Original Manuscript

Social Science Computer Review
2025, Vol. 0(0) 1–25

DOI: 10.1177/08944393251354976
journals.sagepub.com/home/ssc
Sage

From Assistants to Digital Beings: Exploring Anthropomorphism, Humanness Perception, and AI Anxiety in Large-Language-Model Chatbots

Xintong Yao[1] and Yipeng Xi[1]

Abstract

This study examined the impact of anthropomorphic traits in large language model (LLM) chatbots on users' perceptions of humanness and their associated anxiety. Drawing on dehumanization theory, the research investigated how human nature and human uniqueness traits influenced AI-related anxiety through perceptions of humanness in various interaction contexts. A survey of 1000 LLM chatbot users in China, analyzed using validated structural equation modeling, revealed that emotional and moral traits, such as empathy and morality, were positively correlated with perceptions of humanness, which in turn reduced AI anxiety. In contrast, cognitive traits like competence and rationality alleviated anxiety but did not contribute to perceptions of humanness. This study offered valuable theoretical and practical insights into how humans defined and responded to machine personhood in the age of advanced AI.

Keywords

humanness, anthropomorphism, AI anxiety, dehumanization, LLM chatbot

Introduction

The question of how machines resemble humans and how people respond to human-like AI has long been central to human-machine interaction (HMI) research (Breazeal, 2003; Kühne & Peter, 2023). The evolution of AI has progressed from early chatbots like ELIZA to intimate voice

[1]School of Media and Communication, Shanghai Jiao Tong University, China

Corresponding Author:
Yipeng Xi, School of Media and Communication, Shanghai Jiao Tong University, 800 Dongchuan Road, Minhang District, Shanghai 200240, China.
Email: pckxi@sjtu.edu.cn

assistants like Alexa and advanced humanoid robots like Sophia, shifting from physical mimicry to a deeper form of human-likeness (Fetterolf & Hertog, 2023; Rajaraman, 2023). With the rise of large language models (LLMs) such as generative pretrained transformer (GPT), the emphasis has moved beyond superficial mimicry to what can be termed "mental likeness" (Koban & Banks, 2024). AI anxiety, as a psychological response to the increasing human-likeness of machines, has thus become a critical area of study, especially as advanced AI systems continue to challenge human agency (Xi et al., 2024).

Traditional frameworks such as the Computers Are Social Actors and the Media Equation Paradigm have emphasized how anthropomorphic cues like warmth and competence trigger social responses, leading users to treat machines as humans (Lombard & Xu, 2021; Reeves & Nass, 1996). However, these models often conflate anthropomorphism (attributing human traits to machines) with humanness (perceiving machines as genuinely human-like), thereby obscuring the conceptual distinction between attribution and perception (Kühne & Peter, 2023). As AI systems grow more sophisticated, users actively interpret deeper cognitive and emotional traits, a shift emphasized by newer frameworks like the Media Evocation Paradigm (Van Der Goot & Etzrod, 2023) and the Uncanny Valley of Mind (Stein & Ohler, 2017). Despite these advancements, few studies have integrated both surface-level and deep-level anthropomorphic cues to examine their combined effects across various interaction contexts.

This study addressed these gaps by examining how the diverse anthropomorphic cues exhibited by LLM chatbots influenced perceptions of humanness and, in turn, contributed to AI anxiety. Grounded in dehumanization theory, the research investigated how these traits shape user responses in four common usage scenarios: conversation, creation, curation, and contemplation. Through a survey of 1000 LLM chatbot users in mainland China and structural equation modeling, the study found that empathy and morality indirectly reduced anxiety through enhancing humanness perceptions but also directly increased anxiety. In contrast, competence and rationality reduced AI anxiety without affecting humanness perceptions. These effects varied by context, particularly in conversational and contemplative scenarios, offering valuable insights into the complex interplay between humanness perceptions and AI anxiety.

Literature Review

Anthropomorphism and Humanness in Human-Machine Interaction (HMI)

In *A Treatise of Human Nature*, Hume (1739/2007) defined humanness based on three primary dimensions: intellect, emotion, and morality. This framework has greatly influenced both philosophical and psychological approaches to understanding what it means to be human. However, in the context of HMI, a significant concern arises: the operationalization of "humanness" has often focused on superficial anthropomorphic cues, neglecting its deeper existential dimensions. For instance, the widely adopted Godspeed indices (Bartneck et al., 2009) effectively equate a robot's human-like appearance and movement with its overall humanness, without considering whether these features genuinely evoke capacities for agency or intentionality. Similarly, Breazeal (2003) and Złotowski et al. (2016) operationalized humanness by manipulating facial expressiveness and vocal intonation, implicitly assuming that these surface attributes capture the essence of being human.

