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### **User Evaluation of Conversational AI Systems: The Roles of Digital Literacy, Trust, and Perceived Privacy Risk**

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#### **ABSTRACT**

Conversational AI is spreading rapidly, and understanding how users evaluate these systems has become an important issue in information systems research. Drawing on an information systems perspective, this study develops a structural model integrating digital literacy, trust, and perceived privacy risk to examine how digital literacy influences users' evaluations of conversational AI systems through key psychological mechanisms. Using survey data collected from 580 Chinese Generation Z users, the study employs PLS-SEM to test the proposed model. The results indicate that digital literacy significantly enhances trust, which in turn positively influences system evaluation. Digital literacy is also positively associated with perceived privacy risk, suggesting that more digitally literate users are more sensitive to data practices and system uncertainty. However, perceived privacy risk does not significantly affect system evaluation, indicating that users tend to balance potential risks against perceived benefits during interaction. The study extends the application of Privacy Calculus Theory by identifying digital literacy as an important antecedent of user evaluation and highlighting the central role of trust in conversational AI contexts. Practically, the findings suggest that developers should enhance transparency, trust-building mechanisms, and privacy communication to improve user evaluations. Future research may further examine additional system-related factors and diverse user groups to validate and extend the proposed framework.

**Keywords:** Digital literacy, trust, perceived privacy risk, conversational AI, user evaluation.

## INTRODUCTION

Artificial intelligence (AI) technologies, particularly language models such as ChatGPT, have been widely adopted globally (Zhang & Wang, 2025). Generation Z constitutes a significant user group for conversational AI; they generally hold an open attitude toward AI technology and rely extensively on such systems for information retrieval, problem-solving, and daily decision-making (Chan & Lee, 2023; Al-Sharafi et al., 2023). In the Chinese context, its use has shifted from exploratory experimentation to routine practice (Xiao et al., 2025). From an information systems perspective, conversational AI can be understood as a new type of human-computer interaction system, where users continuously evaluate the system's performance, reliability, and interaction quality during ongoing use.

Despite their openness to technology, Generation Z exhibits notable complexity in their use of AI: on the one hand, they recognize its potential to enhance efficiency and user experience; on the other hand, they remain highly sensitive to privacy and security concerns, ethical risks, and data misuse, seeking a balance between transparency, privacy protection, and user experience (Dewalska-Opitek et al., 2024). This contradiction is also reflected at the behavioral level, manifesting as a classic "personalization-privacy paradox" (McKee et al., 2024). However, existing research often discusses this phenomenon as an isolated issue, lacking an integrated explanation grounded in the overall system evaluation process.

Digital literacy serves as a critical prerequisite for understanding how Generation Z interacts with AI technology. As a core competency, digital literacy not only supports information processing but also influences users' understanding and judgment of AI systems (Hwang, 2023). Although Generation Z is often regarded as "digital natives," research indicates significant variations in their technical understanding and risk assessment (Kirschner & De Bruyckere, 2017; Bennett et al., 2008). Therefore, this paper treats digital literacy as a measurable competency variable rather than an innate trait, focusing on its role in specific human-computer interaction contexts. However, existing research largely views it as a general competency, with limited exploration of how it influences users' overall evaluation of AI systems.

Additionally, digital literacy is closely related to trust and risk perception. Research indicates that higher digital literacy helps users assess AI characteristics more accurately, thereby enhancing trust (Pan et al., 2025), while trust in turn promotes user cooperation and continued use (Harris-Watson et al., 2023; Ng & Zhang, 2025). However, most relevant studies treat trust as a standalone variable, lacking an integrated analysis of its role within the system evaluation framework.

At the same time, privacy risks are another key factor influencing user acceptance of AI. When users perceive that their data is being improperly collected or used, their trust and willingness to use the system typically decline (Männasoo et al., 2023). Although some studies suggest that digital literacy helps reduce risk perception (Yang & Wibowo, 2022), others indicate that it may actually heighten users' risk sensitivity (Yu et al., 2026), and conclusions on this matter remain inconsistent.

Furthermore, interface design significantly influences users' judgments of AI professionalism and credibility through visual and interactive cues (Glassberg et al., 2025). Visual presentation, transparency cues, and interaction design jointly shape users' perceptions of system intelligence, trustworthiness, and ethical responsibility (Liao & Sundar, 2022). From an ethical perspective, enhancing transparency and explainability is key to fostering trustworthy AI (Bozkurt & Sharma, 2024). However, existing research has largely focused on interface aesthetics and usability, with little

integration into a comprehensive user evaluation framework. Overall, there remains a lack of integrated models to explain how users comprehensively assess system reliability, interaction quality, and potential risks during use.

Based on this, this paper constructs a user evaluation model for conversational AI to explore how digital literacy influences users' overall evaluation of the system through trust and perceived privacy risks. By treating conversational AI as an interactive information system, this paper explains the formation mechanism of user evaluations from a system-level perspective and provides theoretical and practical insights for building user-centred trustworthy AI systems.

The remainder of this paper is organised as follows. The following section synthesises the relevant literature and develops the core research hypotheses. The subsequent overview presents the research methodology, outlining both the data collection procedures and the selected measurement instruments. This is followed by a comprehensive report of the empirical results, leading directly into a detailed discussion of the key findings and implications. Finally, the study concludes with an overview of its limitations alongside meaningful directions for future research.

