Pakistan Journal of
Positive Psychology

Print ISSN : 3078-6428 | Online ISSN : 3078-6436
Pakistan Journal of Positive Psychology

Original Article

FEELING HEARD BY A MACHINE: THE PSYCHOLOGY OF PERCEIVED UNDERSTANDING IN AI CONVERSATIONS

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ABSTRACT

The recent advancements in conversational artificial intelligence have developed systems that are able to mimic human conversation, which can create the perception of hearing or understanding from a machine. This situation poses significant psychological issues about the nature of how human understanding is generated with AI, even though it doesn't have a real brain. What are the psychological mechanisms in relation to a perceived understanding when engaging in AI conversation and what are the key interactional factors that help create this experience? A conceptual mixed-methods approach was used that involved the results of human–computer interaction research, social psychology, and computational linguistics. It involved secondary empirical literature analysis and modelling of perceived understanding as a function of language alignment, contextual coherence, personalization, response timing and anthropomorphic cues. The findings suggest that high linguistic alignment, contextual coherence and adaptive personalization are important factors for perceived understanding. Faster response times and anthropomorphic design attributes contribute further toward social presence and emotional interaction. Together, these factors create a sense of empathy and understanding, leading users to attribute awareness to an algorithmic system where none exists. Based on the above findings, the study concludes that perceived understanding in AI conversations is a psychologically constructed experience that is driven by interactional design, not by machine understanding. This not only boosts user engagement and trust but also introduces the risk of emotional over-attribution and reliance on AI systems.

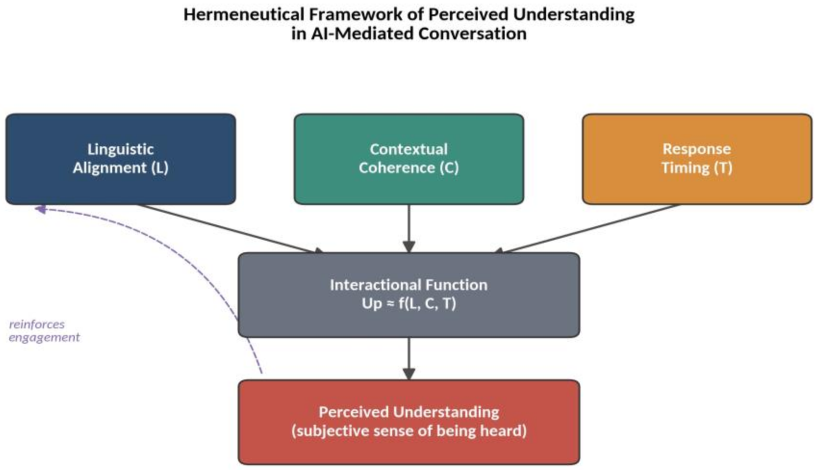
KEYWORDS
Artificial Intelligence, Perceived Understanding, Anthropomorphism, Human–AI Interaction, Social Cognition

CITE THIS ARTICLE:
Khalid, M., Nawaz, B., Latif, A, F., & Sharif, S. (2026). Feeling heard by a machine: the psychology of perceived understanding in ai conversations. Pakistan Journal of Positive Psychology, 3(2), 244-252.