Recent research on the concept of machine humanness has yielded two significant advances. First, scholars have increasingly focused on the psychological mechanisms that trigger the perception of humanness. Anthropomorphic cues—such as facial expressions, speech patterns, or movement styles—do not simply describe observable behaviors but function as inferential triggers that prompt users to attribute internal mental states to nonhuman agents (Epley et al., 2007; Eyssel, 2017). This process, known as mind perception, reflects a cognitive cascade in which visible traits serve as proxies for unobservable attributes like intentions, emotions, or consciousness (Morewedge et al., 2007; Waytz et al., 2010). Crucially, this inferential leap often hinges on the perceived diagnosticity of the cues (Shin, 2024)—namely, the extent to which these traits are seen as meaningful indicators of an underlying mind rather than scripted output. Humanness attributions are not just triggered by surface resemblance, but by the user's confidence in the explanatory value of surface cues.

Second, researchers have begun to refine the conceptual structure of humanness itself, moving beyond surface-level anthropomorphism to emphasize internal, high-dimensional cognitive traits. Rather than equating humanness with physical appearance or mimicry, recent frameworks suggest that the essence of being human lies in capacities such as reasoning, intentionality, and moral judgment. Gray et al. (2007) proposed that people attribute humanness based on two core dimensions—agency (planning, thinking, acting) and experience (feeling, emoting). Similarly, Kühne and Peter (2023) introduced a dual-layered model integrating both physical and cognitive layers of humanness, emphasizing that authentic anthropomorphism requires mental state attribution. These insights converge with the idea that human-likeness is not simply evoked by embodiment, but by the attribution of internal mental architecture—especially when machines demonstrate sustained moral reasoning or complex deliberation (Stein & Ohler, 2017).

While recent research has expanded the understanding of humanness in AI, two key limitations remain. First, existing measures of anthropomorphism are often rooted in tangible, visible features such as appearance and movement, which do not directly apply to non-physical AI systems. In contrast, LLMs primarily engage through language and text, making it crucial to adapt or develop new measures that account for the subtleties of linguistic and cognitive engagement in these systems. Second, humanness is often conceptualized too abstractly, emphasizing cognitive or moral traits while overlooking more natural, everyday mannerisms—such as spontaneity and conversational fluidity—that shape our intuitive sense of human presence in dialogue. To address these gaps, a more integrative approach is needed. Dehumanization theory offers a useful framework for operationalizing these traits, allowing for a broader understanding of how human-like qualities can be applied to LLM chatbots.

Dehumanization Theory as a Framework for Understanding Humanness Perceptions

Dehumanization theory, first developed by Haslam (2006), offers a structured approach to understanding how humans perceive nonhuman entities. This theory conceptualizes humanness as comprising two distinct dimensions: human uniqueness and human nature. Human uniqueness, defined as the set of intellectual and cultural attributes that distinguish humans from other species, includes traits that are often associated with higher-order cognition and societal refinement. Human nature, in contrast, refers to the intrinsic, biological, and affective qualities that differentiate humans from inanimate objects. Initially developed to study prejudice, discrimination, and intergroup relations, dehumanization theory has been widely applied in social psychology to examine how individuals and groups are perceived as more or less human (Kteily et al., 2015; Rai et al., 2017). Applied to HMI, this framework reveals that AI systems are evaluated based on both intellectual traits (e.g., logic) and superficial traits (e.g., warmth), influencing perceptions of their effectiveness, trustworthiness, and social engagement (Eyssel & Kuchenbrandt, 2012; Jo & Park, 2024).

Dehumanization theory is well-suited to the study of LLMs because it treats humanness as a spectrum of socially inferred qualities rather than a property rooted in physical form. Its twin dimensions of human uniqueness and human nature span the full range of capacities people look for when deciding whether an interlocutor is genuinely human-like. Crucially, the theory assumes that those qualities are attributed through an ongoing inferential process: users probe an agent's utterances, infer the presence or absence of psychological depth, and update their judgments accordingly. That attributional logic aligns precisely with language-based interaction, where cues are delivered entirely through discourse. In this way, dehumanization theory provides both a comprehensive vocabulary for cataloging the facets of humanness and a process model for understanding how those facets are inferred in non-physical, LLM-mediated encounters.