## **RELATED WORKS**

### **Digital Literacy**

Digital literacy is typically viewed as a comprehensive competency encompassing various skills and practices related to the use of digital technologies. Ng (2012) notes that digital literacy comprises three core dimensions: technical competence, cognitive competence, and socio-emotional competence. Technical competence emphasises proficiency in operating hardware and software; cognitive competence emphasises critical thinking and information evaluation; and socio-emotional competence involves online communication and collaboration. This definition provides a multidimensional analytical framework for digital literacy research.

Currently, research on digital literacy is exhibiting trends toward diversification and interdisciplinary development (Tinmaz et al., 2022). In educational contexts, research generally agrees that digital literacy is closely related to learning autonomy, problem-solving abilities, and innovative behaviour (Lan et al., 2025; Caroline et al., 2025). However, existing research largely adopts a competency- or education-oriented perspective, treating digital literacy as a cross-contextual, general competency, while paying relatively less attention to its mechanisms of action in specific technology-use contexts.

Regarding Generation Z, relevant studies indicate that they possess high levels of technical proficiency and information retrieval skills, and tend to prefer interactive and multisensory learning methods (Susilawati et al., 2021). However, these studies primarily focus on educational contexts, and discussions of their behavioural logic in complex human-computer interaction environments remain limited.

In conversational AI contexts, digital literacy manifests not only as operational proficiency but also influences users' understanding and judgment of the system. From an information systems perspective, this capability relates not only to usage efficiency but also impacts users' evaluations of system reliability and overall performance. Therefore, digital literacy is not merely a competency attribute but also a critical prerequisite for users' system evaluations, helping to bridge the theoretical gap between "competency—cognition—system evaluation" in existing research.

## **Trust in Conversational AI**

Trust is a core concept in information systems and human-computer interaction research; at its core, it is a psychological attitude characterised by a willingness to assume risk. Mayer et al. (1995) defined it as an individual's propensity to accept potential losses or vulnerabilities within a specific relationship, while McKnight et al. (2002) further noted that trust is a complex psychological structure composed of multiple dimensions, including trust propensity, institutional trust, trust beliefs, and trust intentions. This multidimensional framework provides a systematic foundation for understanding how trust is formed in digital environments.

Given how quickly artificial intelligence is developing, trust is thought to be an essential precondition for encouraging the use of new technologies (Riedl, 2022). From a user experience perspective, trust is a dynamic construct shaped by individual characteristics, system design, and social contexts (Bach et al., 2024). However, existing research has largely focused on its impact on technology adoption or continued use, with relatively insufficient attention paid to the role of trust in the overall process of user system evaluation.

In conversational AI contexts, trust serves as a critical mechanism linking users and systems. Rheu et al. (2021) found that system reliability, social competence, and transparency significantly influence user trust and further impact continued usage behavior; Baughan et al. (2023) also noted that trust plays a foundational role in user acceptance and application expansion. However, these studies largely remain at the behavioural level. When looking at information systems, trust not only influences usage decisions but also plays a central role in users' evaluation of system reliability, interaction quality, and overall performance. Therefore, trust can be viewed as a crucial mediating mechanism linking system characteristics to user evaluations, holding a foundational position in conversational AI research.

## **Perceived Privacy Risk**

Perceived privacy risk is typically defined as an individual's subjective expectation of potential adverse consequences when disclosing personal information (Fox et al., 2022). This concept emphasises users' concerns regarding privacy breaches, data misuse, and unauthorised access, and influences their online behaviour and the formation of trust (Dinev & Hart, 2006).

In specific technological contexts, privacy risk has been shown to have a significant inhibitory effect on behaviour. For example, Koester (2022) found that the higher the perceived risk, the more likely users are to reduce the disclosure of personal data; Zhou and Liu (2023) also noted that Chinese adolescents are more sensitive to privacy risks in online environments and tend to adopt various protective behaviours. Furthermore, Generation Z exhibits a classic "privacy paradox," in which they pursue personalised services while remaining wary of data tracking (McKee et al., 2024). Nevertheless, existing research largely treats privacy risks as a single inhibitory factor, with insufficient attention paid to their underlying mechanisms in user cognition and system evaluation processes. In fact, during ongoing human-computer interactions, privacy risks manifest not only as threat perception but also reflect users' cognitive judgments regarding data processing methods and system transparency.

In conversational AI contexts, privacy risks are also a critical factor influencing trust and willingness to use. Leschanowsky et al. (2024) found that higher privacy risks reduce user trust, while increased transparency and privacy protection help enhance trust. This indicates that privacy risks not only

directly influence user behaviour but also exert an indirect effect through trust. In terms of information systems, the perception of privacy risks is not only a factor that inhibits behaviour but also a key cognitive variable through which users assess system reliability and the rationality of data processing, and it influences users' evaluation of the system's overall performance in more complex ways.

### **Interface Preference**

Interface preference is a crucial subjective dimension of user experience, reflecting users' comprehensive reactions at the levels of aesthetics, emotion, and preference, and particularly embodying the hedonic attributes of the experience (Hassenzahl, 2007). This concept not only reflects emotional orientation but also serves as an important basis for interface design and evaluation, helping to enhance the overall quality of the experience.

In interface usage contexts, visual aesthetics not only provide a pleasurable experience but also enhance users' overall evaluation of the system by evoking positive emotions and forming favorable impressions (Tractinsky et al., 2000). Research indicates that clear, symmetrical, and creative designs are more likely to elicit positive evaluations, while reasonable layouts and structures help improve both usability and visual appeal (Bhandari et al., 2019; Otten et al., 2020). At the specific visual level, elements such as layout, color, and typography also significantly influence user preferences and interaction behaviors (Xing et al., 2021), and higher levels of visual aesthetics can further enhance users' satisfaction, perceived service quality, and trust in digital systems (Ramezani Nia & Shokouhyar, 2020).