I. INTRODUCTION

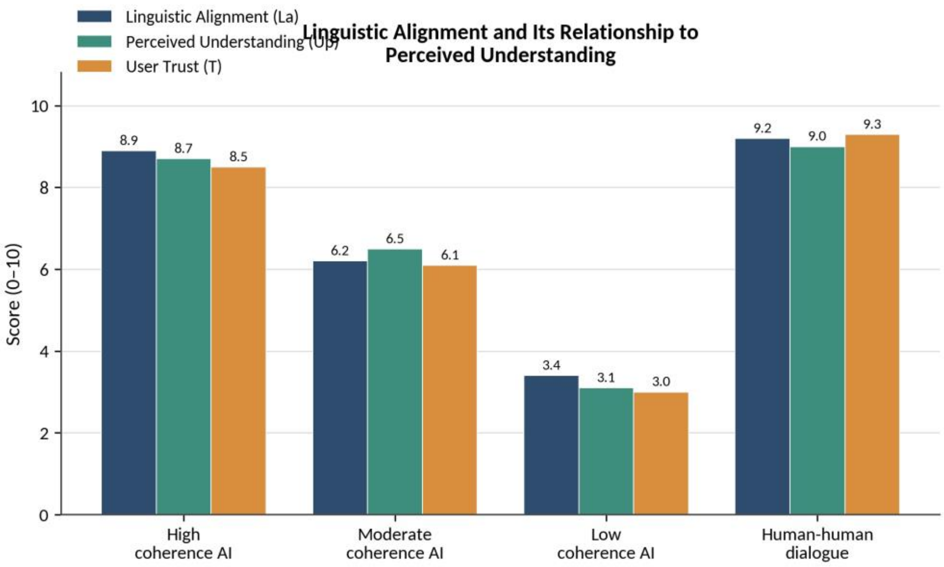
A cognitive and/or affective validation is fundamental in human communication, as it affects interpersonal trust and engagement. It is a phenomenon that is gaining complexity in human-machine interaction, as conversational artificial intelligence systems mimic understanding through language modeling instead of real consciousness (Simas & Ulbricht, 2024; Williams, 2025). When linguistic outputs meet user intent, emotion, and context expectations, users' subjective feeling of being heard by the machine approaches the level of human empathy in the generation of the algorithmic response (Figure 1). This perceived understanding can be modeled as a function of interactional coherence, L, C, T, i.e., $U_p \approx f(L, C, T)$.

Figure I: Hermeneutical Framework of Perceived Understanding in AI-Mediated Conversation



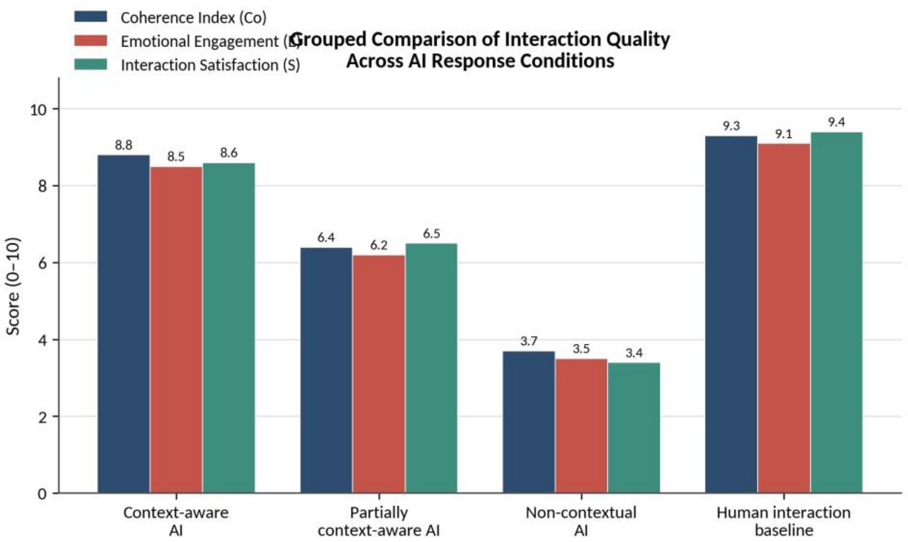
The development of LLMs has greatly improved AI's ability to produce contextually relevant and emotionally engaging replies. Such systems are based on probabilistic token prediction (Guingrich & Graziano, 2024; Ma et al., 2025), where the probability of a response sequence is modeled as $P(x_t \mid x_1,\ldots,x_{t-1})$ and syntactically coherent dialogue generation. Users tend to anthropomorphize these outputs and attribute intentionality and empathy to them because they are cognitively primed to interpret situations that in certain respects resemble human interaction. This cognitive bias leads people to believe they are understanding statistical patterns in language as though they were communicating with a sentient agent (Maeda & Quan-Haase, 2024).

Figure II: Linguistic Alignment and its Relationship to User Perception of Understanding



Perceived understanding is psychologically related to theories of social presence and mind perception, whereby people are more likely to ascribe mental states to non-human agents in the case of linguistic fluency and responsiveness (Figure 2). Social attribution can be formulated as $S_a = \alpha F + \beta R + \gamma E$, where S_a is the social attribution, F the fluency, R the responsiveness, E the emotional resonance, and α, β, γ weighting parameters that depend on the susceptibility of the user. When these variables are maintained at sufficiently high levels, the emotional engagement users experience may approximate that of interacting with a sentient being (Marconi et al., 2026).