Human Uniqueness Traits and Humanness. Dehumanization theory posits that civility, rationality, and morality define human uniqueness. Civility, characterized by polite communication and adherence to social norms, serves as a cognitive heuristic for human-likeness. Politeness enhances social acceptance and fosters interpersonal trust (Ribino, 2023). Civil behaviors that possess social features, such as using honorifics, acknowledging user input, and demonstrating etiquette, significantly improve AI's perceived humanness (Chaves & Gerosa, 2021). For instance, Ribino (2023) found that chatbots displaying politeness strategies were judged as more human-like and more socially acceptable, while Lee and Lee (2022) observed that autonomous vehicles employing courteous behavior (e.g., yielding to pedestrians) were perceived as more trustworthy and sociable. By following social norms and demonstrating respect through polite behaviors, machines are perceived as recognizing and conforming to shared societal expectations.

Rationality, due to its association with logical reasoning and goal-directed behavior, has been attributed to nonhuman entities (Waytz et al., 2014). Studies have demonstrated that rationality's structural components enhance perceptions of cognitive depth in human-AI interactions (Epley, 2007). Individuals often attribute mental states such as intentions, beliefs, and reasoning to entities that exhibit logical behavior. For example, Kim and Im (2023) found that perceptions of cognitive intelligence—such as a robot's ability to think, learn, set goals, and solve problems—were key factors in triggering anthropomorphic responses. Lee and Lee (2023) further observed that when users believed a chatbot possessed thoughts, they rated the chatbot's anthropomorphic profile picture as more human-like.

Morality, the ability to make ethical decisions, further reinforces AI's perceived humanness. While early work suggested skepticism toward machine moral agency, more recent studies highlight users' willingness to attribute moral accountability to AI under specific conditions (Banks, 2019; Wilson et al., 2022). Willems et al. (2022) found that robot engaging in unethical behavior was perceived as significantly less human, suggesting that the ethical behavior of a robot affects how human-like it is perceived to be. Similarly, Kahn et al. (2007) also investigated how to measure robot-like humanity in terms of psychological benchmarks, incorporating dimensions such as "intrinsic moral value" and "moral accountability" into the benchmarks for robots to be perceived as human-like. Given above reasoning regarding human uniqueness traits, we propose:

> **H1:** Perceived civility (a), rationality (b), and morality (c) are positively associated with perceptions of LLM chatbot humanness.

Human Nature Traits and Humanness. Human nature traits—warmth, empathy, and competence—reflect the core emotional and relational dimensions of humanness (Haslam, 2006). Warmth signals approachability and benevolence, prompting users to perceive AI agents as emotionally responsive and socially attuned (Fiske et al., 2007). Cuddy et al. (2007) found that perceiving higher levels of warmth in others elicits admiration and approach-oriented behaviors. When machines display warmth, users are more likely to perceive them as emotionally responsive, thereby enhancing their relatability and social appeal. For instance, the preference for female robots is attributed to the gender stereotype that women are perceived as warmer and more amiable, which significantly enhances the perception of humanness, thereby making them more appealing to users (Borau et al., 2021; Stroessner & Benitez, 2019).

Empathy, defined as the ability to recognize and share emotions, further reinforces humanness perceptions. Xi et al. (2024) argued that empathy fosters a sense of emotional reciprocity—the feeling that the machine not only comprehends but also validates the user's emotional experience. Empirical research shows that affective engagement enhances anthropomorphic attributions. Skjuve et al. (2021) found that chatbots displaying empathetic responses were rated as significantly more human-like than those relying solely on information retrieval. Pataranutaporn et al. (2023) showed that AI agents perceived as compassionate and emotionally attuned were judged as more trustworthy and relatable than those exhibiting neutral or detached communication styles. As such, users are more likely to perceive empathetic machines as more human-like due to their alignment with human emotional needs and relational dynamics.

