond the persuasion context.* (pp. 212–252). Guilford Press.https://api.semanticscholar.org/CorpusID:60694536

Chandra, S., Shirish, A., & Srivastava, S. C. (2022). To Be or Not to Be …Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents. *Journal of Management Information Systems*, *39*(4), 969–1005. https://doi.org/10.1080/07421222.2022.2127441

Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. *Psychology & Marketing*, *39*(8), 1529–1562. https://doi.org/10.1002/mar.21670

Chen, H., Liu, X., Yin, D., & Tang, J. (2017). A Survey on Dialogue Systems: Recent Advances and New Frontiers. *ACM SIGKDD Explorations Newsletter*, *19*(2), 25–35. https://doi.org/10.1145/3166054.3166058

Chen, Q., Lu, Y., Gong, Y., & Xiong, J. (2023). Can AI chatbots help retain customers? Impact of AI service quality on customer loyalty. *Internet Research*. *33*(6), 2205–2243. https://doi.org/10.1108/INTR-09-2021-0686

Chen, Q., & Park, H. J. (2021). How anthropomorphism affects trust in intelligent personal assistants. *Industrial Management & Data Systems*, *121*(12), 2722–2737. https://doi.org/10.1108/IMDS-12-2020-0761

Chen, S., Duckworth, K., & Chaiken, S. (1999). Motivated Heuristic and Systematic Processing. *Psychological Inquiry*, *10*(1), 44–49. https://doi.org/10.1207/s15327965pli1001_6

Cheng, M., Li, X., & Xu, J. (2022). Promoting Healthcare Workers' Adoption Intention of Artificial-Intelligence-Assisted Diagnosis and Treatment: The Chain Mediation of Social Influence and Human–Computer Trust. *International Journal of Environmental Research and Public Health*, *19*(20), 13311. https://doi.org/10.3390/ijerph192013311

Cheng, X., Bao, Y., Zarifis, A., Gong, W., & Mou, J. (2022). Exploring consumers' response to text-based chatbots in e-commerce: The moderating role of task complexity and chatbot disclosure. *Internet Research*, *32*(2), 496–517. https://doi.org/10.1108/INTR-08-2020-0460

Cheng, X., Zhang, X., Cohen, J., & Mou, J. (2022). Human vs. AI: Understanding the impact of anthropomorphism on consumer response to chatbots from the perspective of trust and relationship norms. *Information Processing & Management*, *59*(3), 102940. https://doi.org/10.1016/j.ipm.2022.102940

Cheng, Y., Zhu, S., & Xiao, Y. (2023). A meta-analysis of the effect of chatbot anthropomorphism on the customer journey. *Marketing Intelligence & Planning*, *42*(1), 1–22. https://doi.org/10.1108/MIP-03-2023-0103

Chih, W.-H., Hsu, L.-C., & Liou, D.-K. (2017). Understanding virtual community members' relationships from individual, group, and social influence perspectives. *Industrial Management & Data Systems*, *117*(6), 990–1010. https://doi.org/10.1108/IMDS-03-2016-0119

Choi, S., Jang, Y., & Kim, H. (2023). Influence of Pedagogical Beliefs and Perceived Trust on Teachers' Acceptance of Educational Artificial Intelligence Tools. *International Journal of Human–Computer Interaction*, *39*(4), 910–922. https://doi.org/10.1080/10447318.2022.2049145

Choi, Y. (2021). A study of employee acceptance of artificial intelligence technology. *European Journal of Management and Business Economics*, *30*(3), 318–330. https://doi.org/10.1108/EJMBE-06-2020-0158

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2020). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *117*, 587–595. https://doi.org/10.1016/j.jbusres.2018.10.004

Cui, C. (2023). *Research on the influence of humanoid intelligent robot anthropomorphism on consumers' willingness to us* [Master, Lanzhou University of Finance and Economics]. https://doi.org/10.27732/d.cnki.gnzsx.2023.000256

Dawar, S., Savita Panwar, S. P., Dhaka, S., & Kudal, P. (2022). Antecedents and Role of Trust in Chatbot Use Intentions: An Indian Perspective. *Marketing and Management of Innovations*, *13*(4), 198–206. https://doi.org/10.21272/mmi.2022.4-18

De Andrés-Sánchez, J., & Gené-Albesa, J. (2023). Assessing Attitude and Behavioral Intention toward Chatbots in an Insurance Setting: A Mixed Method Approach. *International Journal of Human–Computer Interaction*, 1–16. https://doi.org/10.1080/10447318.2023.2227833

De Cicco, R., Da Costa E Silva, S. C. L., & Palumbo, R. (2021). Should a Chatbot Disclose Itself? Implications for an Online Conversational Retailer. In A. Følstad, T. Araujo, S. Papadopoulos, E. L.-C. Law, E. Luger, M. Goodwin, & P. B. Brandtzaeg (Eds.), *Chatbot Research and Design* (Lecture Notes in Computer Science, Vol. 12604, pp. 3–15). Springer International Publishing. https://doi.org/10.1007/978-3-030-68288-0_1

De Cicco, R., Iacobucci, S., Aquino, A., Romana Alparone, F., & Palumbo, R. (2022). Understanding Users' Acceptance of Chatbots: An Extended TAM Approach. In A. Følstad, T. Araujo, S. Papadopoulos, E. L.-C. Law, E. Luger, M. Goodwin, & P. B. Brandtzaeg (Eds.), *Chatbot Research and Design* (Vol. 13171, pp. 3–22). Springer International Publishing. https://doi.org/10.1007/978-3-030-94890-0_1

De Cicco, R., Silva, S. C., & Alparone, F. R. (2020). Millennials' attitude toward chatbots: An experimental study in a social relationship perspective. *International Journal of Retail & Distribution Management*, *48*(11), 1213–1233. https://doi.org/10.1108/IJRDM-12-2019-0406

de Oliveira Santini, F., Eberle, L., Ladeira, W. J., Milan, G. S., Graciola, A. P., & Sampaio, C. H. (2023). Trust in the financial services context: A meta-analysis. *International Journal of Bank Marketing*, *41*(7), 1693–1714. https://doi.org/10.1108/IJBM-06-2022-0248

Dekkal, M., Arcand, M., Prom Tep, S., Rajaobelina, L., & Ricard, L. (2023). Factors affecting user trust and intention in adopting chatbots: The moderating role of technology anxiety in insurtech. *Journal of Financial Services Marketing*. *29*(3), 699–728. https://doi.org/10.1057/s41264-023-00230-y

Den Butter, F. A. G., & Mosch, R. H. J. (2003). Trade, Trust and Transaction Costs. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.459501

Deng, X., & Yu, Z. (2023). A Meta-Analysis and Systematic Review of the Effect of Chatbot Technology Use in Sustainable Education. *Sustainability*, *15*(4), 2940. https://doi.org/10.3390/su15042940

Eagly, A. H., & Chaiken, S. (1993). The psychology of attitudes. *Journal of Marketing Research*, *34*, 298.

Ebrahimi, S., Ghasemaghaei, M., & Benbasat, I. (2022). The Impact of Trust and Recommendation Quality on

Adopting Interactive and Non-Interactive Recommendation Agents: A Meta-Analysis. *Journal of Management Information Systems*, *39*(3), 733–764. https://doi.org/10.1080/07421222.2022.2096549

Edwards, C., Edwards, A., Albrehi, F., & Spence, P. (2021). Interpersonal impressions of a social robot versus human in the context of performance evaluations. *Communication Education*, *70*(2), 165–182. https://doi.org/10.1080/03634523.2020.1802495

Egger, M., Smith, G. D., Schneider, M., & Minder, C. (1997). Bias in meta-analysis detected by a simple, graphical test. *BMJ*, *315*(7109), 629–634. https://doi.org/10.1136/bmj.315.7109.629

Ejdys, J. (2020). Trust-based determinants of future intention to use technology. *Foresight and STI governance*, *14*(1), 60–68. https://doi.org/10.17323/2500-2597.2020.1.60.68

Eren, B. A. (2021). Determinants of customer satisfaction in chatbot use: Evidence from a banking application in Turkey. *International Journal of Bank Marketing*, *39*(2), 294–311. https://doi.org/10.1108/IJBM-02-2020-0056

Ferreira, R., Leite, M., Semedo, D., & Magalhaes, J. (2022). Open-domain conversational search assistants: The Transformer is all you need. *Information Retrieval Journal*, *25*(2), 123–148. https://doi.org/10.1007/s10791-022-09403-0