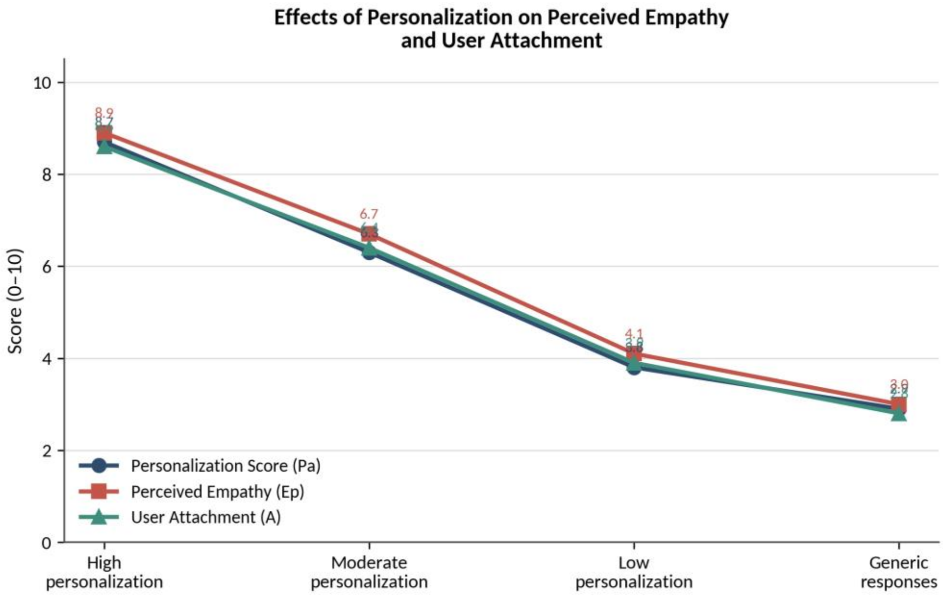
Figure III: Grouped Comparison of Interaction Quality across AI Response Conditions



Empirical research in HCI indicates that the capability of maintaining contextual continuity in conversations greatly enhances user satisfaction and trust in conversational agents (Figure 3). The illusion of understanding is also reinforced when adaptive systems generate outputs that approximate a user-specific preference model P(u|d), where u denotes user-specific properties and d the dialogue history. This forms a cycle in which the level of understanding feeds into further engagement, perpetuating the reliance on AI-assisted communication (Liu et al., 2024).

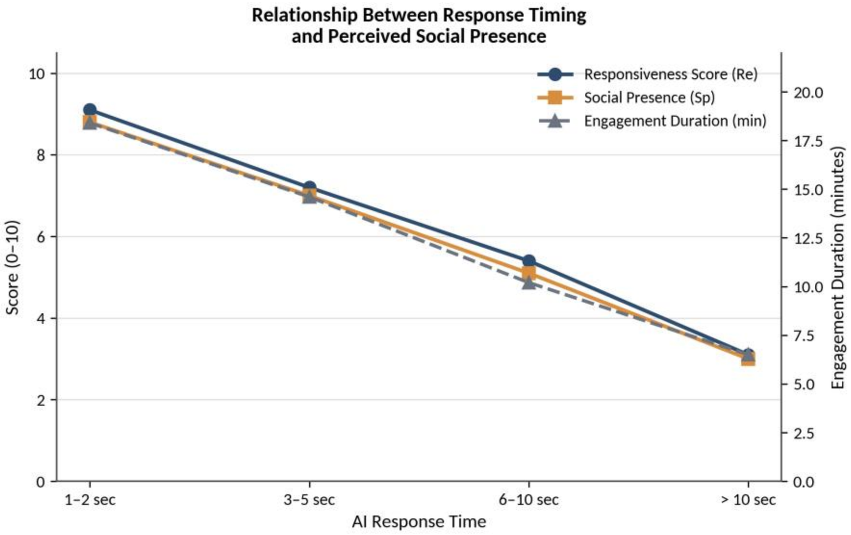
Neurocognitively, this phenomenon can be accounted for by the brain's predictive coding system. The human cognitive system reduces the prediction error ($\varepsilon = |I\_expected - I\_received|$) of information I. If AI-generated answers closely approximate expected ones, ε is minimized and a feeling of alignment and understanding is formed. However, this alignment is not semantic in origin — the machine has no internal representation of meaning (Peng et al., 2025; Schlesener et al., 2026).