However, existing research primarily examines interface preference from aesthetic and usability perspectives, with limited attention to its role in system evaluation. In conversational AI contexts, interfaces not only present information but also shape users' judgments through continuous interaction and feedback. Therefore, interface preference should be viewed as more than an experiential metric; it reflects users' perceptions of system reliability, transparency, and interaction quality. Although user evaluation may include broader dimensions such as usefulness and satisfaction, the interface remains the primary point of contact between users and conversational AI systems. Consequently, interface preference serves as a practical operationalization of users' overall evaluation of conversational AI systems.

### **Research Gaps and Theoretical Perspective**

Previous studies have examined conversational AI from multiple perspectives, including digital literacy, trust, privacy concerns, and interface design. Nevertheless, existing findings remain relatively fragmented, as many studies concentrate on technology adoption, usage intention, or interface usability rather than explaining how users develop overall evaluations during human–AI interaction. Recent studies published in JICT have also focused on users' adoption and continued use of AI-powered technologies from technology acceptance perspectives (Soliman et al., 2025). Despite these advances, existing findings provide limited explanation of how users form overall evaluations during repeated interactions with conversational AI systems.

Existing research on digital literacy has mainly concentrated on users' technical competence and information-processing capability, while limited attention has been paid to how digital literacy shapes users' judgments of conversational AI systems. Similarly, trust and perceived privacy risk are often

examined separately in prior studies, despite the likelihood that these two factors jointly influence users' evaluations during interaction processes. In addition, interface-related studies have largely emphasized aesthetics and usability issues, with relatively little discussion regarding how interface experiences contribute to broader perceptions of reliability, transparency, and interaction quality.

This study draws primarily on Privacy Calculus Theory, which explains that users evaluate digital technologies by weighing expected benefits against potential risks. Within conversational AI contexts, users may simultaneously experience functional convenience and privacy-related concerns, making system evaluation a continuous trade-off process between positive expectations and perceived uncertainty. In this framework, trust represents the perceived benefit dimension, whereas perceived privacy risk reflects the perceived cost dimension associated with conversational AI usage. In addition, trust theory suggests that trust helps reduce uncertainty during human–AI interaction, while digital literacy enhances users' ability to understand system operations and recognize possible risks. Based on these perspectives, this study integrates digital literacy, trust, and perceived privacy risk into a unified framework to explain how users form evaluations of conversational AI systems.

## **RESEARCH MODEL AND HYPOTHESES**

### **Research Model**

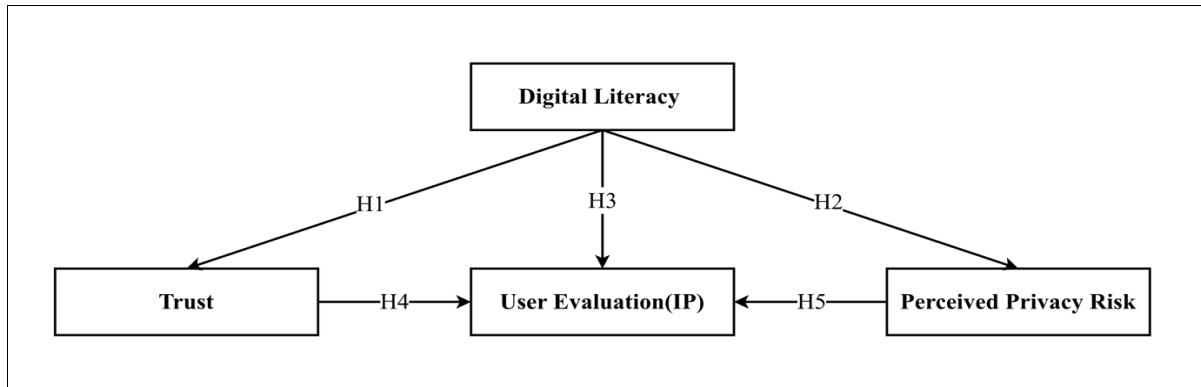
Building upon the preceding literature review and identified research gaps, this study proposes a structural model that integrates digital literacy, trust, and perceived privacy risk to explain how users evaluate conversational AI systems during human–AI interaction.

In the proposed model, digital literacy represents users' capability to understand and effectively use conversational AI systems, which may influence how they interpret and assess system-related information. Trust and perceived privacy risk are treated as two important psychological factors associated with users' perceptions of system reliability and potential privacy concerns. According to Privacy Calculus Theory, trust can be viewed as the perceived benefit dimension, whereas perceived privacy risk reflects the perceived cost dimension involved in the evaluation process.

In this study, user evaluation is operationalized through interface preference-related constructs, as the interface represents the primary point of interaction between users and conversational AI systems. Interface preference therefore reflects users' overall perceptions of system reliability, transparency, and interaction quality developed during conversational AI interaction. Based on these relationships, the proposed model assumes that digital literacy influences user evaluation through the combined effects of trust and perceived privacy risk. The conceptual framework of this study is presented in Figure 1.

**Figure 1**

*Research Model*



**Research Hypotheses**

H1: Digital literacy positively influences trust.

