Privacy and Empathy in AI Chatbots: A Dual-Route Analysis of Cognitive and Emotional Trust in Financial Services

Journal:	*Journal of Global Scholars of Marketing Science*
Manuscript ID	RGAM-2025-0219.R1
Manuscript Type:	Original Article
Keywords:	Artificial Intelligence, Chatbots, Trust, Dual Process Theory, Conversational AI

Privacy and Empathy in AI Chatbots: A Dual-Route Analysis of Cognitive and Emotional Trust in Financial Services

Trust remains a critical barrier to the adoption of artificial intelligence (AI) chatbots in financial services, yet extant research has not systematically examined how distinct communication strategies differentially shape cognitive and emotional trust. Grounded in Dual Process Theory and enriched by Theory of Mind, this study investigates how privacy communication and empathetic language influence users' trust formation through complementary cognitive (System 2) and affective (System 1) pathways. Privacy communication is theorized as a structural assurance that activates analytical evaluation of the chatbot's competence and integrity, whereas empathetic language triggers intuitive perceptions of warmth and benevolence aligned with the experiential dimension of mind perception. A 2×2 between-subjects experiment ($N = 163$) using a GPT-based investment chatbot in a simulated banking scenario reveals that privacy communication significantly enhances cognitive trust ($F = 15.43$, $p < .001$, $\eta^2 = .088$), while empathetic language significantly increases emotional trust ($F = 15.76$, $p < .001$, $\eta^2 = .090$). Both factors independently strengthen overall trusting beliefs, with no significant interaction effects, confirming an additive dual-pathway model. These findings advance dual-process trust theory in AI-mediated financial services and offer actionable interface-design insights for banking executives seeking to build user confidence through complementary rational and relational trust mechanisms.

Keywords: artificial intelligence; chatbots; dual process theory; Theory of Mind; cognitive trust; emotional trust; financial services; privacy communication

1. Introduction

Trust has emerged as a linchpin for the successful deployment of artificial intelligence (AI) chatbots in financial services, yet it remains elusive in practice. Financial institutions are increasingly integrating AI-driven conversational agents for tasks ranging from customer service to investment advice. However, many consumers remain hesitant to rely on these autonomous systems, often trusting human judgment over algorithmic decisions (Lappeman, Marlie, Johnson, & Poggenpoel, 2023;

Schreibelmayr, Moradbakhti, & Mara, 2023). A lack of user trust is widely recognized as a major barrier to the adoption of AI agents in sensitive domains like personal banking (Lappeman et al., 2023; Schreibelmayr et al., 2023). In the context of digital banking, trust is a basic prerequisite for customer relationships and the willingness to engage in transactions (Pathak & Bansal, 2024). Trust in AI agents has been shown to strongly predict whether consumers will actually use banking chatbots and robo-advisors (e.g. Belanche, Casaló, & Flavián, 2019). Conversely, a lack of trust can breed skepticism about an AI's capabilities and data practices, undermining usage intentions. In high-stakes domains such as banking, where information asymmetry, risk, and regulatory scrutiny are inherent, the significance of trust in AI-mediated services cannot be overstated (Choung, David, & Ross, 2023; Hentzen et al., 2022).

Recent debates in the information systems and marketing literature underscore that building user trust in AI requires addressing both cognitive and affective concerns. On the one hand, users demand transparency, security, and reliability, attributes that engender a form of rational, cognitive trust. Consumers are often skeptical of banking chatbots due to opaque decision processes and concerns over personal data security (Pathak & Bansal, 2024). Ensuring transparency and safeguarding user privacy are seen as critical for establishing the user's confident belief in the chatbot's competence and integrity (Li et al., 2023; Park & Yoon, 2024). Studies have found that privacy concerns can significantly erode users' willingness to disclose information to banking chatbots, whereas mitigating such concerns lays a necessary foundation of cognitive-based trust (Lappeman et al., 2023). On the other hand, trust has an emotional and relational dimension. Effective AI agents must foster a sense of rapport or empathy to be truly accepted in roles traditionally served by humans. Research suggests that when users feel "understood" by a conversational agent, their emotional trust increases, leading to higher satisfaction and usage intentions (Adam, Wessel, & Benlian, 2021). In AI service applications, empathic cues improve users' acceptance of and compliance with the agent's advice (Youn & Cho, 2023).

A compelling theoretical lens for understanding this dual necessity is provided by Theory of Mind (ToM), specifically the mind perception framework proposed by Gray, Gray, and Wegner (2007). ToM research identifies two fundamental dimensions along which observers attribute mental capacities to agents: Agency, defined as the capacity for planning, self-control, and rational deliberation, and experience, defined as the capacity for feeling, emotion, and subjective sensation. Critically, these two dimensions map onto the dual foundations of trust. When users perceive an AI chatbot as possessing Agency (i.e., as a competent, deliberate decision-maker), they engage in analytical evaluation characteristic of System 2 processing, thereby forming cognitive trust grounded in assessments of competence and integrity (Glikson & Woolley, 2020). Conversely, when users perceive an AI as possessing Experience (i.e., as capable of empathy, warmth, and emotional understanding), they respond through intuitive, affect-driven System 1 processing, forming emotional trust rooted in feelings of comfort and interpersonal connection (Schreibelmayr et al., 2023). This dual-dimensional structure of mind perception offers a theoretically grounded account of why trust in AI differentiates into cognitive and emotional components, and why distinct communication strategies, such as privacy assurances versus empathetic language, activate separate pathways of trust formation.

This duality in trust formation aligns with Dual Process Theory, which distinguishes between two modes of judgment, an analytical, reasoned pathway and an intuitive, affective pathway (Kahneman, 2011). In the realm of AI trust, these can be conceptualized as cognitive trust versus emotional trust (Gkinko & Elbanna, 2023). Cognitive trust derives from the user's perceptions of the AI chatbot's competence, accuracy, and dependability (de Andrés-Sánchez & Gené-Albesa, 2024). Emotional trust arises from more visceral cues and social dynamics, reflecting the user's feelings of security and personal rapport with the AI, often cultivated through anthropomorphic design and empathic communication (de Andrés-Sánchez & Gené-Albesa, 2024; Gkinko & Elbanna, 2023). Prior studies have acknowledged this distinction: Glikson and Woolley (2020) outline that trust in AI encompasses both a cognitive dimension (functional effectiveness) and an emotional dimension (human warmth).