Föcker, J., Atkins, P., Vantzos, F.-C., Wilhelm, M., Schenk, T., & Meyerhoff, H. S. (2022). Exploring the effectiveness of auditory, visual, and audio-visual sensory cues in a multiple object tracking environment. *Attention, Perception, & Psychophysics*, *84*(5), 1611–1624. https://doi.org/10.3758/s13414-022-02492-5

Fu, J.-R., Lu, I.-W., Chen, J. H. F., & Farn, C. K. (2020). Investigating consumers' online social shopping intention: An information processing perspective. *International Journal of Information Management*, *54*, 102189. https://doi.org/10.1016/j.ijinfomgt.2020.102189

Gazi, M. A. I., Rahman, M. K. H., Masud, A. A., Amin, M. B., Chaity, N. S., Senathirajah, A. R. bin S., & Abdullah, M. (2024). AI Capability and Sustainable Performance: Unveiling the Mediating Effects of Organizational Creativity and Green Innovation with Knowledge Sharing Culture as a Moderator. *SUSTAINABILITY*, *16*(17), 7466. https://doi.org/10.3390/su16177466

Gefen, D., Benbasat, I., & Pavlou, P. (2008). A Research Agenda for Trust in Online Environments. *Journal of Management Information Systems*, *24*(4), 275–286. https://doi.org/10.2753/MIS0742-1222240411

Gillath, O., Ai, T., Branicky, M. S., Keshmiri, S., Davison, R. B., & Spaulding, R. (2021). Attachment and trust in artificial intelligence. *Computers in Human Behavior*, *115*, 106607. https://doi.org/10.1016/j.chb.2020.106607

Gkinko, L., & Elbanna, A. (2023). Designing trust: The formation of employees' trust in conversational AI in the digital workplace. *Journal of Business Research*, *158*, 113707. https://doi.org/10.1016/j.jbusres.2023.113707

Glass, G. V. (1976). Primary, Secondary, and Meta-Analysis of Research. *Educational Researcher*, *5*(10), 3–8. https://doi.org/10.3102/0013189X005010003

Glikson, E., & Woolley, A. W. (2020a). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Glikson, E., & Woolley, A. W. (2020b). Human Trust in Artificial Intelligence: Review of Empirical Research. *Academy of Management Annals*, *14*(2), 627–660. https://doi.org/10.5465/annals.2018.0057

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, *97*, 304–316. https://doi.org/10.1016/j.chb.2019.01.020

Gong, Y. (2021). *Research on Trust and Adoption Intentions of Travel Route Recommendation System Based on Artificial Intelligence* [Master, South Western University of Finance and Economics]. https://doi.org/10.27412/d.cnki.gxncu.2021.000121

Gurevitch, J., Koricheva, J., Nakagawa, S., & Stewart, G. (2018). Meta-analysis and the science of research synthesis. *Nature*, *555*(7695), 175–182. https://doi.org/10.1038/nature25753

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Habbal, A., Ali, M. K., & Abuzaraida, M. A. (2024). Artificial Intelligence Trust, Risk and Security Management (AI TRiSM): Frameworks, applications, challenges and future research directions. *Expert Systems with Applications*, *240*, 122442. https://doi.org/10.1016/j.eswa.2023.122442

Hancock, P. A., Kessler, T. T., Kaplan, A. D., Brill, J. C., & Szalma, J. L. (2021). Evolving Trust in Robots: Specification Through Sequential and Comparative Meta-Analyses. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *63*(7), 1196–1229. https://doi.org/10.1177/0018720820922080

Hassani, H., & Silva, E. S. (2023). The Role of ChatGPT in Data Science: How AI-Assisted Conversational Interfaces Are Revolutionizing the Field. *Big Data and Cognitive Computing*, *7*(2), 62. https://doi.org/10.3390/bdcc7020062

Henkel, T., Linn, A. J., & Van Der Goot, M. J. (2023). Understanding the Intention to Use Mental Health Chatbots

Among LGBTQIA+ Individuals: Testing and Extending the UTAUT. In A. Følstad, T. Araujo, S. Papadopoulos, E. L.-C. Law, E. Luger, M. Goodwin, & P. B. Brandtzaeg (Eds.), *Chatbot Research and Design* (Vol. 13815, pp. 83–100). Springer International Publishing. https://doi.org/10.1007/978-3-031-25581-6_6

Hoff, K. A., & Bashir, M. (2015). Trust in Automation: Integrating Empirical Evidence on Factors That Influence Trust. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *57*(3), 407–434. https://doi.org/10.1177/0018720814547570

Hofstede, G. H. (1984). Culture's consequences: International differences in work-related values (Abridged ed). Sage Publications.

Hsiao, K. L., & Chen, C.-C. (2022). What drives continuance intention to use a food-ordering chatbot? An examination of trust and satisfaction. *Library Hi Tech*, *40*(4), 929–946. https://doi.org/10.1108/LHT-08-2021-0274

Hsieh, S. H., & Lee, C. T. (2021). Hey Alexa: Examining the effect of perceived socialness in usage intentions of AI assistant-enabled smart speaker. *Journal of Research in Interactive Marketing*, *15*(2), 267–294. https://doi.org/10.1108/JRIM-11-2019-0179

Hua, C., Cole, S., & Xu, N. (2021). Rethinking trust in tourism apps: The moderating effect of age. *Journal of Hospitality and Tourism Technology*, *12*(3), 548–562. https://doi.org/10.1108/JHTT-01-2020-0013

Huedo-Medina, T. B., Sánchez-Meca, J., Marín-Martínez, F., & Botella, J. (2006). Assessing heterogeneity in meta-analysis: Q statistic or $I^2$ index? *Psychological Methods*, *11*(2), 193–206. https://doi.org/10.1037/1082-989X.11.2.193

Hunter, J. E., & Schmidt, F. L. (2004). Methods of meta-analysis: Correcting error and bias in research findings (2nd ed.). Sage Publications.

Ismagilova, E., Slade, E., Rana, N. P., & Dwivedi, Y. K. (2020). The effect of characteristics of source credibility on consumer behaviour: A meta-analysis. *Journal of Retailing and Consumer Services*, *53*, 101736. https://doi.org/10.1016/j.jretconser.2019.01.005

Jackson, D., White, I. R., & Riley, R. D. (2012). Quantifying the impact of between-study heterogeneity in multivariate meta-analyses. Statistics in Medicine, 31(29), 3805–3820. https://doi.org/10.1002/sim.5453

James, T. L., Ziegelmayer, J. L., Schuler Scott, A., & Fox, G. (2021). A Multiple-Motive Heuristic-Systematic Model for Examining How Users Process Android Data and Service Access Notifications. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *52*(1), 91–122. https://doi.org/10.1145/3447934.3447941

Jeyaraj, A., & Dwivedi, Y. K. (2020). Meta-analysis in information systems research: Review and recommendations. *International Journal of Information Management*, *55*, 102226. https://doi.org/10.1016/j.ijinfomgt.2020.102226

Jiang, Y., Yang, X., & Zheng, T. (2023). Make chatbots more adaptive: Dual pathways linking human-like cues and tailored response to trust in interactions with chatbots. *Computers in Human Behavior*, *138*, 107485. https://doi.org/10.1016/j.chb.2022.107485

Johnson, D., & Grayson, K. (2005). Cognitive and affective trust in service relationships. *Journal of Business Research*, *58*(4), 500–507. https://doi.org/10.1016/S0148-2963(03)00140-1

Kang, T. C., Hung, S. Y., & Huang, A. H. (2020). The Adoption of Online Product Information: Cognitive and Affective Evaluations. *Journal of Internet Commerce*, *19*(4), 373–403. https://doi.org/10.1080/15332861.2020.1816315

Kaplan, A. D., Kessler, T. T., Brill, J. C., & Hancock, P. A. (2023). Trust in Artificial Intelligence: Meta-Analytic Findings. *Human Factors*, *65*(2), 337–359. https://doi.org/10.1177/00187208211013988

Kaplan, F. (2004). WHO IS AFRAID OF THE HUMANOID? INVESTIGATING CULTURAL DIFFERENCES IN THE ACCEPTANCE OF ROBOTS. *International Journal of Humanoid Robotics*, *01*(03), 465–480. https://doi.org/10.1142/S0219843604000289

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, *62*, 101280. https://doi.org/10.1016/j.techsoc.2020.101280

Khamitov, M., Rajavi, K., Huang, D.-W., & Hong, Y. (2023). Consumer Trust: Meta-analysis of 50 Years of Empirical Research. *Journal of Consumer Research*. *51*(1), 7–18. https://doi.org/10.1093/jcr/ucad065

Kim, G., Shin, B., & Lee, H. G. (2009). Understanding dynamics between initial trust and usage intentions of mobile banking. *Information Systems Journal*, *19*(3), 283–311. https://doi.org/10.1111/j.1365-2575.2007.00269.x