Users with higher digital literacy are better equipped to effectively assess the authenticity and credibility of information, thereby reducing the risk of encountering misinformation or online fraud, and are thus more likely to establish trust relationships based on reliability (Van Laar et al., 2020). Rossini et al. (2021) also noted that users with high digital literacy are better able to identify misinformation and reduce its unintended dissemination, which helps enhance trust in technology. Conversely, users with insufficient digital literacy are often more prone to concerns about data privacy, security vulnerabilities, or algorithmic bias, which in turn weakens their trust in technology (Bhoj & Bhadoria, 2021).

H2: Digital literacy negatively influences perceived privacy risk.

Although existing research suggests that digital literacy may increase users' sensitivity to risk (Yu et al., 2026), the prevailing view remains that higher digital literacy helps reduce uncertainty in digital environments, thereby diminishing risk perception. Users with higher digital literacy can more clearly understand the boundaries of information flow and identify potential risks, thereby reducing privacy concerns arising from operational errors or misjudgments of information (Mannell, 2020). In addition, digital literacy enables users to adopt more rational coping strategies when faced with intelligent technologies such as facial recognition, rather than passively relying on system outputs, thereby achieving a more effective balance between convenience and privacy protection (González-Rodríguez et al., 2020). In contexts characterized by transparency and control, digital literacy helps reduce perceived risk and promotes acceptance of automated systems by enhancing privacy self-efficacy (Langer & Landers, 2021). Therefore, despite opposing viewpoints, this paper proposes—based on mainstream theory—that digital literacy has a negative impact on perceived privacy risk; however, the specific direction of this relationship in conversational AI contexts remains to be further examined.

H3: Digital literacy positively influences user evaluation (operationalised as interface preference).

Research indicates that high levels of digital literacy help users understand and operate digital interfaces more effectively, leading to more active engagement with various digital media and social platforms, while user-friendly interface design further promotes the development of digital literacy

(He et al., 2020). Similarly, young users with higher digital skills are better able to quickly understand the logic and functions of different interfaces, thereby more keenly perceiving the user-friendliness and usability of the interface, which enhances their positive evaluation of the interface design (Smahel et al., 2020). Furthermore, Moll et al. (2010) noted that users with high digital competence can more effectively utilise multimodal interface cues, such as haptic and audio feedback, to enhance their understanding of virtual environments and improve collaboration efficiency, thereby forming more positive interface preferences.

H4: Trust positively influences user evaluation (operationalised as interface preference).

Trust, as a key emotional and cognitive outcome, can directly or indirectly enhance users' positive perceptions of interface aesthetics and the overall experience. Plus, effective color design not only enhances a platform's visual appeal but also strengthens users' trust in the system, thereby encouraging continued engagement (Cyr et al., 2010). Furthermore, by increasing a webpage's social presence (e.g., through richer text and visual elements), users exhibit more positive emotional responses, which further strengthens their level of trust in the website; in turn, higher trust leads users to demonstrate a stronger preference for the interface design (Hassanein & Head, 2007). Along with that, enhancing trust cues such as system transparency, professionalism, and reliability can effectively increase user satisfaction, thereby encouraging users to prefer interface elements that are transparent, user-friendly, and personalised. In other words, building trust can foster user preference for interfaces that are concise, convey information effectively, and offer a strong sense of experience, thereby optimizing the overall user experience (Joshi, 2025).

H5: Perceived privacy risk negatively influences user evaluation (operationalized as interface preference).

In the process of forming user evaluations, privacy risks influence interface preferences by affecting emotional responses and perceptions of security. When privacy risks are low, users are more willing to express themselves within virtual interfaces, thereby driving interface design toward greater personalisation, security, and transparency to meet users' dual needs for authenticity and privacy protection (Midha & Nandedkar, 2012). Conversely, when users' perceived risk of privacy breaches increases, their liking for the platform interface often decreases; this is because heightened privacy risks trigger user distrust and anxiety, thereby weakening positive attitudes toward interface design and even prompting users to reduce usage or switch to platforms perceived as safer (Anderson et al., 2014). Furthermore, a higher perception of privacy risk not only reduces users' preference for the interface but also leads them to actively avoid interfaces that require extensive personal information and to pay closer attention to privacy-related design elements within the interface; these changes collectively influence their overall interface preference and willingness to use it (Kim et al., 2023).

## **THE PROPOSED METHOD**

### **Research Design**

This study employs a quantitative research design aimed at examining how digital literacy influences the comprehensive judgment and reactions formed by Chinese Gen Z users during the use of conversational AI (operationalised through interface preference) via trust and perceived privacy risks. Data were collected through a questionnaire survey, with items based on established scales and revised to align with conversational AI usage contexts to ensure reliability and validity.

The questionnaire was distributed via the “WJX” platform and disseminated through social media platforms such as WeChat and Xiaohongshu to expand the sample coverage. After data collection, the questionnaires were screened and cleaned to exclude invalid samples. The final data were analysed using SPSS 27.0 and SmartPLS 4.0. First, the reliability and validity of the measurement model were tested, followed by structural equation modelling to verify the research hypotheses.

### **Data Collection**

This study employed the questionnaire survey method for data collection. The questionnaire was designed based on the constructs included in the research model. All measurement items utilised a 7-point Likert scale (1 = “Strongly Disagree,” 7 = “Strongly Agree”) to enhance the discriminatory power of responses and improve the stability of the structural equation modelling analysis. The questionnaire consisted of two parts: Part One covers demographic variables (gender, age, educational level, region, whether users pay for AI, frequency of AI use, etc.); Part Two includes measurement items for the research variables (digital literacy, trust, perceived privacy risks, and interface preference). In this study, user evaluation was operationalised through interface preference-related constructs, reflecting users’ comprehensive judgments regarding system reliability, transparency, and interaction quality formed during conversational AI interactions.