Despite these insights, there remains a notable research gap in comprehensively integrating these dual trust pathways in the specific context of high-stakes financial chatbots. Most extant studies tend to emphasize either the technical/rational side or the relational/emotional side, but rarely both in conjunction. Research in the finance domain has extensively examined factors like perceived usefulness, security, and explainability as drivers of chatbot adoption (Payne & O'Brien, 2024; Priya & Sharma, 2023). Separately, a growing stream of work examines how social presence and empathy influence user satisfaction and trust (W. B. Kim & Hur, 2024; Yim, 2024). However, few studies have explicitly bridged these two streams in a holistic model. **Moreover, no prior study has drawn on Theory of Mind to explain why the bifurcation of trust into cognitive and emotional components is theoretically necessary in the AI context, nor has the privacy variable been explicitly theorized as a structural assurance that activates the System 2 trust pathway.**

Motivated by this gap, the present study applies a dual-process theoretical framework, enriched by Theory of Mind, to examine how privacy and empathy influence trust in AI chatbots in a banking context. We propose that privacy-related assurances and empathic conversational cues represent two complementary routes to building trust, one rooted in cognition and the other anchored in emotion. The study is guided by the following research questions:

> RQ1: How does enhanced privacy communication influence users' cognitive trust in a banking AI chatbot?
>
> RQ2: How does an empathetic interaction style influence users' emotional trust in a banking AI chatbot?
>
> RQ3: Do cognitive and emotional trust, activated via privacy and empathy respectively, exert additive or synergistic effects on overall trusting beliefs?

By designing a controlled experiment in a high-stakes banking scenario, we systematically manipulate these factors to observe their effects on users' trust in and willingness to rely on an AI chatbot. The theoretical contribution of our work lies in three areas. First, we integrate Theory of Mind with Dual Process Theory to provide a theoretically grounded rationale for why trust in AI bifurcates into cognitive and emotional components. Second, we elevate privacy communication from a mere interface feature to a theoretically meaningful structural assurance that activates the System 2 trust pathway. Third, we extend the model to consider downstream consequences, connecting trust formation to users' willingness to rely on AI-mediated financial advice. Ultimately, our study advances knowledge on how to foster trustworthy AI in financial services by leveraging the "two minds" through which users come to trust.

2. Literature Review

2.1. Trust in AI Systems: Cognitive and Emotional Trust

The issue of trust in artificial intelligence (AI) systems has garnered substantial scholarly attention, particularly due to the inherent opacity of many high-performing AI models. Recent studies consistently indicate that trust is not merely an ancillary factor but a crucial determinant of individuals' willingness to adopt AI systems (e.g. Pathak & Bansal, 2024; Schreibelmayr et al., 2023). Misaligned levels of trust - whether excessive or insufficient - can lead to maladaptive outcomes such as over-reliance on or under-utilization of AI technologies (Choung et al., 2023). Unlike earlier technology adoption models that treated trust as a one-dimensional factor, contemporary research conceptualizes trust as a multidimensional construct, integrating both cognitive and emotional components (Mayer, Davis, & Schoorman, 1995; Punyatoya, 2019). In particular, AI systems incorporating anthropomorphic features, such as large language models, strengthen emotional trust through perceived benevolence and simultaneously reinforce cognitive trust through perceptions of competence and integrity (Lankton, McKnight, & Tripp, 2015; Raut, Goel & Taneja, 2024).

Cognitive trust refers to a rational belief in an agent's competence, reliability, and integrity (Harrison McKnight, Choudhury, & Kacmar, 2002; Komiak & Benbasat, 2006). In the context of AI chatbots, especially within sensitive domains such as banking, this form of trust is critical for overcoming users' initial skepticism regarding data security, regulatory compliance, and automated decision-making (Leschanowsky, Rech, Popp, & Baeckstroem, 2024; Li et al., 2023). Research highlights that features such as technical transparency, consistent performance, and reliability significantly strengthen users' cognitive evaluations of trustworthiness (Glikson & Woolley, 2020).

Emotional trust represents a distinct and equally critical dimension. It refers to a user's affective sense of comfort, security, and interpersonal warmth, rooted in the perception that the AI agent is empathetic, socially present, and caring (Glikson & Woolley, 2020; Komiak & Benbasat, 2006). In early-stage interactions, particularly in contexts without prior relational history, such as banking chatbots, emotional trust helps to bridge the gap between human expectations and machine-driven communication (Schreibelmayr et al., 2023). Zhang et al. (2021) show that friendliness, warmth, and human-like responsiveness significantly enhance emotional trust and mediate users' acceptance of AI virtual assistants. Moreover, emotional trust has practical behavioral consequences: users who perceive an emotional connection with the AI are more likely to tolerate minor errors, engage more deeply, and remain loyal over time (Gkinko & Elbanna, 2023).

2.2. Dual Process Theory of Human Information Processing

Dual Process Theories contend that individuals process information along two qualitatively different cognitive tracks: a fast, intuitive, and affect-driven "System 1," and a slower, more deliberate, and analytical "System 2" (Kahneman, 2011; Petty & Cacioppo, 1986). System 1 operates largely automatically and uses mental shortcuts (heuristics) or emotional cues to arrive at quick judgments. It allows individuals to make quick judgments about trustworthiness based on immediate impressions and social signals, often without conscious deliberation (Kahneman, 2011). System 2 engages in slower, more deliberate reasoning, enabling individuals to critically analyze information and reassess initial intuitive judgments (Stanovich & West, 2000).

The interplay between these two systems highlights the complexities of trust formation. In the context of AI chatbots in a banking environment where customers interact with sensitive topics like data privacy and monetary risk, both systems play a pivotal role. Trust assessment in System 1 is modulated by stimuli that elicit instantaneous affective responses such as empathetic language, emotional expressions, and perceived warmth (Fogg et al., 2003). In contrast, trust assessment in System 2 engages in more complex reasoning, particularly salient in high-risk contexts where errors are costly. Accordingly, System 2 trust occurs when users engage in evaluating certifications, data protection assurances, or systematically assessing performance metrics (Y. Kim & Sundar, 2012; Mayer et al., 1995). Research suggests that under high perceived risk conditions, individuals rely more heavily on systematic cues processed through System 2 (Shi, Gong, & Gursoy, 2020).