Kim, H. Y., & McGill, A. L. (2018). Minions for the Rich? Financial Status Changes How Consumers See Products with Anthropomorphic Features. *Journal of Consumer Research*, *45*(2), 429–450. https://doi.org/10.1093/jcr/ucy006

Kim, H.-Y., & McGill, A. L. (2018). Minions for the Rich? Financial Status Changes How Consumers See Products with Anthropomorphic Features. *Journal of Consumer Research*, *45*(2), 429–450. https://doi.org/10.1093/jcr/ucy006

Kim, W. B., & Hur, H. J. (2023). What Makes People Feel Empathy for AI Chatbots? Assessing the Role of Competence and Warmth. *International Journal of Human–Computer Interaction*, *40*(17), 4674–4687. https://doi.org/10.1080/10447318.2023.2219961

Kim, Y., & Peterson, R. A. (2017). A Meta-analysis of Online Trust Relationships in E-commerce. *Journal of Interactive Marketing*, *38*(1), 44–54. https://doi.org/10.1016/j.intmar.2017.01.001

Klein, K., & Martinez, L. F. (2022). The impact of anthropomorphism on customer satisfaction in chatbot commerce: An experimental study in the food sector. *Electronic Commerce Research*. 23, 2789–2825. https://doi.org/10.1007/s10660-022-09562-8

Komiak, S. Y. X., & Benbasat, I. (2006). The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents. *MIS Quarterly*, *30*(4), 941. https://doi.org/10.2307/25148760

Kreps, S., George, J., Lushenko, P., & Rao, A. (2023). Exploring the artificial intelligence "Trust paradox": Evidence from a survey experiment in the United States. *PLOS ONE*, *18*(7), e0288109. https://doi.org/10.1371/journal.pone.0288109

Kuen, L., Westmattelmann, D., Bruckes, M., & Schewe, G. (2023). Who earns trust in online environments? A meta-analysis of trust in technology and trust in provider for technology acceptance. *Electronic Markets*, *33*(1), 61. https://doi.org/10.1007/s12525-023-00672-1

Kumar, P., Chauhan, S., Gupta, P., & Jaiswal, M. P. (2023). A meta-analysis of trust in mobile banking: The moderating role of cultural dimensions. *International Journal of Bank Marketing*, *41*(6), 1207–1238. https://doi.org/10.1108/IJBM-02-2022-0075

Kyung, N., & Kwon, H. E. (2022). Rationally trust, but emotionally? The roles of cognitive and affective trust in laypeople's acceptance of AI for preventive care operations. *Production and Operations Management*, poms.13785. https://doi.org/10.1111/poms.13785

Ladeira, W., Perin, M. G., & Santini, F. (2023). Acceptance of service robots: A meta-analysis in the hospitality and tourism industry. *Journal of Hospitality Marketing & Management*, *32*(6), 694–716. https://doi.org/10.1080/19368623.2023.2202168

Lappeman, J., Marlie, S., Johnson, T., & Poggenpoel, S. (2023). Trust and digital privacy: Willingness to disclose personal information to banking chatbot services. *Journal of Financial Services Marketing*, *28*(2), 337–357. https://doi.org/10.1057/s41264-022-00154-z

Lee, J. C., & Chen, X. (2022). Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: The intelligent and anthropomorphic perspectives. *International Journal of Bank Marketing*, *40*(4), 631–658. https://doi.org/10.1108/IJBM-08-2021-0394

Lee, J., Lee, D., & Lee, J. (2022). Influence of Rapport and Social Presence with an AI Psychotherapy Chatbot on Users' Self-Disclosure. *International Journal of Human–Computer Interaction*, 1–12. https://doi.org/10.1080/10447318.2022.2146227

Lee, O. K. D., Ayyagari, R., Nasirian, F., & Ahmadian, M. (2021). Role of interaction quality and trust in use of AI-based voice-assistant systems: *Journal of Systems and Information Technology*, *23*(2), 154–170. https://doi.org/10.1108/JSIT-07-2020-0132

Lei, S. I., Shen, H., & Ye, S. (2021). A comparison between chatbot and human service: Customer perception and reuse intention. *International Journal of Contemporary Hospitality Management*, *33*(11), 3977–3995. https://doi.org/10.1108/IJCHM-12-2020-1399

Lema, R., Kraemer-Mbula, E., & Rakas, M. (2021). Innovation in developing countries: Examining two decades of research. *Innovation and Development*, *11*(2–3), 189–210. https://doi.org/10.1080/2157930X.2021.1989647

Li, B., Chen, Y., Liu, L., & Zheng, B. (2023). Users' intention to adopt artificial intelligence-based chatbot: A meta-analysis. *The Service Industries Journal*, *43*(15–16), 1117–1139. https://doi.org/10.1080/02642069.2023.2217756

Li, J. (2023). Information avoidance in the age of COVID-19: A meta-analysis. *Information Processing & Management*, *60*(1), 103163. https://doi.org/10.1016/j.ipm.2022.103163

Liang, T.-P., Li, Y.-W., Yen, N.-S., Hsu, S.-M., & Banker, S. (2021). How digital assistants evoke social closeness: An fmri investigation. *Journal of Electronic Commerce Research*, *22*(4), 285–304.

Liao, Z., & Zheng, W. (2018). Using a heuristic algorithm to design a personalized day tour route in a time-dependent stochastic environment. *Tourism Management*, *68*, 284–300. https://doi.org/10.1016/j.tourman.2018.03.012

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *Journal of Clinical Epidemiology*, *62*(10), e1–e34. https://doi.org/10.1016/j.jclinepi.2009.06.006

Lin, C. C., Huang, A. Y. Q., & Yang, S. J. H. (2023). A Review of AI-Driven Conversational Chatbots Implementation Methodologies and Challenges (1999–2022). *Sustainability*, *15*(5), 4012. https://doi.org/10.3390/su15054012

Lipsey, M. W., & Wilson, D. B. (2001). *Practical meta-analysis.* Sage Publications, Inc.

Liu, J. (2019). *An empirical study of factors influencing physician adoption of artificial intelligence-assisted diagnostic systems* [Master, Hefei University of Technology]. https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CMFD&dbname=CMFD202001&filename=1019231980.nh&v=

Liu, Y., Yan, W., Hu, B., Li, Z., & Lai, Y. L. (2022). Effects of personalization and source expertise on users' health beliefs and usage intention toward health chatbots: Evidence from an online experiment. *DIGITAL HEALTH*, *8*, 205520762211297. https://doi.org/10.1177/20552076221129718

Liu, Z., Liu, L., & Li, H. (2012). Determinants of information retweeting in microblogging. *Internet Research*, *22*(4), 443–466. https://doi.org/10.1108/10662241211250980

Lomas, T., Diego-Rosell, P., Shiba, K., Standridge, P., Lee, M. T., Case, B., Lai, A. Y., & VanderWeele, T. J. (2023). Complexifying Individualism Versus Collectivism and West Versus East: Exploring Global Diversity in Perspectives on Self and Other in the Gallup World Poll. *Journal of Cross-Cultural Psychology*, *54*(1), 61–89. https://doi.org/10.1177/00220221221130978

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, *80*, 36–51. https://doi.org/10.1016/j.ijhm.2019.01.005

Malodia, S., Ferraris, A., Sakashita, M., Dhir, A., & Gavurova, B. (2023). Can Alexa serve customers better? AI-driven voice assistant service interactions. *Journal of Services Marketing*, *37*(1), 25–39. https://doi.org/10.1108/JSM-12-2021-0488

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. *The Academy of Management Review*, *20*(3), 709. https://doi.org/10.2307/258792

McTear, M. (2021). Conversational AI: Dialogue systems, conversational agents, and chatbots. Morgan & Claypool Publishers.