To ensure the reliability and validity of the measurement instrument, all constructs were adapted from well-established scales that have been widely validated in the information systems and human–computer interaction literature. Specifically, digital literacy was measured based on the frameworks proposed by Ng (2012) and Van Deursen and Van Dijk (2014). Trust was adapted from McKnight et al. (2002) and Hoff and Bashir (2015), while perceived privacy risk was measured using items derived from Dinev and Hart (2006) and Malhotra et al. (2004). In this study, user evaluation was operationalised through interface preference. Accordingly, interface preference-related items were adapted from Hassenzahl and Ullrich (2007) and Tractinsky et al. (2000), which conceptualise users’ evaluations in terms of interface attractiveness, perceived usability, and overall interaction experience. All measurement items were slightly revised to reflect the characteristics of conversational AI systems while maintaining consistency with the original constructs. The complete list of measurement items and their corresponding sources is provided in Appendix A.

### **Sample Group**

This study selected China’s Generation Z (ages 15–30) as the survey participants, primarily due to their representativeness in technology use and AI adoption. Having grown up in a digital environment, Generation Z relies heavily on smartphones and digital applications, places higher demands on technological usability and interactive convenience, and constitutes a highly tech-adaptive user group (Priporas et al., 2017). As “digital natives,” they maintain an open attitude toward smart devices, green technology, and various technological innovations, and are willing to embrace lifestyle changes brought about by new technologies (Djafarova & Foots, 2022). In the Chinese context, recent research reports indicate that Generation Z has integrated AI tools into their daily lives across multiple scenarios, including learning, entertainment, socializing, and creative activities, demonstrating extremely high adoption rates and acceptance of AI. To obtain a representative sample, this study employed a combination of convenience sampling and snowball sampling, distributing questionnaires via online platforms.

## **Ethical Considerations**

Participation in the survey was voluntary, and informed consent was obtained from all respondents. No personally identifiable information was collected, and all responses were treated confidentially. The study complied with ethical guidelines for anonymous survey research, focusing on participants' perceptions and attitudes rather than sensitive personal data.

## **Data Analysis**

To test the research model and hypotheses, this study employed a two-stage data analysis method. First, SPSS 27.0 was used to organise the sample data and perform descriptive statistical analysis, including sample characteristics, means, and standard deviations. PLS-SEM was considered appropriate because this study aimed to examine complex relationships among latent constructs and prioritise prediction-oriented analysis. Subsequently, SmartPLS 4.0 was used to construct the measurement model and assess the reliability and validity of each latent variable, including internal consistency reliability, convergent validity, and discriminant validity. After confirming the quality of the measurement model, SmartPLS 4.0 was further used to construct the structural model, and Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to analyse the path relationships among variables. The significance of path coefficients was tested using a bootstrapping procedure with 5,000 resamples to verify the research hypotheses. The evaluation of the structural model was primarily based on indicators such as explanatory power ( $R^2$ ), effect size ( $f^2$ ), and path significance.

## **RESULTS AND DISCUSSION**

A total of 591 questionnaires were collected for this study. After excluding invalid samples (e.g., those with inconsistent responses), 580 valid questionnaires were ultimately obtained. Following Hair et al. (2021), the sample size of 580 substantially exceeds the minimum requirements for PLS-SEM and provides adequate statistical power for model estimation. The model in this study includes five paths, requiring a minimum sample size of 50; therefore, the sample size meets the basic requirements for PLS-SEM analysis. It should be noted that user evaluation in this study was operationalised through interface preference. Therefore, the construct primarily reflects users' overall judgments formed during interactions with conversational AI systems, including perceptions of reliability, transparency, and interaction quality, rather than normative evaluations of AI ethical issues.

### **Descriptive Analysis and Statistics**

A total of 580 valid responses were collected. The sample consisted of 54.8% males and 45.2% females. Most respondents were aged between 21 and 25 years (55.7%), held an undergraduate degree (72.4%), and resided in China's first-tier, new first-tier, or second-tier cities (72.9%). These characteristics are generally consistent with the profile of China's Generation Z population.

Regarding generative AI usage, 47.1% of respondents reported having paid for AI services. Most respondents used generative AI either 3–4 times per week (37.2%) or almost daily (27.2%), indicating a relatively high level of familiarity with conversational AI technologies. The most common usage duration was 10–30 minutes per session (56.6%). Respondents primarily used generative AI for work and content creation (65.9%), information searching (62.1%), and learning-related activities (61.2%).

Descriptive statistics further showed that all four constructs—digital literacy (DL), trust (TR), perceived privacy risk (PPR), and interface preference (IP)—recorded relatively high mean scores. Digital literacy exhibited the highest mean value ( $M = 5.48$ ,  $SD = 0.862$ ), followed by trust ( $M = 5.41$ ,  $SD = 0.891$ ) and interface preference ( $M = 5.41$ ,  $SD = 0.868$ ). Perceived privacy risk showed a slightly lower mean score ( $M = 5.21$ ,  $SD = 1.199$ ). Overall, the results suggest that respondents were experienced users of conversational AI systems and capable of providing informed evaluations of the constructs examined in this study.