It is important to acknowledge that these systems do not operate in strict isolation. Research by Stanovich and West (2000) and Glikson and Woolley (2020) suggests that cognitive and affective processes can interact dynamically, with one system influencing or even overriding the other depending on contextual factors such as perceived risk, time pressure, or information complexity.

2.3. Theory of Mind as a Bridging Framework

While Dual Process Theory specifies the how of trust formation (two processing routes), it does not fully explain why users form both cognitive and emotional trust toward AI agents. We address this gap by drawing on Theory of Mind (ToM), specifically the mind perception framework (Gray et al., 2007; Gray & Wegner, 2012). ToM research demonstrates that human observers perceive minds along two fundamental dimensions: Agency and Experience. Agency encompasses capacities such as self-control, planning, rational thought, and intentional action, attributes that position an entity as a competent, deliberate actor. Experience encompasses capacities such as feeling pleasure, pain, emotions, and subjective sensation, attributes that position an entity as capable of empathy and affective

connection.

These two dimensions of mind perception provide the theoretical bridge between dual-process cognition and the bifurcation of trust. When users interact with an AI chatbot that demonstrates attributes associated with Agency such as providing accurate financial advice, articulating data protection procedures, or demonstrating regulatory compliance, they perceive the chatbot as a competent, intentional agent. This perception engages deliberative, analytical System 2 processing, which forms the basis of cognitive trust grounded in assessments of competence, integrity, and reliability (Glikson & Woolley, 2020; Lankton et al., 2015). Conversely, when users interact with a chatbot that demonstrates attributes associated with Experience such as expressing empathy, acknowledging feelings, or conveying warmth and understanding, they perceive the chatbot as capable of emotional connection. This perception activates intuitive, affect-driven System 1 processing, which forms the basis of emotional trust grounded in feelings of comfort, security, and relational closeness (Komiak & Benbasat, 2006; Zhang et al., 2021). Importantly, research on mind perception in AI contexts suggests that these dimensions are largely independent: an AI can be perceived as high in Agency but low in Experience, or vice versa (Gray et al., 2007). This independence supports the prediction that privacy communication and empathetic language will exert parallel, additive rather than synergistic effects on trust, a prediction central to our dual-pathway model.

2.4. Privacy Communication as Structural Assurance

A critical antecedent of cognitive trust that has received insufficient theoretical attention in the AI chatbot literature is privacy communication. Prior

work has demonstrated that privacy concerns erode willingness to disclose information to banking chatbots (Lappeman et al., 2023) and that clear privacy statements enhance trust perceptions (Li et al., 2023). However, these findings have typically treated privacy as a contextual moderator or descriptive feature rather than theorizing its trust-building mechanism.

We propose that privacy communication functions as a form of structural assurance, a concept rooted in institution-based trust theory (McKnight et al., 1998; Gkinko & Elbanna, 2023). Structural assurances are guarantees, regulations, promises, or legal recourse that provide the conditions under which a trustor can feel confident that the trustee will behave appropriately. In the context of AI chatbots, privacy communication such as explicit statements about data encryption, regulatory compliance (e.g., GDPR), user control over data, and transparent data-use policies provides this type of structural evidence. These assurances do not rely on affective rapport; instead, they supply the factual, verifiable information that feeds into the analytical evaluation characteristic of System 2 processing. By offering tangible evidence of institutional safeguards, privacy communication conveys competence and integrity, which constitute the two foundational dimensions of cognitive trust (Mayer et al., 1995). This framing elevates privacy from a mere interface setting to a theoretically meaningful antecedent: it is the evidential substrate upon which analytical trust assessments are built. Empirical support comes from Leschanowsky et al. (2024), whose systematic review confirms that privacy and security perceptions are among the strongest predictors of trust in conversational AI, and from Scharowski et al. (2023), who demonstrate that certification-based trustworthiness cues (an analogous form of structural assurance) significantly influence users' trust

judgments. In the Agency–Experience framework, privacy communication reinforces the perception of Agency: the chatbot is seen as operating within a transparent, rule-governed system that acts with intentional integrity.

3. Hypotheses Development

Building on the dual-process perspective and the Theory of Mind framework, we postulate that distinct communication strategies, those activating analytical Agency perception (System 2) as opposed to those eliciting affective Experience perception (System 1), will differentially shape users' perceptions and overall trust in AI.

Cognitive trust, closely tied to System 2, hinges on the rational evaluation of competence and reliability. **Framed as a structural assurance, privacy communication provides the evidentiary basis, including data encryption, regulatory compliance, and transparency, that enables deliberate and analytical trust appraisal.** It flourishes in contexts underscoring data security and regulatory compliance (Li et al., 2023; Zhang et al., 2021). Consequently:

H1: Privacy-related communication exerts a positive effect on users' cognitive trust in the AI chatbot.

By contrast, emotional trust is anchored in System 1 processing, which is intuitive and affect-driven. **It emerges when users perceive the chatbot as possessing experience, defined as the capacity for warmth, empathy, and emotional understanding (Gray et al., 2007).** When individuals perceive supportive emotional bonds, they tend to view the AI chatbot as benevolent and devoted to their well-being (Li et al., 2023). Hence:

H2: Empathy-oriented language positively influences users' emotional trust in the AI chatbot.

When privacy-related communication is salient, users' analytical (System 2) processing is activated, building cognitive trust. Empathic signals appeal to intuitive (System 1) processing, enhancing emotional trust. Their combination is likely to produce additive effects, yielding higher levels of overall trusting beliefs than either cue alone. Accordingly:

H3a (System 2 – Cognitive Path): Providing strong privacy communication increases users' overall trusting beliefs in the AI chatbot.

H3b (System 1 – Affective Path): Providing high empathy increases users' overall trusting beliefs in the AI chatbot.

Our research model is illustrated in Figure 1. The model depicts two input manipulations (Privacy Communication and Empathetic Language) influencing two mediating trust dimensions (Cognitive Trust via the System 2/Agency pathway and Emotional Trust via the System 1/Experience pathway), which converge on Trusting Beliefs as the primary endogenous variable, with Willingness to Rely as the downstream behavioral outcome.