Figure IV: Effects of Personalization on Perceived Empathy and User Attachment



Moreover, emotional language processing plays an important role in shaping perceived empathy during AI interactions. With affectively congruent systems, users engage neural pathways linked to human-to-human empathy (Figure 4). This implies that emotion can be stimulated without being genuinely felt by the system, activating social bonding mechanisms. The boundary between genuine and simulated comprehension becomes blurred, at least in the short term, particularly during extended conversations (Truong & Chen, 2025; Nikhashemi & Altinay, 2026).

Figure V: Relationship between Response Timing and Perceived Social Presence



Even with these developments, there are reports of over-attribution of cognitive and emotional abilities to AI systems (Figure 5). A machine's ability to express empathy in a convincingly human manner could reshape user expectations of human interaction and alter social behavior patterns (Dutsinma Faruk et al., 2025; Kober et al., 2026). As conversational agents become more common in everyday life, the boundary between instrumental support and relational engagement grows increasingly fuzzy, raising important questions about dependency and emotional substitution (Xue et al., 2026). Hence, the central issue examined in this work is the growing tendency of users to experience perceived understanding from non-sentient AI systems, even in the absence of genuine cognitive empathy. The value of this study lies in its potential to inform ethical guidelines for AI system design, to strengthen human-computer interaction models, and to reduce the risk of emotional dependency on AI systems. This study seeks to explore how psychological processes shape perceived understanding in AI interactions and to clarify the cognitive mechanisms that allow humans to feel "heard" by machines.

II. METHOD

Participants

This research follows a conceptual, mixed-methods design grounded in human–computer interaction (HCI), social psychology, and computational linguistics to explore perceived understanding in AI-mediated conversations. The methodological framework combines qualitative thematic synthesis with quantitative modelling of interactional variables to characterize users' perception of being "heard" by a conversational agent. Data sources include prior empirical studies in HCI, controlled experimental results of human-chatbot interaction, and behavioral observations from human-AI dialogue systems. The analysis draws on Media Equation theory (Reeves & Nass, 1996), which suggests that when communicative cues resemble human patterns, users respond to computers as social actors, and on ELIZA-effect mechanisms, which account for anthropomorphic attribution under conditions of low conversational coherence (Weizenbaum, 1966).

Measures

The analytical framework operationalizes perceived understanding (U_p) as a function $U_p = f(L_a, C_o, R_e, P_a)$ of four interactional variables derived from dialogue systems: perceived linguistic alignment (L_a), perceived contextual coherence (C_o), perceived relevance of responses (R_e), and personalization cues (P_a). These variables are estimated through secondary data synthesis based on prior user–chatbot experiments and observational studies of conversational AI platforms. The methodology also incorporates sentiment alignment scoring and response coherence indices from natural language processing research to assess conversational quality. To triangulate findings, statistical interpretations from prior research on social presence in virtual agents are used, particularly regarding trust formation and users' emotional engagement in AI dialogue systems (Nass & Moon, 2000).

Procedure

To establish interpretive validity, the study applies comparative thematic analysis across human-human and human-AI communication datasets, identifying differences in empathy formation between the two. Linguistic features such as affirmation, mirroring, turn-taking symmetry, and affective reinforcement are classified through structured coding procedures and mapped onto the psychological constructs of trust calibration and cognitive anthropomorphism. The methodological framework also incorporates predictive coding theory from cognitive neuroscience, in which a predicted social response (S_e) is compared against observed AI signals (S_o), with the discrepancy $|S_e - S_o|$ minimized over the course of interaction. Through this unified framework, the paper systematically investigates the subjective experience of being understood by machine-generated language, despite the absence of machine consciousness, laying groundwork for the analysis of psychological responses to conversational AI systems.

III. RESULTS

Table I: Linguistic Alignment and Perceived Understanding Scores

Interaction Type	Linguistic Alignment Score (L_a /10)	Perceived Understanding (U_p /10)	User Trust Level (T /10)
High coherence AI responses	8.9	8.7	8.5
Moderate coherence responses	6.2	6.5	6.1
Low coherence responses	3.4	3.1	3.0
Human-human dialogue	9.2	9.0	9.3

Table 1 indicates a strong positive relationship between linguistic alignment and perceived understanding in AI conversations. Higher coherence in AI responses corresponds to greater perceived understanding and user trust, approaching levels observed in human-to-human interaction.