### **Common Method Bias**

Since the data in this study were collected through a self-reported questionnaire, Harman's single-factor test was conducted using SPSS 27.0 to assess common method bias. The results showed that the first unrotated factor accounted for 35.87% of the total variance, which is below the recommended threshold of 50%. Therefore, common method bias was not considered a serious concern in this study. The result indicates that no single factor accounted for the majority of the covariance among the measurement items.

### **Reliability and Convergent Validity**

The validity analysis results show that the KMO value was 0.922 ( $> 0.90$ ), indicating that the sample was suitable for factor analysis. The chi-square value for Bartlett's sphericity test was 5551.061, with 190 degrees of freedom and a significance level of  $p < 0.001$ , indicating significant correlations among the variables and satisfactory construct validity (see Table 1).

The reliability and convergent validity of the measurement model were further assessed using SmartPLS 4.0, including Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). As shown in Table 2, all Cronbach's alpha and CR values exceeded the recommended threshold of 0.70, while all AVE values were above 0.50, indicating satisfactory reliability and convergent validity. In addition, most factor loadings exceeded 0.70, except for one item (DL1 = 0.698), which was retained because it was close to the acceptable threshold and did not negatively affect construct reliability.

**Table 1**

#### *Validity Analysis*

|                                   |                        |          |
|-----------------------------------|------------------------|----------|
| KMO Sampling Adequacy Coefficient |                        | 0.922    |
| Bartlett's Test of Sphericity     | Approximate Chi-Square | 5551.061 |
|                                   | Degrees of freedom     | 190      |
|                                   | Significance           | 0.000    |

**Table 2**

#### *Reliability and Convergent Validity Assessment*

| Construct | Cronbach's Alpha | CR    | AVE   |
|-----------|------------------|-------|-------|
| DL        | 0.804            | 0.865 | 0.562 |
| IP        | 0.844            | 0.889 | 0.616 |
| PPR       | 0.891            | 0.919 | 0.695 |
| TR        | 0.830            | 0.881 | 0.596 |

## Discriminant Validity

According to the Fornell–Larcker criterion, the square root of the AVE for each construct should exceed its correlations with other constructs. As shown in Table 3, all diagonal values are greater than the corresponding inter-construct correlations, indicating satisfactory discriminant validity.

To further assess discriminant validity, the HTMT (Heterotrait–Monotrait Ratio) criterion proposed by Henseler et al. (2015) was applied. As shown in Table 4, all HTMT values were below the recommended threshold of 0.90. Although the HTMT value between IP and TR (0.853) slightly exceeded the more conservative threshold of 0.85, it remained within the acceptable range. Therefore, the results confirm adequate discriminant validity and support the distinctiveness of the study constructs.

**Table 3**

*Fornell–Larcker Criterion*

| Construct | DL    | IP    | PPR   | TR    |
|-----------|-------|-------|-------|-------|
| DL        | 0.749 |       |       |       |
| IP        | 0.639 | 0.785 |       |       |
| PPR       | 0.209 | 0.172 | 0.834 |       |
| TR        | 0.660 | 0.715 | 0.143 | 0.772 |

**Table 4**

*Discriminant Validity (HTMT)*

|     | DL    | IP    | PPR   | TR |
|-----|-------|-------|-------|----|
| DL  |       |       |       |    |
| IP  | 0.775 |       |       |    |
| PPR | 0.240 | 0.193 |       |    |
| TR  | 0.807 | 0.853 | 0.162 |    |

## Collinearity Assessment

To ensure multicollinearity did not affect the structural model estimation, Variance Inflation Factor (VIF) values were calculated for all indicator variables. As shown in Table 5, all VIF values for both the outer (measurement) and inner (structural) models are below the commonly accepted threshold of 5, indicating no serious multicollinearity issues.

**Table 5**

*Variance Inflation Factor (VIF) for Outer and Inner Models*

| Construct | Indicator | Outer Model VIF | Inner Model VIF |
|-----------|-----------|-----------------|-----------------|
| DL        | DL1       | 1.500           |                 |
| DL        | DL2       | 1.786           |                 |
| DL        | DL3       | 1.650           | 1.815           |
| DL        | DL4       | 1.472           |                 |
| DL        | DL5       | 1.574           |                 |

(continued)

| Construct | Indicator | Outer Model VIF | Inner Model VIF |
|-----------|-----------|-----------------|-----------------|
| IP        | IP1       | 1.698           |                 |
| IP        | IP2       | 1.807           |                 |
| IP        | IP3       | 1.767           |                 |
| IP        | IP4       | 1.777           |                 |
| IP        | IP5       | 1.726           |                 |
| PPR       | PPR1      | 2.119           |                 |
| PPR       | PPR2      | 2.558           |                 |
| PPR       | PPR3      | 2.283           | 1.046           |
| PPR       | PPR4      | 2.365           |                 |
| PPR       | PPR5      | 1.935           |                 |
| TR        | TR1       |                 | 1.697           |
| TR        | TR2       |                 | 1.811           |
| TR        | TR3       |                 | 1.498           |
| TR        | TR4       |                 | 1.756           |
| TR        | TR5       |                 | 1.611           |

### Path Coefficients and Hypothesis Testing

In the PLS-SEM model, the  $R^2$  value is used to assess the model's explanatory power. The results show that the  $R^2$  for Interface Preference (IP) is 0.562 and for Trust (TR) is 0.436, both reaching moderate to high levels, indicating that the model has strong explanatory power for system evaluation. In contrast, the  $R^2$  for Perceived Privacy Risk (PPR) is 0.044, indicating low explanatory power, which suggests that it may be more influenced by factors outside the model.