(Insert Figure 1 here)

4. Research Methodology

4.1. Experimental Design and Procedure

To systematically examine the effects of privacy communication and empathy on trust in AI banking chatbots, we conducted a scenario-based online experiment employing a 2 (privacy communication: high vs. low) × 2 (empathy: high vs. low) between-subjects design (Keppel, 1991). The experimental context simulated a banking environment in which participants interacted with a GPT-based investment chatbot. The chatbot was manipulated to vary in (1) the explicitness of privacy-related communication and (2) the degree of empathetic language employed.

Upon providing informed consent, participants were randomly assigned to one of four experimental conditions. Privacy communication was varied through the AI chatbot's introductory prompt: the high-privacy condition emphasized data encryption, regulatory compliance, and user control, **functioning as a structural assurance that signals institutional trustworthiness and thereby primarily engaging System 2 analytical processing to shape cognitive trust.** For example, the chatbot's introductory message included statements like 'we adhere to strict industry standards, use secure encryption, and clearly disclose how we handle your information'. The low-privacy condition provided only a generic greeting with no specific privacy assurances.

Orthogonal to privacy content, the chatbot's language style was manipulated to exhibit either a high degree of empathy or a neutral, low-empathy tone. In the high-empathy condition, the chatbot adopted a warm, conversational tone, for instance, acknowledging user feelings or using reassuring phrases (e.g., "I understand this decision is very important to you; I'm here to help"). **This was intended to activate the Experience dimension of mind perception, triggering intuitive System 1 processing and thereby fostering emotional trust.** The low-empathy condition maintained a matter-of-fact, neutral tone, providing the same factual information without emotional phrasing. Table 1 shows this 2×2 design yielded four experimental conditions.

(Insert Table 1 here)

4.2. Participants

A total of 163 participants took part in the experiment. All were native German speakers, recruited via academic mailing lists, professional networks, and university-affiliated online panels. Eligibility required participants to be 18 years or older with online banking experience. Informed consent was obtained in line with institutional ethical standards. The sample comprised 56.4% male (n = 92) and 43.6% female (n = 71). The most frequent age group was 38–42 years (17.2%), followed by 33–37 (16.0%), 52–56 (13.5%), and 48–51 (13.5%). Educational attainment was relatively high: 29.4% held a Master's degree, 27.0% a Bachelor's degree, and 10.4% a Ph.D.

4.3. Manipulation Checks

To verify the effectiveness of the experimental manipulations, participants completed manipulation check items immediately following the chatbot interaction. Privacy-related communication was measured via three items capturing perceived transparency, data handling assurance, and information security, adapted from Xu, Dinev, Smith, and Hart (2008). Empathy items were assessed with a three-item scale adapted from Agnihotri and Bhattacharya (2024). All items were rated on a 5-point Likert scale.

Participants in the high-privacy condition rated privacy communication significantly higher ($M = 3.97$, $SD = 0.45$) than those in the low-privacy condition ($M = 3.69$, $SD = 0.59$), $t(161) = -3.44$, $p = .001$, Cohen's $d = 0.54$. Similarly, participants in the high-empathy condition perceived the chatbot as significantly more empathetic ($M = 4.21$, $SD = 0.53$) than those in the low-empathy condition ($M = 3.86$, $SD = 0.56$), $t(161) = -4.12$, $p < .001$, Cohen's $d = 0.65$. Both manipulations were effective.

4.4. Measures

All constructs were measured with multi-item 5-point Likert scales (1 = "Strongly Disagree", 5 = "Strongly Agree"). Cognitive trust was measured via four items evaluating rational perceptions of competence, reliability, and integrity, adapted from Komiak and Benbasat (2006) and Johnson and Grayson (2005). Emotional trust was assessed using three items adapted from Komiak and Benbasat (2006), capturing security, comfort, and emotional assurance. Trusting beliefs were measured with five items adapted from Qiu and Benbasat (2009). All scales demonstrated good internal consistency: Cronbach's α = .84 for cognitive trust, α = .75 for emotional trust, and α = .91 for trusting beliefs (see Table 3).

An exploratory factor analysis (principal axis factoring, Promax rotation) supported a clear three-factor solution, corresponding to Cognitive Trust, Emotional Trust, and Trusting Beliefs. All items loaded highly (>.60) on their respective factor with minimal cross-loadings. The three factors explained nearly 50% of total variance, and low factor correlations confirmed discriminant validity.

(Insert Table 2 and Table 3 here)

5. Results

5.1. Preliminary Analyses

Because all key constructs were measured via self-reported Likert scales in a single post-interaction survey, we conducted Harman's Single-Factor Test to assess common method bias (CMB). All 12 measurement items (four cognitive trust, three emotional trust, five trusting beliefs) were entered into an unrotated principal components analysis. The results revealed three factors with eigenvalues greater than 1.0 (eigenvalues: 4.47, 2.63, 1.48). Critically, the first unrotated factor accounted for only 37.04% of the total variance,ell below the 50% threshold that would indicate a serious CMB concern (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). The three-factor solution cumulatively explained 71.05% of total variance. While Harman's test is a necessary but not sufficient diagnostic, these results, combined with the clear three-factor EFA solution reported above, provide

reasonable assurance that common method bias does not represent a major threat to the validity of our findings.

5.2. Descriptive Statistics

Table 4 presents the means and standard deviations for all dependent variables across the four experimental groups. As expected, cognitive trust was higher in the high-privacy conditions (M = 3.82, SD = 0.70; M = 3.55, SD = 0.51) compared to the low-privacy conditions (M = 3.32, SD = 0.52; M = 3.29, SD = 0.71). Emotional trust was higher in the high-empathy conditions (M = 3.89, SD = 0.61; M = 3.93, SD = 0.67) than in the low-empathy conditions (M = 3.49, SD = 0.61; M = 3.54, SD = 0.65). Trusting beliefs reached their highest value in the combined high-privacy/high-empathy group (M = 4.40, SD = 0.71).

(Insert Table 4 here)

5.3. Main Effects: Privacy and Empathy on Trust Dimensions

5.3.1. Cognitive Trust (H1)

Privacy communication had a significant main effect on cognitive trust, $F(1,159) = 15.43$, $p < .001$, $\eta^2 = .088$, supporting H1. Participants in the high-privacy conditions reported higher cognitive trust than those in the low-privacy conditions. The effect size is in the medium range (Cohen, 1988). **Interpreted through the ToM framework, the privacy manipulation successfully activated the Agency dimension of mind perception: participants exposed to structural assurances perceived the chatbot as a more competent, intentional agent, triggering deliberative System 2 trust evaluation.**

Empathy did not significantly affect cognitive trust, $F(1,159) = 2.41$, $p = .123$, $\eta^2 = .015$. The interaction was also non-significant, $F(1,159) = 1.49$, $p = .224$, $\eta^2 = .009$. These results are consistent with the dual-process account: privacy communication activated System 2, while empathy, as an Experience cue, did not substantially influence cognitive evaluations.