Competence, understood as the ability to navigate tasks, adapt to new situations, and act coherently toward goals, reflects intuitive, biologically grounded capacities that illustrate the core dimensions of human nature within dehumanization studies—agency, desire, and vitality—that represent a life force (Haslam et al., 2008). Competence may evoke perceptions of humanness because it signals intentional agency. When users observe a chatbot performing tasks effectively—responding coherently, completing requests efficiently, or adapting language to context—they often infer a capacity for goal-directed behavior. According to mind perception theory (Gray et al., 2007), such inferences are foundational to attributing a "mind" to nonhuman agents. This does not require the agent to outperform humans, but rather to demonstrate purposiveness and coherence in action—qualities closely tied to human social functioning (Carpinella et al., 2017; Fiske et al., 2007; Harris-Watson et al., 2023). While competence alone may not convey emotional depth or selfhood, it serves as a threshold condition for recognizing an entity as more than reactive or mechanistic. Even in pragmatic contexts where users associate competence with technology (Ullrich et al., 2018), its consistent execution under uncertainty may blur the line between automation and intentionality, triggering low-level humanness perceptions. Given above reasoning regarding human nature traits, we propose:

H2: Perceived warmth (a), empathy (b), and competence (c) are positively associated with LLM chatbot humanness.

Humanness Perception and AI Anxiety

AI anxiety is a psychological state of discomfort, hesitation, and cognitive strain arising from unfamiliarity, loss of control, and uncertainty in AI interactions (Li & Huang, 2020). It reflects deeper fears about AI's autonomy, human-likeness, and its potential to disrupt human identity, agency, and social norms. Beyond surface-level discomfort, AI anxiety reveals concerns over technological dependency, ethical dilemmas, and the blurring of boundaries between humans and machines (Li & Huang, 2020). Centering AI anxiety as an outcome allows for a more nuanced understanding of the ambiguous, ambivalent position users occupy in response to anthropomorphic AI, aligning with the Media Evocation Paradigm's (Van Der Goot & Etzrod, 2023) view that such anxiety captures the tension and uncertainty inherent in the interaction between humans and AI's perceived human traits.

Recent research shows that while certain anthropomorphic features may increase AI-related anxiety, a broader range of human-like attributes can reduce stress. This effect operates through three mechanisms: first, perceived humanness lowers psychological distance, making interactions more intuitive and socially aligned (Li & Sung, 2021). Second, human-like traits enhance predictability, offering cognitive stability and reducing mental effort (Epley, 2007). Finally, reframing AI as a social partner alleviates existential unease, shifting users' perception from a disruptive force to a cooperative presence (Lee et al., 2020). The integration of external and internal human-like markers fosters familiarity and relational harmony, ultimately reducing AI-induced anxiety. We thus propose:

H3: Perceived LLM chatbot humanness is negatively associated with AI anxiety.

Wang and Wang's (2022) validation of a general AI anxiety scale, which highlights concerns about AI replacing humans, offering incorrect services, its humanness, and the challenge of learning to use it, underscores fundamental tension between the increasing anthropomorphism of AI systems and the human need to maintain ontological distinctions between humans and machines. However, this anxiety is not merely a reaction to the presence of human-like traits in AI but is instead shaped by how these traits are cognitively processed and socially interpreted (Guzman & Lewis, 2020). Specifically, both human uniqueness traits and human nature traits must first be recognized as constitutive of humanness before they can meaningfully influence users' emotional and psychological responses, including AI anxiety. This mediation occurs because perceived humanness serves as a cognitive framework that determines whether AI is interpreted as a social actor rather than a functional tool (Edwards et al., 2016; Reeves & Nass, 1996). When AI displays attributes commonly associated with humans, individuals do not immediately experience a reduction in anxiety; rather, they first assess whether these characteristics are sufficiently human-like to warrant engagement through social, rather than mechanical, interaction norms (Złotowski et al., 2015). Thus, we hypothesize:

H4: Perceived human uniqueness traits, specifically civility (a), rationality (b), and morality (c), reduce AI anxiety by enhancing perceived LLM chatbot humanness.
H5: Perceived human nature traits, specifically warmth (a), empathy (b), and competence (c), reduce AI anxiety by enhancing perceived LLM chatbot humanness.

The Moderating Role of AI Communicators

The role of an AI communicator refers to its functional capacity shaped by user expectations and contextual demands (Christoforakos & Diefenbach, 2023; Guzman & Lewis, 2020). As the Mediated Actor-Social Actor (MASA) paradigm suggests, humanness is co-constructed by cues, individuals, and context (Lombard & Xu, 2021), with its psychological impact contingent on alignment with the AI's purpose (Rapp et al., 2024). When humanness aligns with AI function—such as warmth in a conversational agent—it fosters trust and reduces anxiety (Edwards et al., 2016). However, mismatches, such as human-like expressiveness in objective roles (e.g., financial or medical AI) or detachment in relational roles, create cognitive dissonance and heighten anxiety (Shank et al., 2019).