Meng, F., Guo, X., Peng, Z., Ye, Q., & Lai, K. H. (2022). Trust and elderly users' continuance intention regarding mobile health services: The contingent role of health and technology anxieties. *Information Technology & People*, *35*(1), 259–280. https://doi.org/10.1108/ITP-11-2019-0602

Min, F., Fang, Z., He, Y., & Xuan, J. (2021). Research on users' trust of chatbots driven by AI: An empirical analysis based on system factors and user characteristics. *In proceedings of the 2021 IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE),*55–58. https://doi.org/10.1109/ICCECE51280.2021.9342098

Mohd Rahim, N. I., A. Iahad, N., Yusof, A. F., & A. Al-Sharafi, M. (2022). AI-Based Chatbots Adoption Model for Higher-Education Institutions: A Hybrid PLS-SEM-Neural Network Modelling Approach. *Sustainability*, *14*(19), 12726. https://doi.org/10.3390/su141912726

Mostafa, R. B., & Kasamani, T. (2022). Antecedents and consequences of chatbot initial trust. *European Journal of Marketing*, *56*(6), 1748–1771. https://doi.org/10.1108/EJM-02-2020-0084

Mou, J., & Benyoucef, M. (2021). Consumer behavior in social commerce: Results from a meta-analysis. *Technological Forecasting and Social Change*, *167*, 120734. https://doi.org/10.1016/j.techfore.2021.120734

Mou, J., Shin, D.-H., & Cohen, J. F. (2017). Trust and risk in consumer acceptance of e-services. *Electronic Commerce Research*, *17*(2), 255–288. https://doi.org/10.1007/s10660-015-9205-4

Mou, Y., & Xu, K. (2017). The media inequality: Comparing the initial human-human and human-AI social interactions. *Computers in Human Behavior*, *72*, 432–440. https://doi.org/10.1016/j.chb.2017.02.067

Moussawi, S., Koufaris, M., & Benbunan Fich, R. (2021). How perceptions of intelligence and anthropomorphism affect adoption of personal intelligent agents. *Electronic Markets*, *31*(2), 343–364. https://doi.org/10.1007/s12525-020-00411-w

Murtarelli, G., Collina, C., & Romenti, S. (2023). "Hi! How can I help you today?": Investigating the quality of chatbots–millennials relationship within the fashion industry. *The TQM Journal*, *35*(3), 719–733. https://doi.org/10.1108/TQM-01-2022-0010

Nguyen, D. M., Chiu, Y. T. H., & Le, H. D. (2021). Determinants of Continuance Intention towards Banks' Chatbot Services in Vietnam: A Necessity for Sustainable Development. *Sustainability*, *13*(14), 7625. https://doi.org/10.3390/su13147625

Nikolopoulou, K. (2022, October 29). *What Is Publication Bias? | Definition & Examples*. Scribbr. https://www.scribbr.com/research-bias/publication-bias/

Nordheim, C. B., Følstad, A., & Bjørkli, C. A. (2019). An Initial Model of Trust in Chatbots for Customer

Service—Findings from a Questionnaire Study. *Interacting with Computers*, *31*(3), 317–335. https://doi.org/10.1093/iwc/iwz022

Ogonowski, A., Montandon, A., Botha, E., & Reyneke, M. (2014). Should new online stores invest in social presence elements? The effect of social presence on initial trust formation. *Journal of Retailing and Consumer Services*, *21*(4), 482–491. https://doi.org/10.1016/j.jretconser.2014.03.004

Oldeweme, A., Märtins, J., Westmattelmann, D., & Schewe, G. (2021). The Role of Transparency, Trust, and Social Influence on Uncertainty Reduction in Times of Pandemics: Empirical Study on the Adoption of COVID-19 Tracing Apps. *Journal of Medical Internet Research*, *23*(2), e25893. https://doi.org/10.2196/25893

Omrani, N., Rivieccio, G., Fiore, U., Schiavone, F., & Agreda, S. G. (2022). To trust or not to trust? An assessment of trust in AI-based systems: Concerns, ethics and contexts. *Technological Forecasting and Social Change*, *181*, 121763. https://doi.org/10.1016/j.techfore.2022.121763

Pal, D., Babakerkhell, M. D., & Roy, P. (2022). How perceptions of trust and intrusiveness affect the adoption of voice-activated personal assistants. *IEEE Access,* 10, 123094–123113. https://doi.org/10.1109/ACCESS.2022.3224236

Pantano, E., & Pizzi, G. (2020). Forecasting artificial intelligence on online customer assistance: Evidence from chatbot patents analysis. *Journal of Retailing and Consumer Services*, *55*, 102096. https://doi.org/10.1016/j.jretconser.2020.102096

Park, G., Chung, J., & Lee, S. (2023). Human vs. machine-like representation in chatbot mental health counseling: The serial mediation of psychological distance and trust on compliance intention. *Current Psychology*. https://doi.org/10.1007/s12144-023-04653-7

Patil, K., & Kulkarni, M. (2022). Can we trust Health and Wellness Chatbot going mobile? Empirical research using TAM and HBM. *2022 IEEE Region 10 Symposium (TENSYMP)*, 1–6. https://doi.org/10.1109/TENSYMP54529.2022.9864368

Peng, G., Cheng, X., & Liu, C. (2022). Research on Influencing Factors of Internet Users' Willingness to Disclose Personal Information Based on Meta-Analysis. *Journal of Modern Information*, *42*(11), 111–120. https://doi.org/10.3969/j.issn.1008-0821.2022.11.010

Pesonen, J. A. (2021). 'Are You OK?' Students' Trust in a Chatbot Providing Support Opportunities. In P. Zaphiris & A. Ioannou (Eds.), *Learning and Collaboration Technologies: Games and Virtual Environments for Learning* ,12785, 99–215. Springer International Publishing. https://doi.org/10.1007/978-3-030-77943-6_13

Petty, R. E., & Cacioppo, J. T. (1986). The Elaboration Likelihood Model of Persuasion. In *Advances in Experimental Social Psychology*, 19, 123–205. Elsevier. https://doi.org/10.1016/S0065-2601(08)60214-2

Piçarra, N., Giger, J.-C., Pochwatko, G., & Gonçalves, G. (2016). Making sense of social robots: A structural analysis of the layperson's social representation of robots. *European Review of Applied Psychology*, *66*(6), 277–289. https://doi.org/10.1016/j.erap.2016.07.001

Pillai, R., & Sivathanu, B. (2020). Adoption of AI-based chatbots for hospitality and tourism. *International Journal of Contemporary Hospitality Management*, *32*(10), 3199–3226. https://doi.org/10.1108/IJCHM-04-2020-0259

Pillai, R., Sivathanu, B., Metri, B., & Kaushik, N. (2023). Students' adoption of AI-based teacher-bots (T-bots) for learning in higher education. *Information Technology & People*. 37(1), 328-355. https://doi.org/10.1108/ITP-02-2021-0152

Pizzi, G., Vannucci, V., Mazzoli, V., & Donvito, R. (2023). I, chatbot! The impact of anthropomorphism and gaze direction on willingness to disclose personal information and behavioral intentions. *Psychology & Marketing*, *40*(7), 1372–1387. https://doi.org/10.1002/mar.21813

Prakash, A. V., Joshi, A., Nim, S., & Das, S. (2023). Determinants and consequences of trust in AI-based customer service chatbots. *The Service Industries Journal*, *43*(9–10), 642–675. https://doi.org/10.1080/02642069.2023.2166493

Qahri Saremi, H., & Montazemi, A. R. (2019). Factors Affecting the Adoption of an Electronic Word of Mouth Message: A Meta-Analysis. *Journal of Management Information Systems*, *36*(3), 969–1001. https://doi.org/10.1080/07421222.2019.1628936

Radić, M., Vienken, C., Nikschat, L., Dietrich, T., Koenig, H., Laderick, L., & Radić, D. (2022). AI-Based Business Models in Healthcare: An Empirical Study of Clinical Decision Support Systems. In M. A. Bach Tobji, R. Jallouli, V. A. Strat, A. M. Soares, & A. A. Davidescu (Eds.), *Digital Economy. Emerging Technologies and Business Innovation*, 461, 70–79. Springer International Publishing. https://doi.org/10.1007/978-3-031-17037-9_5

Rafiq, F., Dogra, N., Adil, M., & Wu, J.-Z. (2022). Examining Consumer's Intention to Adopt AI-Chatbots in Tourism Using Partial Least Squares Structural Equation Modeling Method. *Mathematics*, *10*(13), 2190. https://doi.org/10.3390/math10132190

Rajaobelina, L., Prom Tep, S., Arcand, M., & Ricard, L. (2021). Creepiness: Its antecedents and impact on loyalty when interacting with a chatbot. *Psychology & Marketing*, *38*(12), 2339–2356. https://doi.org/10.1002/mar.21548

Rao, S. R., Graubard, B. I., Schmid, C. H., Morton, S. C., Louis, T. A., Zaslavsky, A. M., & Finkelstein, D. M. (2008). Meta-analysis of survey data: Application to health services research. *Health Services and Outcomes Research Methodology*, *8*(2), 98–114. https://doi.org/10.1007/s10742-008-0032-0

Roh, T., Park, B. I., & Xiao, S. (2023). Adoption of ai-enabled robo-advisors in fintech: Simultaneous employment of utaut and the theory of reasoned action. *Journal of Electronic Commerce Research*, *24*(1), 29–47.