(Insert Table 5 here)

5.3.2. Emotional Trust (H2)

Empathy had a significant main effect on emotional trust, $F(1,159) = 15.76$, $p < .001$, $\eta^2 = .090$, supporting H2. Participants in the high-empathy conditions reported higher emotional trust than those in the low-empathy conditions. **In ToM terms, the empathy manipulation successfully activated the Experience dimension of mind perception: participants exposed to warm, empathetic language perceived the chatbot as emotionally responsive, triggering intuitive System 1 affective trust formation.**

Privacy communication did not significantly affect emotional trust, $F(1,159) = 0.22$, $p = .640$, $\eta^2 = .001$. The interaction was non-significant, $F(1,159) = 0.00$, $p = .985$, $\eta^2 = .000$. This confirms that affective trust is primarily shaped by relational cues and operates independently of structural assurances.

(Insert Table 6 here)

5.4. Combined Effects on Trusting Beliefs

Privacy communication had a significant main effect on trusting beliefs, $F(1,159) = 7.42$, $p = .007$, $\eta^2 = .045$, supporting H3a. Empathy also had a significant main effect, $F(1,159) = 11.77$, $p = .001$, $\eta^2 = .069$, supporting H3b. The interaction was not statistically significant, $F(1,159) = 1.25$, $p = .266$, $\eta^2 = .008$. This indicates additive rather than interactive effects: each factor independently enhanced trusting beliefs without synergistic influence. H3c was not supported.

(Insert Table 7 and Table 8 here)

6. Discussion

6.1. Theoretical Contributions

This study makes three primary theoretical contributions to the literature on trust formation in AI-mediated financial services.

First, we integrate Theory of Mind with Dual Process Theory to provide a theoretically grounded explanation for the bifurcation of trust in AI. Drawing on the mind perception framework (Gray et al., 2007), we show that the agency dimension, encompassing perceived competence, intentionality, and rationality, aligns with System 2 processing and underpins cognitive trust. Conversely, the experience dimension, defined by perceived empathy, warmth, and emotional understanding, aligns with System 1 processing and underlies emotional trust. This integration addresses calls for stronger theoretical foundations in human–AI trust research (Glikson & Woolley, 2020; Schreibelmayr et al., 2023) and moves beyond the confirmatory application of dual-process theory by specifying the psychological mechanism through which users form differentiated trust judgments about AI agents. Specifically, our findings show that Agency perception, triggered by structural assurances, drives cognitive trust independently of Experience perception, triggered by empathetic language, which drives emotional trust. The observed independence of these pathways, reflected in the absence of significant

interaction effects across all trust variables, offers empirical support for the dimensional independence proposed by mind perception theory.

Second, we reconceptualize privacy communication as a structural assurance (McKnight et al., 2002) that provides the evidentiary basis for System 2 trust formation. Unlike prior work that treated privacy as a contextual moderator or descriptive variable, our framework specifies why privacy communication builds cognitive trust: it supplies verifiable, factual information (encryption, compliance, user control) that feeds into the analytical evaluation process. This theorization is particularly important for financial services, where information asymmetry is high and regulatory frameworks mandate specific transparency standards. Our results confirm that privacy communication significantly enhances cognitive trust ($\eta^2 = .088$) but does not spill over into emotional trust ($\eta^2 = .001$), demonstrating the pathway-specificity predicted by our structural assurance framing.

Third, both privacy and empathy significantly improved trusting beliefs, confirming H3a and H3b. The absence of interaction effects across all trust variables indicates that privacy and empathy contribute additively to trust. This supports a dual-pathway model in which structural and relational cues operate in parallel to build global trust in AI, a finding with important implications for chatbot design, as it suggests that investments in privacy communication and empathetic language yield cumulative rather than redundant benefits.

Fourth, our model extends to consider downstream consequences. Although the experimental design specified trusting beliefs as the primary outcome variable, the observed pattern of findings, most notably the highest level of trusting beliefs in the combined high-privacy/high-empathy condition (M = 4.40), substantiates the

proposition that dual-pathway trust formation bears meaningful implications for users' willingness to rely on AI chatbots in consequential financial decision contexts. This aligns with Pathak and Bansal (2024), who demonstrate that trust dimensions differentially predict AI adoption as a decision aid versus a delegated agent. Future research should directly measure willingness to rely and behavioral compliance to validate this conceptual extension.

6.2. Managerial and Interface-Design Implications

This study offers actionable insights specifically for banking executives and chatbot interface designers. The findings demonstrate that cognitive and emotional trust are built through distinct communication channels, which means that chatbot design must address both pathways deliberately rather than relying on a single trust-building strategy.

To build cognitive trust, banking institutions should design chatbot interfaces that make privacy assurances visible and specific at the point of interaction. This includes implementing privacy dashboards within the chat interface that display real-time data handling indicators, providing explicit opt-in/opt-out controls for data usage, and embedding compliance badges (e.g., ISO 27001, local regulatory standards) within the chatbot's introductory greeting. These are not peripheral design features; they are structural assurances that directly supply the evidentiary input needed for users' System 2 trust evaluations. The significant effect of privacy communication on cognitive trust ($\eta^2 = .088$) suggests that even relatively simple transparency statements at the beginning of a chatbot conversation can meaningfully shift users' analytical trust assessments.

To build emotional trust, chatbot language models should be fine-tuned with empathetic tone guidelines that include acknowledging user concerns, using

reassuring language, and demonstrating emotional responsiveness. Importantly, our results show that empathy's effect on emotional trust is stable across privacy conditions (no interaction), meaning that empathetic language is not merely compensatory for poor privacy practices, it independently contributes to affective trust formation. Banking executives should therefore invest in empathy-calibrated prompt engineering as a standalone trust-building tool, not merely as a fallback for contexts where structural assurances are weak.