Within the context of AI chatbots, drawing on the categorization proposed by Sundar and Lee (2022), Huang and Wang's (2023) typology further identifies four distinct roles—converser, creator, curator, and contemplator—that can be grouped into two overarching categories: emotion-oriented and function-oriented. Conversers represent the emotion-oriented category, designed for real-time social communication, such as casual conversation and companionship. By contrast, creators, curators, and contemplators fall under the function-oriented category. Creators assist in creative tasks like content generation or design, prompting users to appreciate AI's innovative potential. Curators, responsible for information filtering and recommendation, cater to users who often emphasize efficiency and neutrality. Contemplators operate in decision-making scenarios where objectivity and computational precision are paramount.

When AI acts as a converser, its ability to mimic human warmth and social presence does not always lead to reduced anxiety. Research on hyper-anthropomorphism (Becker et al., 2023) suggests that excessive emotional realism in AI can paradoxically heighten anxiety rather than alleviate it. This occurs because users may experience authenticity concerns—the AI appears too human-like but lacks true sentience, prompting existential discomfort and trust ambiguity (Mozafari et al., 2022). Furthermore, AI's emotional expressiveness may blur the boundary between human-machine relationships, raising concerns about its social appropriateness and long-term implications (Malle & Thapa Magar, 2017). As a result, rather than reducing AI anxiety, higher humanness in conversers can introduce interpersonal uncertainty, weakening its expected anxiety-buffering effects.

In contrast, when chatbots are used for functional roles—such as creators, curators, or contemplators—users prioritize efficiency, accuracy, and reliability for complex work over emotional engagement. Here, humanness plays a different role: rather than evoking social presence, humanness enhances perceptions of cognitive sophistication, adaptability, and ethical reasoning. Research shows that users trust AI more in high-risk, logic-driven tasks when it demonstrates transparent reasoning and moral accountability (Shin, 2021). Furthermore, in these function-oriented scenarios, human-like attributes reduce algorithmic opacity—users feel more in control when AI exhibits intuitive decision-making cues akin to human cognition, thereby mitigating the technological uncertainty that fuels AI anxiety (Kim & Sundar, 2012). We thus propose:

H6: The negative relationship between perceived humanness and AI anxiety is weakened when users increasingly engage with chatbots as conversers (a); Conversely, this negative relationship is strengthened when users increasingly engage with chatbots as creators (b), curators (c), or contemplators (d).

Based on the six research hypotheses mentioned above, this study constructs a theoretical model with moderated mediation effects shown in Figure 1.

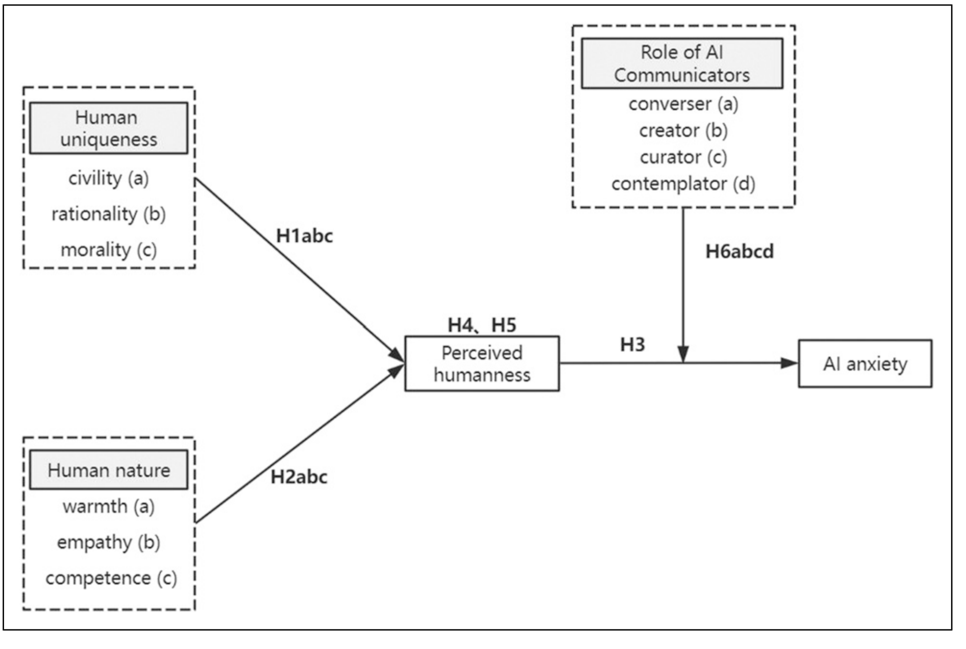

Figure 1. Theoretical model of the study.