Roy, R., & Naidoo, V. (2021). Enhancing chatbot effectiveness: The role of anthropomorphic conversational styles and time orientation. *Journal of Business Research*, *126*, 23–34. https://doi.org/10.1016/j.jbusres.2020.12.051

R, R. (2014). Heterogeneity and subgroup analyses in Cochrane Consumers and Communication Review Group reviews: Planning the analysis at protocol stage Heterogeneity

Saaida, M. (2023). *Cultural Studies: Unraveling the Influence of Culture on Society*. *1*, 1–15. https://doi.org/10.5281/zenodo.10832527

Said, N., Ben, M. K., Bahri-Ammari, N., Yousaf, A., & Mishra, A. (2023). Customer acceptance of humanoid service robots in hotels: Moderating effects of service voluntariness and culture. *International Journal of Contemporary Hospitality Management*, *36(6), 1844-1867*. https://doi.org/10.1108/IJCHM-12-2022-1523

Sarkar, S., Chauhan, S., & Khare, A. (2020). A meta-analysis of antecedents and consequences of trust in mobile commerce. *International Journal of Information Management*, *50*, 286–301. https://doi.org/10.1016/j.ijinfomgt.2019.08.008

Schuetz, S., & Venkatesh, V. (2020). Research Perspectives: The Rise of Human Machines: How Cognitive Computing Systems Challenge Assumptions of User-System Interaction . *Journal of the Association for Information Systems*, 21(2), 460–482. https://doi.org/10.17705/1jais.00608

Shao, Z., Zhang, L., Pan, Z., & Benitez, J. (2023). Uncovering the dual influence processes for click-through intention in the mobile social platform: An elaboration likelihood model perspective. *Information & Management*, *60*(5), 103799. https://doi.org/10.1016/j.im.2023.103799

Shi, S., Gong, Y., & Gursoy, D. (2021). Antecedents of Trust and Adoption Intention toward Artificially Intelligent Recommendation Systems in Travel Planning: A Heuristic–Systematic Model. *Journal of Travel Research*, *60*(8), 1714–1734. https://doi.org/10.1177/0047287520966395

Shin, D., Al-Imamy, S., & Hwang, Y. (2022). Cross-cultural differences in information processing of chatbot journalism: Chatbot news service as a cultural artifact. *Cross Cultural & Strategic Management*, *29*(3), 618–638. https://doi.org/10.1108/CCSM-06-2020-0125

Short, J., Williams, E., & Christie, B. (1976). *The social psychology of telecommunications*. Wiley.

Shumanov, M., & Johnson, L. (2021). Making conversations with chatbots more personalized. *Computers in Human Behavior*, *117*, 106627. https://doi.org/10.1016/j.chb.2020.106627

Silva, F. A., Shojaei, A. S., & Barbosa, B. (2023). Chatbot-Based Services: A Study on Customers' Reuse Intention. *Journal of Theoretical and Applied Electronic Commerce Research*, *18*(1), 457–474. https://doi.org/10.3390/jtaer18010024

Silva, S. C., De Cicco, R., Vlačić, B., & Elmashhara, M. G. (2023). Using chatbots in e-retailing – how to mitigate perceived risk and enhance the flow experience. *International Journal of Retail & Distribution Management*, *51*(3), 285–305. https://doi.org/10.1108/IJRDM-05-2022-0163

Simon, O., Neuhofer, B., & Egger, R. (2020). Human-robot interaction: Conceptualising trust in frontline teams through LEGO® Serious Play®. *Tourism Management Perspectives*, *35*, 100692. https://doi.org/10.1016/j.tmp.2020.100692

Skalski, P., & Tamborini, R. (2007). The Role of Social Presence in Interactive Agent-Based Persuasion. *Media Psychology*, *10*(3), 385–413. https://doi.org/10.1080/15213260701533102

Stower, R., Calvo-Barajas, N., Castellano, G., & Kappas, A. (2021). A Meta-analysis on Children's Trust in Social Robots. *International Journal of Social Robotics*, *13*(8), 1979–2001. https://doi.org/10.1007/s12369-020-00736-8

Stroup, D. F. (2000). Meta-analysis of Observational Studies in EpidemiologyA Proposal for Reporting. *JAMA*, *283*(15), 2008. https://doi.org/10.1001/jama.283.15.2008

Tang, Y. (2021). *A study of the factors influencing the willingness to use smart investment advisors* [Master, South Western University of Finance and Economics]. https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CMFD&dbname=CMFD202202&filename=1021735443.nh&v=

Tanihatu, M. C., Suryanto, & Syahchari, D. H. (2023). Factors influencing users to use chatbots in banking and fintech industry in Indonesia. In *Proceedings of the 2023 International Conference on Inventive Computation Technologies (ICICT)*, 846–851. https://doi.org/10.1109/ICICT57646.2023.10134013

Tisland, I., Sodefjed, M. L., Vassilakopoulou, P., & Pappas, I. O. (2022). The Role of Quality, Trust, and Empowerment in Explaining Satisfaction and Use of Chatbots in e-government. In S. Papagiannidis, E. Alamanos, S. Gupta, Y. K. Dwivedi, M. Mäntymäki, & I. O. Pappas (Eds.), *The Role of Digital Technologies in Shaping the Post-Pandemic World* (Vol. 13454, pp. 279–291). Springer International Publishing. https://doi.org/10.1007/978-3-031-15342-6_22

Touré-Tillery, M., & McGill, A. L. (2015). Who or What to Believe: Trust and the Differential Persuasiveness of Human and Anthropomorphized Messengers. *Journal of Marketing*, *79*(4), 94–110. https://doi.org/10.1509/jm.12.0166

Van Dis, E. A. M., Bollen, J., Zuidema, W., Van Rooij, R., & Bockting, C. L. (2023). ChatGPT: Five priorities for research. *Nature*, *614*(7947), 224–226. https://doi.org/10.1038/d41586-023-00288-7

Wan, Y., Zhang, Y., & Yan, M. (2020). What influences patients' willingness to choose in online health consultation? An empirical study with PLS–SEM. *Industrial Management & Data Systems*, *120*(12), 2423–2446. https://doi.org/10.1108/IMDS-11-2019-0633

Wang, J., Shahzad, F., Ahmad, Z., Abdullah, M., & Hassan, N. M. (2022). Trust and Consumers' Purchase Intention in a Social Commerce Platform: A Meta-Analytic Approach. *SAGE Open*. 12(2). https://doi.org/10.1177/21582440221091262

Wang, X., Lin, X., & Shao, B. (2022). How does artificial intelligence create business agility? Evidence from chatbots. *International Journal of Information Management*, *66*, 102535. https://doi.org/10.1016/j.ijinfomgt.2022.102535

Wang, X., Lin, X., & Shao, B. (2023). Artificial intelligence changes the way we work: A close look at innovating with chatbots. *Journal of the Association for Information Science and Technology*, *74*(3), 339–353. https://doi.org/10.1002/asi.24621

Wang, X., Luo, R., Liu, Y., & Wuji, S. (2023). Influencing Factors and Empirical Research on the Usage Behavior of Smart Library Online Chatbots. *Journal of the China Society for Scientific and Technical Information*, *42*(2), 217–230.

Wang, Y., Min, Q., & Han, S. (2016). Understanding the effects of trust and risk on individual behavior toward social media platforms: A meta-analysis of the empirical evidence. *Computers in Human Behavior*, *56*, 34–44. https://doi.org/10.1016/j.chb.2015.11.011

Wu, J., Zhang, D., Liu, T., Liu, X., & Zhao, S. (2023). A study on the acceptance of human trust in artificial intelligence and the mechanism of brain cognition: A meta-analysis of empirical research and neuroscience experiments. *Journal of Industrial Engineering*, 38(1), 60-73.

Wu, K., Zhao, Y., Zhu, Q., Tan, X., & Zheng, H. (2011). A meta-analysis of the impact of trust on technology acceptance model: Investigation of moderating influence of subject and context type. *International Journal of Information Management*, *31*(6), 572–581. https://doi.org/10.1016/j.ijinfomgt.2011.03.004

Yan, W., Chen, R., & Zhang, M. (2021). A Meta-Analysis of Factors Influencing Online Knowledge and Payment Intention. *Journal of the China Society for Scientific and Technical Information*, *40*(2), 204–212. https://doi.org/10.3772/j.issn.1000-0135.2021.02.010

Yang, B., Hu, Y., Cheng, X., Bao, Y., & Chen, W. (2022). Exploring the factors affecting content dissemination through WeChat official accounts: A heuristic-systematic model perspective. *Electronic Commerce Research*. 23, 2713-2735. https://doi.org/10.1007/s10660-022-09559-3

Yen, C., & Chiang, M. C. (2021). Trust me, if you can: A study on the factors that influence consumers' purchase intention triggered by chatbots based on brain image evidence and self-reported assessments. *Behaviour & Information Technology*, *40*(11), 1177–1194. https://doi.org/10.1080/0144929X.2020.1743362

Zhang, B. (2022). The impact of intelligent customer service communication style, empathic responses and reliability on customer trust and intention to use [Master]. Shaanxi Normal University.