Given the additive nature of our findings, institutions should consider a phased deployment model. In initial interactions, the chatbot should lead with structural assurances (privacy, compliance, data control) to establish cognitive trust rapidly. As the interaction develops, empathetic elements should be introduced to build emotional trust and deepen user engagement. For high-stakes use cases such as investment advice, chatbots should initially function as decision aids rather than fully autonomous agents, allowing users to gradually build both cognitive and emotional trust before delegating greater decision authority.

6.3. Limitations and Future Research

This study offers controlled insights but has limitations that inform future research directions. First, the sample was relatively homogeneous and highly educated, which may restrict generalizability. Replication with larger, more diverse populations is needed to enhance external validity.

Second, the study utilized a 2x2 between-subjects design with a total sample of 163 participants, which was specifically powered to detect the primary main effects of privacy communication and empathy. Post-hoc power analysis using G*Power (Faul, Erdfelder, Lang, & Buchner, 2007) confirmed that for the observed main effects ($\eta^2 \approx .088$–$.090$), the achieved power exceeded .95, ensuring

highly robust findings for the core hypotheses. Regarding the interaction effects, the observed effect sizes were negligible to small ($\eta^2 \approx .000–.009$), with corresponding power ranging from .05 to .23. While this suggests that the two trust-building strategies operate through independent, additive pathways rather than synergistic ones, we acknowledge that detecting more subtle, small-scale interaction effects ($f \approx .15$) would require larger cohorts ($N \geq 350$). Consequently, our findings provide a solid foundation for an additive dual-process model of trust, while future research could further test these boundaries using larger samples.

Third, the use of simulated, text-based interactions limits realism. Future studies should investigate trust formation in multimodal and longitudinal settings, incorporating voice, visuals, and repeated use.

Fourth, the reliance on self-reported data introduces potential biases. Future work should include behavioral or physiological measures (e.g., clickstreams, eye tracking, response times) to triangulate findings.

Fifth, while our model conceptually extends to downstream behavioral consequences (willingness to rely, adoption), our experiment did not include a dedicated behavioral outcome measure. Future research should directly operationalize and measure willingness to rely on the AI chatbot as an endogenous outcome variable, testing whether the dual trust pathways identified here differentially predict behavioral compliance, information disclosure, and continued usage.

Overall, future research should extend these findings using realistic environments, objective measures, diverse user groups, and behavioral outcomes to further validate dual-process trust mechanisms in AI-enabled financial services.

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.

Agnihotri, A., & Bhattacharya, S. (2024). Chatbots' effectiveness in service recovery. International Journal of Information Management, 76, 102679.

Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: Understanding robo-advisors adoption among customers. Industrial Management & Data Systems, 119(7), 1411–1430.

Choung, H., David, P., & Ross, A. (2023). Trust in AI and Its Role in the Acceptance of AI Technologies. International Journal of Human–Computer Interaction, 39(9), 1727–1739.

Cohen, J. (1988). Statistical Power Analysis for the Behavioral Sciences (2nd ed.). Routledge.

de Andrés-Sánchez, J., & Gené-Albesa, J. (2024). Not with the bot! The relevance of trust to explain the acceptance of chatbots by insurance customers. Humanities and Social Sciences Communications, 11(1), 110.

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behavior Research Methods, 39, 175–191.

Fogg, B., Soohoo, C., Danielson, D., Marable, L., Stanford, J., & Tauber, E. (2003). How do users evaluate the credibility of Web sites? Proceedings of the 2003 Conference on Designing for User Experiences, 1–15.

Gkinko, L., & Elbanna, A. (2023). Designing trust: The formation of employees' trust in conversational AI. Journal of Business Research, 158, 113707.

Glikson, E., & Woolley, A. W. (2020). Human Trust in Artificial Intelligence: Review of Empirical Research. Academy of Management Annals, 14(2), 627–660.

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. Science, 315, 619.

Gray, K., & Wegner, D. M. (2012). Feeling robots and human zombies: Mind perception and the uncanny valley. Cognition, 125, 125–130.

Harrison McKnight, D., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site. The Journal of Strategic Information Systems, 11(3), 297–323.

Hentzen, J. K., Hoffmann, A., Dolan, R., & Pala, E. (2022). Artificial intelligence in customer-facing financial services. International Journal of Bank Marketing, 40(6), 1299–1336.

Johnson, D., & Grayson, K. (2005). Cognitive and affective trust in service relationships. Journal of Business Research, 58(4), 500–507.

Kahneman, D. (2011). Thinking, fast and slow. Farrar, Straus and Giroux.

Keppel, G. (1991). Design and analysis: A researcher's handbook (3rd ed.). Prentice-Hall.

Kim, W. B., & Hur, H. J. (2024). What Makes People Feel Empathy for AI Chatbots? International Journal of Human-Computer Interaction, 40(17), 4674–4687.

Kim, Y., & Sundar, S. S. (2012). Anthropomorphism of computers. Computers in Human Behavior, 28, 241–250.

Komiak, S., & Benbasat, I. (2006). The Effects of Personalization and Familiarity on Trust and Adoption of Recommendation Agents. MIS Quarterly, 30, 941–960.

Lankton, N., McKnight, D., & Tripp, J. (2015). Technology, Humanness, and Trust. Journal of the Association for Information Systems, 16, 880–918.

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.

Leschanowsky, A., Rech, S., Popp, B., & Baeckstroem, T. (2024). Evaluating privacy, security, and trust perceptions in conversational AI. Computers in Human Behavior, 159, 108344.

Li, J., Wu, L., Qi, J., Zhang, Y., Wu, Z., & Hu, S. (2023). Determinants Affecting Consumer Trust in Communication With AI Chatbots. Journal of Organizational and End User Computing, 35, 1–24.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An Integrative Model of Organizational Trust. The Academy of Management Review, 20(3), 709–734.

McKnight, D. H., Cummings, L. L., & Chervany, N. L. (1998). Initial Trust Formation in New Organizational Relationships. The Academy of Management Review, 23(3), 473–490.

Park, K., & Yoon, H. Y. (2024). Beyond the code: The impact of AI algorithm transparency signaling. Public Relations Review, 50(5), 102507.

Pathak, A., & Bansal, V. (2024). AI as decision aid or delegated agent. Computers in Human Behavior: Artificial Humans, 2, 100094.