Method and Data

Data Collection

Upon receiving approval from the institutional review board, a comprehensive online survey was conducted in October 2023 using Wenjuanwang.com, a leading Chinese market research platform similar to Amazon's Mechanical Turk. Leveraging its extensive network of over 30 million users, the platform facilitated an exploration of usage patterns among users of LLM chatbots. For the purposes of this study, LLM chatbots were defined as advanced, general-purpose conversational agents, such as ChatGPT, Bard, and Ernie, that utilize sophisticated language models to simulate human-like interactions across diverse tasks.

Participants were recruited through a screening question confirming prior interaction with any of the top 10 LLM chatbots[1]. This approach ensured the sample consisted of users with relevant experience, enabling accurate insights into their behaviors and perceptions. Wenjuanwang distributed 3846 questionnaires to this targeted group, yielding 1000 valid responses that met the study's inclusion criteria, corresponding to an effective response rate of 26%. To ensure data quality, Wenjuanwang implemented measures such as trap questions, strict timing protocols, duplicate IP address verification, and real-time monitoring to filter out invalid responses. Participants received a compensation of 5 RMB (approximately USD0.70) upon survey completion. The demographic characteristics of respondents are summarized in Appendix I.

Measurements

Participants evaluated chatbots on several dimensions, including warmth, competence, empathy, rationality, civility, morality, perceived humanness, AI anxiety, and the role of the AI communicator. Warmth (Andrei & Zait, 2014), competence (Belanche et al., 2021), and empathy (Yim, 2023) were assessed using three to five items each, with descriptors such as "kind," "effective," and "empathetic." Rationality (Lelieveld & Hendriks, 2021) and civility (Kenski et al., 2020; Wang, 2020) were evaluated using three items each, with indicators like "reasonable" and "polite." Morality (Banks, 2019) was measured with six items, including statements like "The LLM chatbot has a sense of what is right and wrong."

Perceived humanness was assessed with a four-item scale adapted from Jin and Youn (2023), which included indicators such as "natural" and "conscious." AI anxiety was measured using a four-item scale adapted from Li et al. (2021), with items like "I hesitate to use LLM chatbot services for fear of making mistakes I cannot correct."

Finally, the role of LLM chatbots—spanning converser, creator, curator, and contemplator—was measured using a single-item statement reflecting participants' agreement with the respective function (Huang & Wang, 2023). Specifically, converser was assessed by asking participants to indicate their level of agreement with the statement: "I use LLM chatbots for daily conversations and sharing opinions." Creator was measured through the statement: "I use LLM chatbots for content creation, such as writing, image generation, and video editing." Curator was captured with the item: "I use LLM chatbots to seek knowledge-based answers or recommendations for information products." Contemplator was evaluated through the statement: "I use LLM chatbots to analyze, assess, and predict outcomes for my decision-making."

All variables were measured through a self-administered questionnaire employing a 7-point Likert scale, with responses ranging from 1 (Strongly Disagree) to 7 (Strongly Agree) and 4 indicating a neutral position. All scale items were adapted from well-established measurement instruments to fit the context of LLM interaction. Specifically, items were reworded to reflect text-based, non-embodied AI agents and revised for relevance to LLM-driven conversational scenarios. A pilot test was conducted with a sample of 100 participants to assess the reliability and validity of the adapted items. Based on the results of confirmatory factor analysis, items with factor loadings below 0.6 were removed to ensure construct clarity. The final measurement model included only items that demonstrated strong psychometric properties, with all constructs showing acceptable levels of internal consistency (Cronbach's $\alpha > 0.75$) and satisfactory construct validity for use in the main survey. Details of each construct's items are provided in Appendix II. Social and demographic characteristics, including age, gender, income, education level, frequency of LLM chatbot usage, and AI literacy, were also collected as control variables.

Data Analysis

We used the statistical software R to conduct descriptive analyses, assess discriminant validity, and examine bivariate correlations among variables, with detailed results presented in Appendix II. Given that the data were self-reported and cross-sectional, common method bias (CMB) was a potential concern (Podsakoff et al., 2003). To address this, we performed Harman's one-factor test using R. The analysis revealed that a single factor accounted for only 22.14% of the total variance, well below the recommended threshold of 50% (Podsakoff et al., 2003), indicating that CMB was unlikely to significantly influence the results. To assess multicollinearity, we calculated the Variance Inflation Factor (VIF) for each variable. All VIF values were below the threshold of 5, suggesting that multicollinearity was not an issue (O'Brien, 2007).