Zhang, B., Zhu, Y., Deng, J., Zheng, W., Liu, Y., Wang, C., & Zeng, R. (2023). "I Am Here to Assist Your Tourism": Predicting Continuance Intention to Use AI-based Chatbots for Tourism. Does Gender Really Matter? *International Journal of Human–Computer Interaction*, *39*(9), 1887–1903. https://doi.org/10.1080/10447318.2022.2124345

Zhang, J., Chen, Q., Lu, J., Wang, X., Liu, L., & Feng, Y. (2024). Emotional expression by artificial intelligence chatbots to improve customer satisfaction: Underlying mechanism and boundary conditions. *Tourism Management*, *100*, 104835. https://doi.org/10.1016/j.tourman.2023.104835

Zhang, K. Z. K., Lee, M. K. O., Cheung, C. M. K., Shen, A. X. L., Jin, X.-L., & Chen, H. (2010). Exploring the Moderating Effect of Information Inconsistency in a Trust-Based Online Shopping Model. In *proceedings of the 43rd Hawaii International Conference on System Sciences,* 1–9. https://doi.org/10.1109/HICSS.2010.202

Zhang, K. Z. K., Zhao, S. J., Cheung, C. M. K., & Lee, M. K. O. (2014). Examining the influence of online reviews on consumers' decision-making: A heuristic–systematic model. *Decision Support Systems*, *67*, 78–89.

https://doi.org/10.1016/j.dss.2014.08.005

Zhang, Z., Feng, Y., & Feng, T. (2023). Research on the Impact of Social Media Relationship Strategies on Customer Trust——Based on Smartpls. In Z. Zhan, D. Zhou, & H. Wu (Eds.), *In proceedings of the 2022 2nd International Conference on Education, Information Management and Service Science (EIMSS 2022)* (pp. 200–210). Atlantis Press International BV. https://doi.org/10.2991/978-94-6463-024-4_22

Zhang, Z., Takanobu, R., Zhu, Q., Huang, M., & Zhu, X. (2020). Recent advances and challenges in task-oriented dialog systems. *Science China Technological Sciences*, *63*(10), 2011–2027. https://doi.org/10.1007/s11431-020-1692-3

Zhao, K. (2022). *A study of factors influencing banks' willingness to use intelligent robots* [Master, South Western University of Finance and Economics]. https://kns.cnki.net/KCMS/detail/detail.aspx?dbcode=CMFD&dbname=CMFD202301&filename=1022562038.nh&v=

Zhao, K. (2023). *Research On Influence Factors Of Use Intention To Bank Intelligent Robot——Based On Heuristic-Systematic Model* [Master, South Western University of Finance and Economics]. https://doi.org/10.27412/d.cnki.gxncu.2022.002043

Zhou, X., Smith, C. J. M., & Al-Samarraie, H. (2023). Digital technology adaptation and initiatives: A systematic review of teaching and learning during COVID-19. *Journal of Computing in Higher Education*. 36, 813-834. https://doi.org/10.1007/s12528-023-09376-z

Zhu, Y., Zhang, R. (Renata), Zou, Y., & Jin, D. (2023). Investigating customers' responses to artificial intelligence chatbots in online travel agencies: The moderating role of product familiarity. *Journal of Hospitality and Tourism Technology*, *14*(2), 208–224. https://doi.org/10.1108/JHTT-02-2022-0041

Zierau, N., Engel, C., Söllner, M., & Leimeister, J. M. (2021). Trust in smart personal assistants: A systematic literature review and development of a research agenda [Preprint]. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3920577

## APPENDIXES

Appendix A. Frequency statistics of variables.

| Variable | Frequency | Literature | Variable names in the literature |
|---|---|---|---|
| Competence | 11 | (X. Cheng, Zhang, et al., 2022) | Perceived competence of chatbots |
| | | (Pesonen, 2021) | Competence |
| | | (Yen & Chiang, 2021) | Competence |
| | | (Hsiao & Chen, 2022) | Problem-solving |
| | | (Jiang et al., 2023) | Perceived task-solving competence |
| | | (B. Zhang, 2022) | Perceived competence |
| | | (Mostafa & Kasamani, 2022) | Compatibility |
| | | (Gong, 2021) | Functional performance |
| | | (J. Liu, 2019) | Performance expectations |
| | | (Lei et al., 2021) | Task attraction |
| | | (Q. Chen & Park, 2021) | Task attraction |
| Risk | 6 | (Alagarsamy & Mehrolia, 2023) | Perceived risk |
| | | (Pesonen, 2021) | Risk perception |
| | | (Malodia et al., 2023) | Risk barrier |
| | | (Patil & Kulkarni, 2022) | Safety risk |
| | | (Dekkal et al., 2023) | Privacy concerns |
| | | (Zhao, 2022) | Perceived security |
| Personalization | 3 | (Alimamy, 2023) | Personalization |
| | | (Gong, 2021) | Perception personalization |
| | | (Tang, 2021) | Personalized service |
| Perceived usefulness | 4 | (Alagarsamy & Mehrolia, 2023) | Perceived usefulness |
| | | (Patil & Kulkarni, 2022) | Perceived usefulness |
| | | (Zhu et al., 2023) | Perceived usefulness |
| | | (Tang, 2021) | Personalized service |
| Perceived ease of use | 3 | (Mostafa & Kasamani, 2022) | Perceived ease of use |
| | | (Alagarsamy & Mehrolia, 2023) | Perceived Ease of Use |
| | | (Patil & Kulkarni, 2022) | Perceived Ease of Use |
| Perceived interactivity | 2 | (O. K. D. Lee et al., 2021) | Interaction quality |
| | | (Hsieh & Lee, 2021) | Parasocial interaction |
| Information quality | 4 | (Nguyen et al., 2021) | Information quality |
| | | (Alagarsamy & Mehrolia, 2023) | Information quality |
| | | (Tisland et al., 2022) | Information quality |
| | | (O. K. D. Lee et al., 2021) | Information quality |
| Service quality | 4 | (Nguyen et al., 2021) | Service quality |
| | | (Alagarsamy & Mehrolia, 2023) | Service quality |
| | | (Q. Chen et al., 2023) | Service quality |
| | | (Tisland et al., 2022) | Service quality |
| System quality | 3 | (Nguyen et al., 2021) | System quality |
| | | (Tisland et al., 2022) | System quality |
| | | (O. K. D. Lee et al., 2021) | System quality |
| User interface/design | 2 | (Hsiao & Chen, 2022) | User interface |
| | | (Alagarsamy & Mehrolia, 2023) | Interface and Design |

| Variable | Frequency | Literature | Variable names in the literature |
|---|---|---|---|
| Perceived transparency | 2 | (Shin et al., 2022) | Perceived transparency |
| | | (Tang, 2021) | Lack of transparency |
| Anthropomorphism | 8 | (Klein & Martinez, 2022) | Anthropomorphic |
| | | (Yen & Chiang, 2021) | Anthropomorphic |
| | | (J. C. Lee & Chen, 2022) | Perceived anthropomorphism |
| | | (Q. Chen & Park, 2021) | Anthropomorphism |
| | | (Gong, 2021) | Anthropomorphism |
| | | (Zhao, 2022) | Anthropomorphism |
| | | (Lei et al., 2021) | Social attraction |
| | | (Hsiao & Chen, 2022) | Anthropomorphic |
| Social influence | 4 | (Mostafa & Kasamani, 2022) | Social influence |
| | | (Patil & Kulkarni, 2022) | Social influence |
| | | (Liu, 2019) | Social influence |
| | | (Gong, 2021) | Social influence |
| Social presence | 6 | (F. A. Silva et al., 2023) | Perceived social presence |
| | | (De Cicco et al., 2020) | Social presence |
| | | (Yen & Chiang, 2021) | Social presence |
| | | (Jiang et al., 2023) | Social presence |
| | | (Min et al., 2021) | Social presence |
| | | (De Cicco et al., 2021) | Social presence |
| Perceived Enjoyment /playfulness | 3 | (Alagarsamy & Mehrolia, 2023) | Perceived enjoyment |
| | | (Dekkal et al., 2023) | Enjoyment |
| | | (Yen & Chiang, 2021) | Playfulness |
| Creepiness | 2 | (Rajaobelina et al., 2021) | Creepiness |
| | | (Dekkal et al., 2023) | Creepiness |
| Technology fear | 2 | (Alagarsamy & Mehrolia, 2023) | Technology fear |
| | | (Dekkal et al., 2023) | Technology anxiety |
| Empathy | 2 | (Cheng, Bao, et al., 2022) | Empathy |
| | | (Wang et al., 2023) | Empathy |
| Perceived warmth | 2 | (X. Cheng, Zhang, et al., 2022) | Perceived warmth of chatbots |
| | | (B. Zhang, 2022) | Perceived warmth |
| Friendliness | 2 | (X. Cheng, Bao, et al., 2022) | Friendliness |
| | | (X. Wang, Luo, et al., 2023) | Friendliness |