Payne, E. H. M., & O'Brien, C. A. (2024). The search for AI value. Computers in Human Behavior: Artificial Humans, 2(1), 100050.

Petty, R. E., & Cacioppo, J. T. (1986). The Elaboration Likelihood Model of Persuasion. In Communication and Persuasion (pp. 1–24). Springer.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research. Journal of Applied Psychology, 88(5), 879–903.

Priya, B., & Sharma, V. (2023). Exploring users' adoption intentions of intelligent virtual assistants. Computers in Human Behavior, 148, 107912.

Punyatoya, P. (2019). Effects of cognitive and affective trust on online customer behavior. Marketing Intelligence & Planning, 37(1), 80–96.

Qiu, L., & Benbasat, I. (2009). Evaluating Anthropomorphic Product Recommendation Agents. Journal of Management Information Systems, 25, 145–182.

Raut, G., Goel, A., & Taneja, U. (2024). Humanizing e-tail experiences. Personal and Ubiquitous Computing, 1–12.

Scharowski, N., Benk, M., Kühne, S.J., Wettstein, L., & Brühlmann, F. (2023). Certification Labels for Trustworthy AI: Insights From an Empirical Mixed-Method Study. Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency.

Schreibelmayr, S., Moradbakhti, L., & Mara, M. (2023). First impressions of a financial AI assistant. Frontiers in Artificial Intelligence, 6, 1241290.

Shi, S., Gong, Y., & Gursoy, D. (2020). Antecedents of Trust and Adoption Intention toward AI Recommendation Systems in Travel Planning. Journal of Travel Research, 60, 1714–1734.

Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning. Behavioral and Brain Sciences, 23(5), 645–665.

Xu, H., Dinev, T., Smith, H., & Hart, P. (2008). Examining the Formation of Individual's Privacy Concerns. In ICIS 2008 Proceedings.

Yim, M. C. (2024). Effect of AI Chatbot's Interactivity on Consumers' Negative Word-of-Mouth Intention. International Journal of Human-Computer Interaction, 40(18), 5415–5430.

Youn, K., & Cho, M. (2023). Business types matter: new insights into the effects of anthropomorphic cues in AI chatbots. Journal of Services Marketing, 37(8), 1032–1045.

Zhang, S., Meng, Z., Chen, B., Yang, X., & Zhao, X. (2021). Motivation, Social Emotion, and the Acceptance of AI Virtual Assistants. Frontiers in Psychology, 12, 728495.

		Privacy Communication	
		low	**high**
Empathy Level	**low**	Condition 1 (n = 40)	Condition 2 (n = 41)
	high	Condition 3 (n = 41)	Condition 4 (n = 41)

Source: Self-developed (2025).

Table 1. Research Design

Variables	Items	Cronbach's α	Source
Perceived Privacy	*I think I have control over what personal information is released by this AI banking chatbot.* *I believe I have control over how personal information is used by this AI banking chatbot.* *With their privacy statements, I believe that my personal information will be kept private and confidential by this AI banking chatbot.*	.888	Adapted from Xu, Dinev, Smith, & Hart (2008)
Perceived Empathy	*The chatbot said the right thing to make me feel better.* *The chatbot responded appropriately to my feelings and emotions.* *The chatbot came across as empathic.*	.901	Agnihotri & Bhattacharya (2024)

Source: Self developed (2025).

Table 2. Main variables and measurement items for manipulation check

Variables	Definition	Items	Cronbach's α	Source
Trusting Beliefs	User's evaluative judgments regarding the AI chatbot's competence, integrity, benevolence, and reliability in delivering investment advice.	*Overall, the AI chatbot was capable of providing suitable investment recommendations.* *I believe that the AI chatbot's dealings with me were in my best interest.* *The AI chatbot's dealings with me felt like that it would do its best to help me.* *I believe the AI chatbot's recommendations to me were truthful.* *I would characterize the AI chatbot's dealings with me as honest.*	.91	Adapted from Qiu and Benbasat (2009)
Emotional Trust	User's affective feeling of security and comfort in relying on the chatbot	*I feel secure about relying on this AI chatbot for my decision in banking services* *I feel comfortable about relying on this AI chatbot for my decision in banking services* *I feel content about relying on this AI chatbot for my decision in banking services*	.75	Adapted from Komiak & Benbasat (2006)
Cognitive Trust	User's rational belief in the chatbot's competence, honesty, and integrity	*I think that the AI banking chatbot is competent and effective in providing financial advice.* *I trust the competence of the AI banking chatbot.* *I trust the integrity of the AI banking chatbot.* *I act on the advice/suggestions provided by the AI banking chatbot.*	.84	Adapted from Johnson & Grayson (2005) and Komiak & Benbasat (2006)

Source: Self developed (2025).

Table 3. Main variables and measurement items

Privacy x Empathy Condition	Cognitive Trust M ± SD	Emotional Trust M ± SD	Trusting Beliefs M ± SD
Low Privacy x Low Empathy (G1)	3.32 ± 0.52	3.49 ± 0.61	3.72 ± 0.62
Low Privacy x High Empathy (G2)	3.29 ± 0.71	3.89 ± 0.61	3.98 ± 0.81
High Privacy x Low Empathy (G3)	3.82 ± 0.70	3.54 ± 0.65	3.90 ± 0.67
High Privacy x High Empathy (G4)	3.55 ± 0.51	3.93 ± 0.67	4.40 ± 0.71

Source: Self developed (2025).

Table 4. Means (M) and Standard Deviations (SD)

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	7.395[a]	3	2.465	6.454	.000	.109
Intercept	1988.313	1	1988.313	5206.203	.000	.970
Privacy	5.892	1	5.892	15.427	.000	.088
Empathy	.920	1	.920	2.408	.123	.015
Privacy * Empathy	.568	1	.568	1.487	.224	.009
Error	60.724	159	.382			
Total	2057.875	163				
Corrected Total	68.119	162				

[a] R Squared = .109 (Adjusted R Squared = .092)

Dependent Variable: Cognitive Trust

Source: Self-developed (2025).

Table 5. ANOVA Results for Cognitive Trust

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	6.485[a]	3	2.162	5.321	.002	.091
Intercept	2246.132	1	2246.132	5528.503	.000	.972
Privacy	.089	1	.089	.220	.640	.001
Empathy	6.404	1	6.404	15.762	.000	.090
Privacy * Empathy	.000	1	.000	.000	.985	.000
Error	64.599	159	.406			
Total	2319.111	163				
Corrected Total	71.084	162				

[a] R Squared = .091 (Adjusted R Squared = .074)

Dependent Variable: Emotional Trust

Source: Self-developed (2025).