The path coefficients and hypothesis test results are shown in Table 6 and Figure 2. Digital literacy has a significant positive effect on both trust (H1:  $\beta = 0.660$ ,  $p = 0.000$ ,  $f^2 = 0.772$ ) and interface preference (H3:  $\beta = 0.289$ ,  $p = 0.000$ ,  $f^2 = 0.105$ ), and the hypotheses are supported. Trust also has a significant positive effect on interface preference (H4:  $\beta = 0.519$ ,  $p = 0.000$ ,  $f^2 = 0.348$ ).

Contrary to the hypothesis, although the effect of digital literacy on perceived privacy risk was significant (H2:  $\beta = 0.209$ ,  $p = 0.000$ ,  $f^2 = 0.046$ ), the direction was positive; therefore, H2 was not supported. Perceived privacy risk had no significant effect on interface preference (H5:  $\beta = 0.037$ ,  $p = 0.214$ ,  $f^2 = 0.003$ ), and H5 was also not supported.

In summary, H1, H3, and H4 are supported, while H2 and H5 are not supported. The results indicate that interface preference, as the operationalized manifestation of user evaluation, is primarily influenced by digital literacy and trust, whereas the effect of perceived privacy risk remains relatively weak.

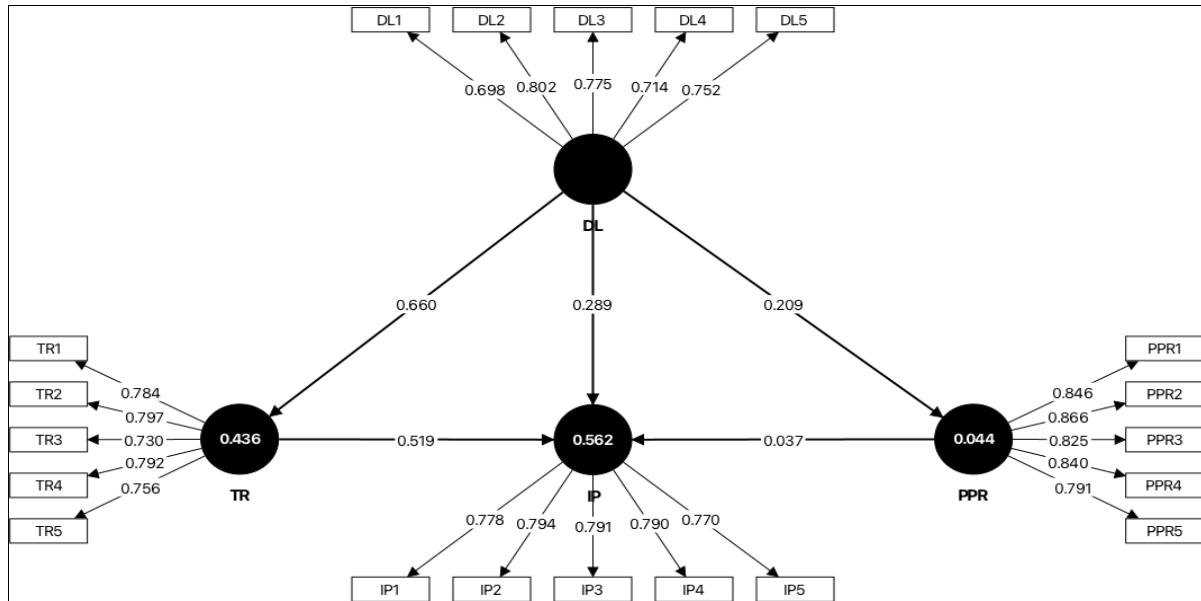
**Table 6**

#### Hypothesis Testing Results

| Hypothesis | Path   | $\beta$ | P     | F2    | Result        |
|------------|--------|---------|-------|-------|---------------|
| H1         | DL→TR  | 0.660   | 0.000 | 0.772 | Supported     |
| H2         | DL→PPR | 0.209   | 0.000 | 0.046 | Not Supported |
| H3         | DL→IP  | 0.289   | 0.000 | 0.105 | Supported     |
| H4         | TR→IP  | 0.519   | 0.000 | 0.348 | Supported     |
| H5         | PPR→IP | 0.037   | 0.214 | 0.003 | Not Supported |

**Figure 2**

*PLS-SEM Results Model*



This study examined how digital literacy influences user evaluation through trust and perceived privacy risk, framed within the Privacy Calculus Theory. User evaluation is conceptualised as a cognitive balancing process in which users consider expected benefits and potential risks during system interaction.

The results indicate that digital literacy positively affects trust. Users with higher digital literacy demonstrate greater understanding of system operations and reduced uncertainty in interactions. This suggests that digital literacy extends beyond technical proficiency to encompass cognitive skills that facilitate stable judgments and expectations regarding system behaviour. Additionally, digital literacy directly impacts user evaluation, indicating that users form assessments not only based on interface experience but also through broader perceptions of system reliability, transparency, and interaction quality.

Trust serves as a key mediating mechanism. In complex and opaque system environments, trust reduces uncertainty and fosters more positive evaluations, highlighting its central role in shaping user responses and confirming prior findings on trust in technology adoption (Ghozali & Fortwengel, 2025).

Regarding perceived privacy risk, digital literacy was positively associated with risk perception, indicating that higher literacy enhances awareness of data practices and system uncertainty. However, privacy risk did not significantly affect user evaluation, suggesting that users maintain favourable assessments despite recognising potential risks. This outcome aligns with the logic of Privacy Calculus Theory and reflects the privacy paradox observed in technology use.