Appendix B. Literature coding results.

| Number | Author and Publication Date | Variables | Sample | Trust | E-commerce? | Industry | Culture | Type (a) | Type (b) |
|---|---|---|---|---|---|---|---|---|---|
| 1 | (Klein & Martinez, 2022) | 2 | 401 | E | Y | Retailing | W | Task | Text |
| 2 | (Hsiao & Chen, 2022) | 3 | 111 | C | Y | Hotels & Tourism | E’ | Task | Text |
| 3 | (Mostafa & Kasamani, 2022) | 6 | 184 | C &E | Y | Retailing | W | Task | Text |
| 4 | (Rajaobelina et al., 2021) | 1 | 430 | C | N | Finance | W | Task | Text |
| 5 | (Park et al., 2023) | 1 | 385 | E | N | Medical and Health | W | Task | Voice |
| 6 | (Nguyen et al., 2021) | 1 | 359 | C | N | Finance | E’ | Task | Text |
| 7 | (X. Wang, Lin, et al., 2023) | 1 | 202 | C | N | Inside the Enterprise | W | CON | Text |
| 8 | (Gong, 2021) | 7 | 364 | C &E | N | Hotels & Tourism | E’ | Task | Text |
| 9 | (J. Liu, 2019) | 3 | 191 | C | N | Finance | E’ | Task | Text |
| 10 | (Zhao, 2022) | 5 | 399 | C &E | N | Finance | E’ | Task | Text |
| 11 | (X. Wang, Luo, et al., 2023) | 1 | 326 | E | N | Library | E’ | Task | Text |
| 12 | (B. Zhang, 2022) | 3 | 99 | C &E | Y | Retailing | E’ | Task | Text |
| 13 | (Tang, 2021) | 2 | 316 | C | N | Finance | E’ | Task | Text |
| 14 | (Alagarsamy & Mehrolia, 2023) | 4 | 435 | C &E | N | Finance | E’ | Task | Text |
| 15 | (F. A. Silva et al., 2023) | 2 | 201 | C | - | - | E’ | Task& CON | Text& Voice |
| 16 | (X. Cheng, Zhang, et al., 2022) | 3 | 302 | C &E | Y | Retailing | E’ | Task | Text |
| 17 | (Shin et al., 2022) | 1 | 350 | C | N | Media | W | Task | Text |
| 18 | (Shin et al., 2022) | 1 | 340 | C | N | Media | W | Task | Text |
| 19 | (Pesonen, 2021) | 3 | 49 | C | N | Education | W | Task | Text |
| 20 | (De Cicco et al., 2020) | 2 | 193 | C | Y | Retailing | W | Task | Text |
| 21 | (De Cicco et al., 2021) | 2 | 160 | E | Y | Retailing | W | Task | Text |
| 22 | (Lei et al., 2021) | 6 | 200 | C &E | N | Hotels & Tourism | E’ | Task | Text& Voice |
| 23 | (Q. Chen et al., 2023) | 2 | 459 | C &E | - | - | E’ | Task& CON | Text& Voice |
| 24 | (X. Cheng, Bao, et al., 2022) | 1 | 299 | E | Y | Retailing | E’ | Task | Text |
| 25 | (Dekkal et al., 2023) | 2 | 430 | C | N | Finance | W | Task | Text |
| 26 | (Tisland et al., 2022) | 1 | 105 | C | N | Government | W | Task | Text |
| 27 | (Alimamy, 2023) | 2 | 243 | C &E | N | Personal Assistant | W | CON | Voice |
| 28 | (Balakrishnan & Dwivedi, 2021) | 1 | 410 | C | N | Realty | E’ | Task | Text& Voice |
| 29 | (Yen & Chiang, 2021) | 8 | 204 | C &E | Y | Retailing | E’ | Task | Text |
| 30 | (S. Choi et al., 2023) | 1 | 215 | C | N | Education | E’ | Task | Text& Voice |
| 31 | (Malodia et al., 2023) | 2 | 290 | C | N | Personal | E’ | CON | Voice |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Assistant | | | |
| 32 | (O. K. D. Lee et al., 2021) | 2 | 221 | C &E | N | Finance | W | CON | Voice |
| 33 | (J. C. Lee & Chen, 2022) | 2 | 451 | E | N | Personal Assistant | E’ | Task | Text |
| 34 | (Hsieh & Lee, 2021) | 1 | 391 | C | N | Personal Assistant | W& E’ | CON | Voice |
| 35 | (Pillai et al., 2023) | 1 | 1380 | C | N | Education | E’ | Task | Text& Voice |
| 36 | (Tanihatu et al., 2023) | 1 | 442 | C | N | Finance | E’ | Task | Text |
| 37 | (S. C. Silva et al., 2023) | 1 | 226 | E | Y | Retailing | W | Task | Text |
| 38 | (Behera et al., 2021) | 1 | 325 | C | N | Medical and Health | E’ | Task | Text |
| 39 | (Lappeman et al., 2023) | 1 | 142 | E | N | Finance | W | Task | Text |
| 40 | (Lappeman et al., 2023) | 1 | 142 | E | N | Finance | W | Task | Text |
| 41 | (Patil & Kulkarni, 2022) | 6 | 265 | C &E | N | Medical and Health | E’ | CON | Text |
| 42 | (Pillai & Sivathanu, 2020) | 1 | 1480 | C | N | Hotels & Tourism | E’ | Task | Text& Voice |
| 43 | (Kasilingam, 2020) | 1 | 350 | C | Y | Retailing | E’ | Task | Text |
| 44 | (Zhu et al., 2023) | 2 | 566 | C &E | N | Hotels & Tourism | E’ | Task | Text |
| 45 | (Dawar et al., 2022) | 2 | 354 | C &E | - | - | E’ | CON | Text |
| 46 | (De Cicco et al., 2022) | 1 | 208 | C | Y | Retailing | W | Task | Text |
| 47 | (Behera et al., 2022) | 1 | 300 | C | - | - | E’ | Task | Text |
| 48 | (Eren, 2021) | 1 | 240 | C | N | Finance | W | Task | Text& Voice |
| 49 | (Albayrak et al., 2023) | 1 | 340 | C | N | Hotels & Tourism | W | Task | Text |
| 50 | (Chandra, Shirish, et al., 2022) | 2 | 213 | C &E | - | - | E’ | CON | Text |
| 51 | (Andrés-Sánchez & Gené-Albesa, 2023) | 2 | 119 | C &E | N | Finance | W | Task | Text |
| 52 | (Murtarelli et al., 2023) | 1 | 191 | C | Y | Retailing | W | Task | Text |
| 53 | (Y. Choi, 2021) | 1 | 454 | E | N | Inside the Enterprise | E’ | Task | Text |
| 54 | (Jiang et al., 2023) | 4 | 615 | C &E | - | - | E’ | CON | Text |
| 55 | (Min et al., 2021) | 2 | 377 | C &E | Y | Retailing | E’ | Task | Text |
| 56 | (Q. Chen & Park, 2021) | 5 | 263 | C &E | N | Personal Assistant | E’ | CON | Voice |

Note: C: Cognitive trust; E: Emotional trust; W: Western culture; E’: Eastern culture; CON: Conversational.