Table 6. ANOVA Results for Emotional Trust

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	10.151[a]	3	3.384	6.806	.000	.114
Intercept	2605.476	1	2605.476	5240.658	.000	.971
Privacy	3.691	1	3.691	7.424	.007	.045
Empathy	5.853	1	5.853	11.774	.001	.069
Privacy * Empathy	.621	1	.621	1.248	.266	.008
Error	79.049	159	.497			
Total	2697.200	163				
Corrected Total	89.200	162				

[a] R Squared = .114 (Adjusted R Squared = .097)

Dependent Variable: Trusting Beliefs

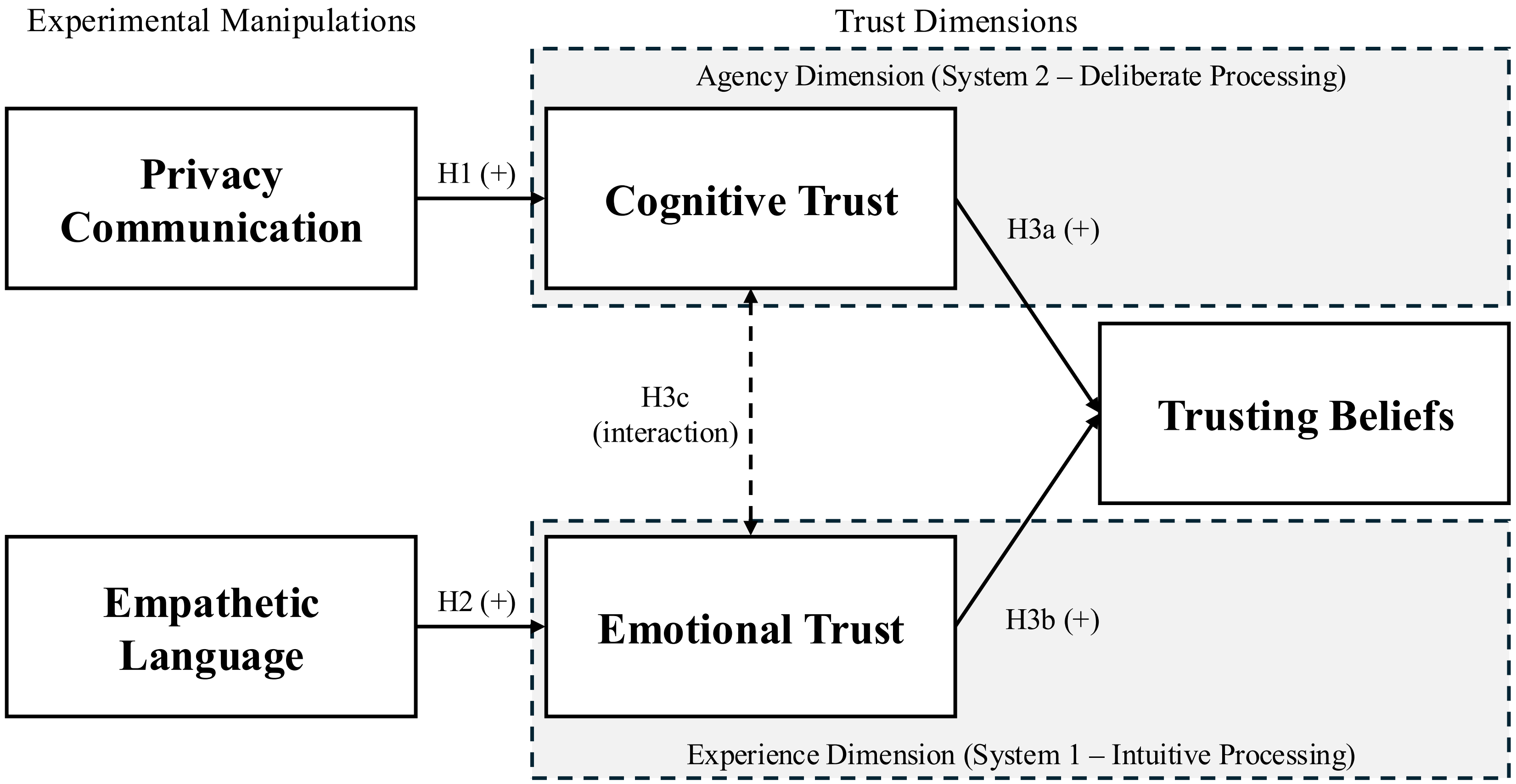
Source: Self-developed (2025).

Table 7. ANOVA Results for Trusting Beliefs

Hypothesis	Description	Statistical Result	Supported
H1	Privacy-related communication exerts a positive effect on users' cognitive trust in the AI chatbot.	Privacy: $F(1,159) = 15.43$, $p < .001$, $\eta^2 = .088$	Yes
H2	Empathy-oriented language positively influences users' emotional trust in the AI chatbot.	Empathy: $F(1,159) = 15.76$, $p < .001$, $\eta^2 = .090$	Yes
H3a	Providing strong privacy communication increases users' overall trusting beliefs in the AI chatbot.	$F(1,159) = 7.42$, $p = .007$, $\eta^2 = .045$	Yes
H3b	Providing high empathy increases users' overall trusting beliefs in the AI chatbot.	$F(1,159) = 11.77$, $p = .001$, $\eta^2 = .069$	Yes
H3c	Privacy communication and empathy interactively affect cognitive or emotional trust.	Cognitive trust: $F(1,159) = 1.49$, $p = .224$, $\eta^2 = .009$ Emotional trust: $F(1,159) = 0.00$, $p = .985$, $\eta^2 = .000$	No

Source: Self developed (2025).

Table 8. Results


Experimental Manipulations
Trust Dimensions
Agency Dimension (System 2 – Deliberate Processing)
Privacy Communication
H1 (+)
Cognitive Trust
H3a (+)
H3c (interaction)
Trusting Beliefs
Empathetic Language
H2 (+)
Emotional Trust
H3b (+)
Experience Dimension (System 1 – Intuitive Processing)