We employed structural equation modeling (SEM) using the lavaan package in R, selected for its robustness in handling complex models with extensive interrelationships among predictors and outcomes. Maximum likelihood estimation was applied to evaluate model fit to the observed data. The measurement model was validated through confirmatory factor analysis (CFA), laying the groundwork for subsequent hypothesis testing. For mediation analysis, we used bootstrap techniques with 1000 cases and 5000 samples to generate reliable confidence intervals for path estimates, as recommended by Cheung (2007).

Model Validation

The evaluation of the measurement model, based on unit-loading indicators to calibrate latent constructs, demonstrated a strong goodness-of-fit across several key indices. The chi-square to degrees of freedom ratio (χ^2/df) was 2.58, with a statistically significant p-value of <0.001, confirming the model's significance. Further validation of the model's fit was supported by a Comparative Fit Index (CFI) of 0.96, a Tucker-Lewis Index (TLI) of 0.95, a Root Mean Square Error of Approximation (RMSEA) of 0.04, and a Standardized Root Mean Square Residual (SRMR) of 0.06. These results exceed the accepted benchmarks: a χ^2/df ratio below 3, RMSEA less than 0.08, SRMR around 0.05, and CFI and TLI values above 0.90, which indicate an acceptable fit, as recommended by Kline (2023). According to Hu and Bentler's (1999) criteria, a model is considered a good fit if it meets either the condition of CFI >0.95 and SRMR <0.09, or RMSEA <0.05 and SRMR <0.06. Based on these criteria, the measurement model is determined to have a good fit. Additionally, the validity of the measurement model is supported by all factor loadings exceeding 0.5 (Fornell & Larcker, 1981).

Results

As shown in Table 1, the findings of this study provide a nuanced understanding of how human perceptions of humanness are shaped in interactions with LLM chatbots. H1 explored how the three human uniqueness traits—civility, rationality, and morality—affect humanness perception.

The results revealed that while morality (β = 0.22, $p < .001$) significantly enhanced perceptions of humanness, civility (β = −0.16, $p < .001$) had the opposite effect, significantly lowering perceptions of humanness, and rationality (β = 0.03, $p > .05$) had no significant impact. These findings suggest that morality, often associated with human-like ethical decision-making, plays a critical role in enhancing human-like perceptions of LLM chatbot, while civility might hinder such perceptions. Hence, we accept H1c but reject H1a and H1c.

H2 examined the role of human nature traits in shaping perceptions of humanness. The results indicated that warmth (β = 0.13, $p < .001$) and empathy (β = 0.32, $p < .001$) significantly enhanced humanness perceptions, whereas competence (β = 0.04, $p > .05$) did not. Emotional and relational qualities were more influential in making AI systems appear more human-like. Thus, H2a and H2c were supported, but H2b was not. Moving on to H3, which examined the relationship between perceived humanness and AI anxiety, we found that as perceptions of humanness increased, AI anxiety significantly decreased (β = −0.08, $p < .05$). Human-like traits in LLM chatbots help alleviate anxiety and foster a more positive user experience. Therefore, H3 was supported.

Table 2 presents the mediating effect of humanness perception on the relationship between human nature and uniqueness traits and AI anxiety. The results indicated that human nature traits—particularly warmth (effect = −0.02, SE = 0.01, CI = [−0.06, −0.01]) and empathy (effect = −0.02, SE = 0.01, CI = [−0.06, −0.01])—played a significant role in reducing AI anxiety by enhancing perceptions of humanness (effect = −0.05, SE = 0.01, CI = [−0.12, −0.01]). The direct effects revealed that warmth (effect = −0.14, SE = 0.08, CI = [−0.36, −0.06]) and competence (effect = −0.23, SE = 0.01, CI = [−0.51, −0.22]) directly reduced AI anxiety, whereas empathy (effect = 0.17, SE = 0.01, CI = [0.11, 0.33]) paradoxically increased anxiety. In contrast, the effects of human uniqueness traits (effect = −0.01, SE = 0.01, CI = [−0.03, 0.01]) on AI anxiety were less pronounced, particularly due to the opposing effects of civility (effect = 0.02, SE = 0.01, CI = [0.01, 0.06]) and morality (effect = −0.02, SE = 0.01, CI = [−0.06, −0.01]). Furthermore, the direct effects demonstrated that rationality (effect = −0.13, SE = 0.01, CI = [−0.40, −0.03]) directly reduced AI anxiety, while morality (effect = 0.13, SE = 0.06, CI = [0.06, 0.28]) paradoxically increased anxiety. Consequently, H4c, H5a, and H5b were supported, while H4a, H4b, and H5c were rejected.