Appendix C. Construct definition.

| Variables | Definition | Names of variables commonly used in the studies | |
|---|---|---|---|
| | | Variable names | Authors |
| Competence | Competence reflects a chatbot's ability to perform tasks and provide information accurately and reliably, which includes an evaluation of its objective characteristics such as intelligence, dexterity, and efficiency (Pizzi et al., 2023) | Perceived competence of chatbots | (Cheng et al., 2022) |
| | | Competence | (Pesonen, 2021) |
| | | Competence | (Yen & Chiang, 2021) |
| | | problem-solving | (Hsiao & Chen, 2022) |
| | | perceived task-solving competence | (Jiang et al., 2023) |
| | | Perceived competence | (Zhang, 2022) |
| | | Compatibility | (Mostafa & Kasamani, 2022) |
| | | Functional performance | (Gong, 2021) |
| | | Performance expectations | (Liu, 2019) |
| | | Task Attraction | (Lei et al., 2021) |
| | | Task attraction | (Chen & Park, 2021) |
| Risk | Risk includes technical errors and security breaches, which have the potential to compromise users' rights and interests across financial, psychological, physical, or social dimensions (Habbal et al., 2024). | Perceived risk | (Alagarsamy & Mehrolia, 2023) |
| | | Risk perception | (Pesonen, 2021) |
| | | Risk barrier | (Malodia et al., 2023) |
| | | Safety risk | (Patil & Kulkarni, 2022) |
| | | Privacy concerns | (Dekkal et al., 2023) |
| | | Perceived safety | (Zhao, 2022) |
| Personalization | Personalization is a process that involves tailoring and customizing products, services, or experiences based on an individual's specific needs, preferences, behaviors, and contextual information (Chandra et al., 2022). | Personalization | (Alimamy, 2023) |
| | | Perceived personalization | (Gong, 2021) |
| | | personalized service | (Tang, 2021) |
| Anthropomorphism | Anthropomorphism refers to the AI possessing certain human characteristics (i.e., appearance or speech style), which can transform human-computer interaction into a process similar to human-to-human interaction (Cai et al., 2022; Lu et al., 2019). | anthropomorphic | (Klein & Martinez, 2022) |
| | | anthropomorphic | (Yen & Chiang, 2021) |
| | | Perceived anthropomorphism | (J. C. Lee & Chen, 2022) |
| | | anthropomorphism | (Chen & Park, 2021) |
| | | anthropomorphism | (Gong, 2021) |
| | | anthropomorphism | (Zhao, 2022) |
| | | Social Attraction | (Lei et al., 2021) |
| | | anthropomorphic | (Hsiao & Chen, 2022) |
| Social presence | Social presence denotes the prominence of an individual's existence within social exchanges and the significance of interpersonal connections (Short et al., 1976) | Perceived social presence | (Mostafa & Kasamani, 2022) |
| | | Social presence | (Patil & Kulkarni, 2022) |
| | | Social presence | (Liu, 2019) |
| | | Social presence | (Gong, 2021) |
| | | Social presence | (F. A. Silva et al., 2023) |

| Variables | Definition | Names of variables commonly used in the studies | |
|---|---|---|---|
| | | Variable names | Authors |
| Social influence | Social influence encompasses the impact of a user's social environment, including the opinions of their relatives and friends (Mostafa & Kasamani, 2022) | Social presence | (De Cicco et al., 2020) |
| | | Social influence | (Yen & Chiang, 2021) |
| | | Social influence | (Jiang et al., 2023) |
| | | Social influence | (Min et al., 2021) |
| | | Social influence | (De Cicco et al., 2021) |

Appendix D. Assessment of Survey Quality.

| | Whether to report on the response rate | Whether representative sample | Whether or not questionnaire pre-surveys are conducted | Whether to follow up on uncovered samples or consider non-response bias |
|---|---|---|---|---|
| (Klein & Martinez, 2022) | No | No | No | No |
| (Mostafa & Kasamani, 2022) | Yes | Yes | No | No |
| (Yen & Chiang, 2021) | No | Yes | No | No |
| (B. Zhang, 2022) | No | No | Yes | No |
| (X. Cheng, Zhang, et al., 2022) | No | No | Yes | No |
| (De Cicco et al., 2020) | No | No | No | No |
| (Kasilingam, 2020) | No | Yes | No | No |
| (Gong, 2021) | No | No | Yes | No |
| (De Cicco et al., 2022) | No | No | No | No |
| (Liu, 2019) | Yes | Yes | Yes | No |
| (Murtarelli et al., 2023) | No | Yes | No | No |
| (De Cicco et al., 2021) | No | No | No | No |
| (Zhao, 2022) | No | No | Yes | No |
| (X. Cheng, Bao, et al., 2022) | No | No | Yes | No |
| (Hsiao & Chen, 2022) | No | No | No | Yes |
| (Tang, 2021) | No | Yes | Yes | Yes |
| (Lei et al., 2021) | Yes | Yes | No | No |
| (S. C. Silva et al., 2023) | No | No | No | No |
| (Alagarsamy & Mehrolia, 2023) | Yes | Yes | Yes | No |
| (Pillai & Sivathanu, 2020) | Yes | Yes | Yes | Yes |
| (Zhu et al., 2023) | No | No | No | No |
| (Albayrak et al., 2023) | Yes | Yes | No | No |
| (Rajaobelina et al., 2021) | No | No | Yes | No |
| (Nguyen et al., 2021) | Yes | Yes | Yes | No |
| (Dekkal et al., 2023) | No | No | No | No |
| (Pesonen, 2021) | No | Yes | No | No |
| (O. K. D. Lee et al., 2021) | No | No | No | No |
| (Alimamy, 2023) | No | No | No | No |
| (Tanihatu et al., 2023) | No | No | No | No |
| (Eren, 2021) | No | No | No | No |
| (Min et al., 2021) | No | No | No | No |
| (Andrés-Sánchez & Gené-Albesa, 2023) | Yes | Yes | Yes | No |
| (Patil & Kulkarni, 2022) | No | No | No | No |
| (Lappeman et al., 2023) | No | No | Yes | No |
| (S. Choi et al., 2023) | No | No | No | No |
| (J. C. Lee & Chen, 2022) | No | Yes | Yes | Yes |
| (Pillai et al., 2023) | No | Yes | Yes | Yes |
| (Behera et al., 2022) | No | Yes | Yes | Yes |
| (Shin et al., 2022) | Yes | No | Yes | No |
| (Park et al., 2023) | No | No | No | No |

| | Whether to report on the response rate | Whether representative sample | Whether or not questionnaire pre-surveys are conducted | Whether to follow up on uncovered samples or consider non-response bias |
|---|---|---|---|---|
| (Malodia et al., 2023) | Yes | Yes | Yes | No |
| (Tisland et al., 2022) | No | No | No | No |
| (X. Wang, Lin, et al., 2023) | No | Yes | No | No |
| (Y. Choi, 2021) | Yes | No | Yes | Yes |
| (X. Wang, Luo, et al., 2023) | No | Yes | No | No |
| (Q. Chen et al., 2023) | No | No | No | No |
| (Hsieh & Lee, 2021) | No | Yes | No | Yes |
| (Balakrishnan & Dwivedi, 2021) | No | Yes | Yes | No |
| (F. A. Silva et al., 2023) | No | No | No | No |
| (Dawar et al., 2022) | No | No | No | No |
| (Chandra, Shirish, et al., 2022) | No | No | Yes | No |
| (Behera et al., 2021) | No | Yes | No | No |
| (Q. Chen & Park, 2021) | No | No | No | No |
| (Jiang et al., 2023) | No | No | Yes | No |

Appendix E. Robustness analysis results.

| Assumption | K | N | Effect size and 95% CI | | | Two-tailed test | |
|---|---|---|---|---|---|---|---|
| | | | Point estimate | Lower limit | Upper limit | Z-value | P-value |
| COM - CT | 1 | 99 | 0.577 | 0.428 | 0.695 | 6.447 | 0 |
| RI - CT | 2 | 695 | -0.094 | -0.348 | 0.173 | -0.689 | 0.491 |
| RI - ET | 1 | 265 | -0.23 | -0.341 | -0.113 | -3.791 | 0 |
| PE - CT | 1 | 243 | 0.575 | 0.485 | 0.654 | 10.154 | 0 |
| ANT - ET | 1 | 401 | 0.802 | 0.764 | 0.834 | 22.029 | 0 |
| SP - CT | 2 | 570 | 0.574 | 0.399 | 0.708 | 5.55 | 0 |
| SP - ET | 2 | 537 | 0.582 | 0.426 | 0.705 | 6.193 | 0 |
| SI - CT | 1 | 265 | 0.53 | 0.437 | 0.611 | 9.552 | 0 |
| SI - ET | 1 | 265 | 0.53 | 0.437 | 0.611 | 9.552 | 0 |
| CT - AI | 18 | 5620 | 0.547 | 0.444 | 0.635 | 8.804 | 0 |
| ET - AI | 8 | 2151 | 0.689 | 0.556 | 0.787 | 7.599 | 0 |

*Note: k:* number of studies; *N:* sample size; *SE:* standard error; COM: Competence; RI: Risk; ANT: Anthropomorphism; SP: Social presence; SI: Social influence; ET: Emotional trust; CT: Cognitive trust; AI: Adopt intention.