Theoretically, this study contributes in three ways. First, it positions digital literacy as a key antecedent of user evaluation. Second, it emphasises trust as a central psychological mechanism rather than a mere predictor of behavioural intention. Third, by integrating digital literacy, trust, and perceived privacy risk into a unified framework, it provides a more comprehensive explanation of user evaluation processes.

Practically, the findings suggest that system designers should enhance transparency, explainability, and privacy communication to accommodate varying levels of user literacy. Trust cues and clear privacy controls can further improve perceptions of reliability and interaction quality. Interface design should extend beyond usability to convey credibility and facilitate informed user judgments.

## CONCLUSION

This study demonstrates that user evaluation of conversational AI systems reflects the combined effects of digital literacy, trust, and perceived privacy risk. Users' assessments are influenced by both functional experience and cognitive judgments regarding benefits, uncertainty, and potential risks. Overall, the findings enhance understanding of the mechanisms underlying user evaluation and provide insights for the design of conversational AI systems that are perceived as reliable, transparent, and user-centred.

Despite these contributions, several limitations should be acknowledged. First, the sample was limited to Chinese Generation Z users, which may restrict the generalisability of the findings to other cultural contexts and age groups. Future studies could examine more diverse populations to validate the proposed model. Second, this study focused on digital literacy, trust, and perceived privacy risk, while other system-related factors, such as transparency and explainability, were not considered. Future research may incorporate these variables to provide a more comprehensive understanding of user evaluation and its manifestation through interface preference. Third, all variables were measured using self-reported survey data, which may introduce subjective bias despite the assessment of common method bias. Finally, the cross-sectional design limits the ability to capture changes in user evaluation over time. Future studies could employ longitudinal or experimental approaches to examine how user evaluation evolves through continued interaction with conversational AI systems.

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## Appendix A. Measurement Items

| Construct                    | Code | Measurement item                                                                                                       | Source                                                             |
|------------------------------|------|------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------|
| Digital Literacy (DL)        | DL1  | I can quickly learn how to use a new mobile application or digital feature.                                            | Adapted from Ng (2012); Van Deursen & Van Dijk (2014)              |
|                              | DL2  | I can generally determine whether information found online is reliable.                                                | Adapted from Ng (2012); Van Deursen & Van Dijk (2014)              |
|                              | DL3  | I generally understand how conversational AI may use my data.                                                          | Adapted from Ng (2012); Van Deursen & Van Dijk (2014)              |
|                              | DL4  | When encountering digital technology problems, I can usually find solutions by myself.                                 | Adapted from Ng (2012); Van Deursen & Van Dijk (2014)              |
|                              | DL5  | I know how to adjust privacy and security settings on mobile devices or applications.                                  | Adapted from Ng (2012); Van Deursen & Van Dijk (2014)              |
| Trust (TR)                   | TR1  | I believe this conversational AI will try its best to provide useful responses.                                        | Adapted from McKnight et al. (2002); Hoff & Bashir (2015)          |
|                              | TR2  | I consider this conversational AI to be reliable.                                                                      | Adapted from McKnight et al. (2002); Hoff & Bashir (2015)          |
|                              | TR3  | I believe this conversational AI will not intentionally harm my interests.                                             | Adapted from McKnight et al. (2002); Hoff & Bashir (2015)          |
|                              | TR4  | I trust this conversational AI to handle the information I provide appropriately.                                      | Adapted from McKnight et al. (2002); Hoff & Bashir (2015)          |
|                              | TR5  | For study- or work-related tasks, I am willing to rely on this conversational AI.                                      | Adapted from McKnight et al. (2002); Hoff & Bashir (2015)          |
| Perceived Privacy Risk (PPR) | PPR1 | I am concerned that my conversations with this conversational AI may be viewed by others.                              | Adapted from Dinev & Hart (2006); Malhotra et al. (2004)           |
|                              | PPR2 | I believe using this conversational AI may lead to misuse of my personal information.                                  | Adapted from Dinev & Hart (2006); Malhotra et al. (2004)           |
|                              | PPR3 | I feel uneasy about providing personal information to this conversational AI.                                          | Adapted from Dinev & Hart (2006); Malhotra et al. (2004)           |
|                              | PPR4 | I believe using this conversational AI involves privacy risks.                                                         | Adapted from Dinev & Hart (2006); Malhotra et al. (2004)           |
|                              | PPR5 | If the platform does not explain how it protects user data, I feel uncomfortable using it.                             | Adapted from Dinev & Hart (2006); Malhotra et al. (2004)           |
| Interface Preference (IP)    | IP1  | I like the interface design of this conversational AI.                                                                 | Adapted from Hassenzahl & Ullrich (2007); Tractinsky et al. (2000) |
|                              | IP2  | The interface style of this conversational AI is attractive to me.                                                     | Adapted from Hassenzahl & Ullrich (2007); Tractinsky et al. (2000) |
|                              | IP3  | Compared with similar products, I prefer this interface design.                                                        | Adapted from Hassenzahl & Ullrich (2007); Tractinsky et al. (2000) |
|                              | IP4  | Even if alternative options are available, I would still prefer to use a conversational AI with this interface design. | Adapted from Hassenzahl & Ullrich (2007); Tractinsky et al. (2000) |
|                              | IP5  | This interface design makes me more willing to use this conversational AI more frequently.                             | Adapted from Hassenzahl & Ullrich (2007); Tractinsky et al. (2000) |