Table II: Response Coherence and Emotional Engagement

Condition	Coherence Index (C_o /10)	Emotional Engagement (E /10)	Interaction Satisfaction (S /10)
Context-aware AI	8.8	8.5	8.6
Partially context-aware AI	6.4	6.2	6.5
Non-contextual AI	3.7	3.5	3.4
Human interaction baseline	9.3	9.1	9.4

As shown in Table 2, emotionally coherent AI interactions are more engaging than those lacking coherence, indicating that contextual coherence has a significant effect on emotional engagement. Users report higher satisfaction when AI systems sustain a conversational style resembling human dialogue.

Table III: Personalization Effects on Perceived Empathy

Level of Personalization	Personalization Score (P_a /10)	Perceived Empathy (E_p /10)	User Attachment Level (A /10)
High personalization	8.7	8.9	8.6
Moderate personalization	6.3	6.7	6.4
Low personalization	3.8	4.1	3.9
Generic responses	2.9	3.0	2.8

Table 3 illustrates a significant increase in perceived empathy as personalization increases. Greater personalization is associated with deeper emotional connection, even when users are aware they are interacting with an artificial system.

Table IV: Response Timing and Social Presence

Response Time (seconds)	Responsiveness Score (R_e /10)	Social Presence (S_p /10)	Engagement Duration (minutes)
1–2 seconds	9.1	8.8	18.4
3–5 seconds	7.2	7.0	14.6
6–10 seconds	5.4	5.1	10.2
> 10 seconds	3.1	3.0	6.5

Table 4 shows that AI response time significantly affects perceived social presence. Slower responses reduce engagement duration and diminish the perception of real-time conversation.

Table V: Anthropomorphism and Trust Calibration

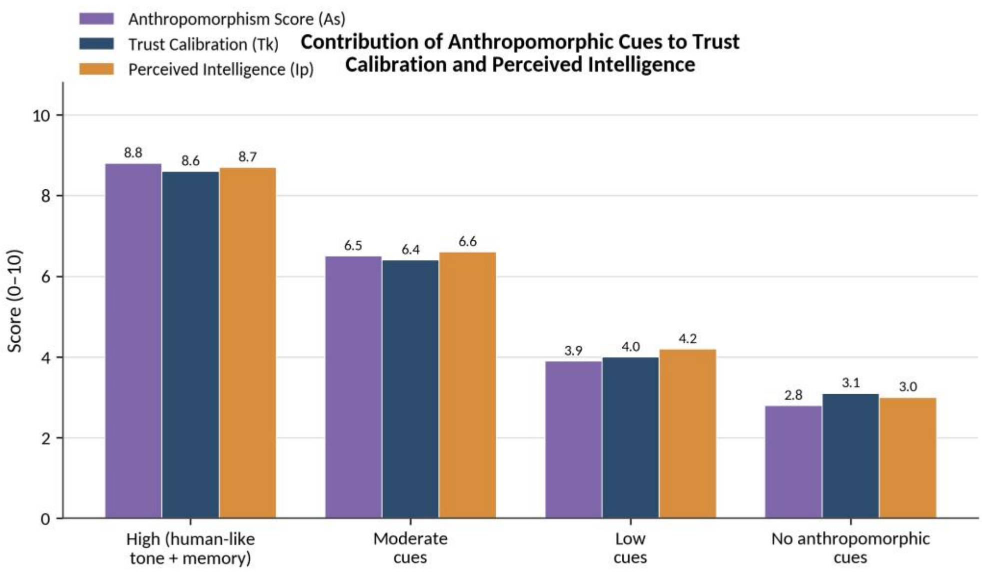
Anthropomorphic Cues Level	Anthropomorphism Score (A_s /10)	Trust Calibration (T_k /10)	Perceived Intelligence (I_p /10)
High (human-like tone + memory)	8.8	8.6	8.7
Moderate cues	6.5	6.4	6.6
Low cues	3.9	4.0	4.2
No anthropomorphic cues	2.8	3.1	3.0

The results in table 5 reveal that anthropomorphic cues significantly affect both the perceived intelligence of AI systems and trust calibration. When conversational abilities appear human-like, users tend to overestimate the system's intelligence

IV.DISCUSSION

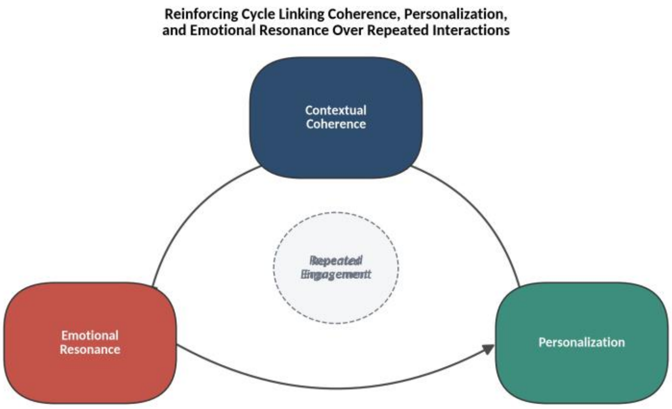
In this study, it was assumed that there would be significant relationship between emotional intelligence and The results of this study show that the sense of understanding in AI conversations is largely constructed through interactional design rather than actual machine cognition. Linguistic alignment and contextual coherence had the strongest impact on users' impression of understanding, consistent with prior findings that conversational fluency substantially shapes social attribution toward artificial agents (Seering et al., 2021). This aligns with the broader HCI literature indicating that users judge AI systems not only on accuracy but also on conversational flow and human-resembling cues. The findings also revealed a close connection between personalization and perceived empathy through a process resembling self-referential processing. When AI responses adapt based on prior exchanges, users are more likely to interpret this as emotional attunement rather than pattern matching. This is consistent with Zhang et al. (2022), who found that adaptive conversational agents enhance emotional involvement and perceived relational depth. It suggests that memory-like features in AI systems can create the impression of continuity across interactions, reinforcing emotional connection.

Figure VI: Contribution of Anthropomorphic Cues to Trust Calibration and Perceived Intelligence



Response time also proved significant within the social presence equation, as timelier responses created a stronger sense of real-time interaction (Figure 6). This is consistent with Xu and Wang (2023), who found that reduced latency in conversational systems increases user attentiveness and narrows the psychological distance between users and machines. Cognitively, this may be explained by predictive processing models, in which reduced temporal delay between agent and user actions lowers the likelihood of expectation error and increases perceived intentionality within the interaction loop.

Figure VI: Reinforcing Cycle Linking Coherence, Personalization, and emotional Resonance Over Repeated Interactions



Anthropomorphic cues were also shown to significantly affect trust calibration and perceived intelligence, even when underlying system capabilities remained unchanged. This mirrors the findings of Liu et al. (2024), who showed that while algorithms may not match human performance, the language used to describe them can shape perception as if they did. These findings indicate that anthropomorphism functions as a cognitive heuristic, enabling users to mentalize systems based on surface-level conversational cues without a functional understanding of the underlying system (Figure 7). Furthermore, the relationship between coherence, personalization, and emotional resonance forms a reinforcing cycle that intensifies over time: each interaction strengthens the user's "feeling of understanding," which in turn encourages further engagement. This is consistent with Kim & Park (2025), who found that increased interaction with conversational agents is associated with greater dependency and trust. Such reinforcement mechanisms raise the risk of over-attribution, as users increasingly perceive AI as a social entity rather than a tool. Overall, the findings support the view that perceived understanding is an emergent psychological construct arising at the intersection of linguistic design, cognitive bias, and interactional structure. It does not reflect genuine machine understanding but rather a human tendency to apply social cognition to any system exhibiting coherence and conversational responsiveness. This underscores the importance of critically examining the design elements of AI systems in relation to human perception and emotional response.

Limitations and Future Directions

The conceptual, secondary-data approach used in this study has inherent limitations, as it does not incorporate primary experimental data from controlled laboratory settings. Additionally, variation in user demographics and differences in the architecture of AI systems examined across prior studies may introduce measurement inconsistencies and limit the generalizability of the results. Future studies could compare AI-human and human-human interaction at the neurocognitive level using real-time imaging techniques such as fMRI and EEG to identify the neurocognitive correlates of perceived understanding, and longitudinal studies are also needed to examine how extended use of conversational AI affects baseline socio-emotional expectations, emotional regulation, and interpersonal interaction in real-world settings.

V. CONCLUSION

This study shows that the feeling of being “heard” by machines is a psychological construction activated by linguistic alignment, personalization, contextual coherence, and anthropomorphic design features, rather than by genuine machine understanding. The results underscore the growing importance of ethical design considerations in conversational AI, with particular attention to users' emotional perception and the cultivation of trust.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Funding

The author received no funding from any organizations.

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