Lastly, the analysis of H6 revealed that among the four chatbot roles, only converser (β = 0.57, $p < .001$) and contemplator (β = −0.77, $p < .001$) exhibited significant moderating effects on the relationship between perceived humanness and AI anxiety. The converser role (β = −0.31, $p < .001$) was also found to directly reduce AI anxiety. However, as the perceived converser role increased, the anxiety-reducing impact of humanness weakened. As shown in Figure 2, in conditions where users strongly associated the chatbot with being a converser, perceived humanness had a diminishing effect on alleviating anxiety—and at high levels of the converser role, humanness even began to significantly increase AI anxiety. This suggests that while users may feel comfortable engaging in casual conversations with AI, excessive human-likeness in such contexts could paradoxically heighten unease.

In contrast, the contemplator role, which is primarily decision-oriented, was found to significantly increase AI anxiety (β = 0.33, $p < .001$). However, perceived humanness moderated this effect in a compensatory manner: as the contemplator role increased, the negative relationship between humanness and AI anxiety strengthened. As shown in Figure 3, when users engaged with chatbots as contemplators infrequently, perceived humanness might even exacerbate AI anxiety. However, as the frequency of using chatbots in this role increased, the anxiety-reducing effect of perceived humanness became more pronounced and progressively strengthened. Hence, H6a and H6d were supported, but H6b and H6c were not. Figure 4 provides a comprehensive overview of the model's construction and the hypothesis validation processes for all examined variables.

Table 1. Research Model: Direct and Moderating Effects.

	Dependent variable					
	Perceived humanness	AI anxiety (AA)	AI anxiety (AA)	AI anxiety (AA)	AI anxiety (AA)	AI anxiety (AA)
Predictors	β(SE)	β(SE)	β(SE)	β(SE)	β(SE)	β(SE)
Perceived civility (PCV)	−0.16 (0.06)***					
Perceived rationality (PRN)	0.03 (0.07)					
Perceived morality (PMR)	0.22 (0.05)***					
Perceived warmth (PWA)	0.13 (0.05)***					
Perceived competence (PCM)	0.04 (0.06)					
Perceived empathy (PEP)	0.32 (0.05)***					
Perceived humanness (PH)		−0.08 (0.03)*	−0.51 (0.14)***	0.15 (0.18)	0.19 (0.19)	0.52 (0.15)***
Converser			−0.31 (0.02)***			
Creator				0.17 (0.14)		
Curator					0.14 (0.14)	
Contemplator						0.33 (0.11)***
PH x converser			0.57 (0.03)***			
PH x creator				−0.35 (0.03)		
PH x curator					−0.37 (0.03)	
PH x contemplator						−0.77 (0.11)***
Age		−0.00 (0.01)	−0.00 (0.01)	−0.00 (0.01)	−0.00 (0.01)	−0.01 (0.01)
Gender (reference: Male)		0.02 (0.10)	0.01 (0.10)	0.02 (0.10)	0.02 (0.10)	0.01 (0.10)
Education (reference: High school and lower)						
college Level		−0.04 (0.43)	−0.03 (0.39)	−0.03 (0.39)	−0.04 (0.40)	−0.04 (0.36)
graduate Level		−0.01 (0.46)	−0.00 (0.41)	−0.00 (0.41)	−0.01 (0.42)	−0.02 (0.38)
Income (reference: Low income)		−0.06 (0.09)	−0.04 (0.09)	−0.04 (0.09)	−0.05 (0.09)	−0.03 (0.09)
Frequency		0.02 (0.08)	0.02 (0.07)	0.01 (0.07)	0.02 (0.07)	0.01 (0.07)
Literacy		−0.13 (0.05)***	−0.11 (0.05)***	−0.13 (0.05)	−0.12 (0.05)***	−0.10 (0.05)***
N	1000	1000	1000	1000	1000	1000
Adjusted R^2	0.27	0.08	0.34	0.10	0.13	0.50

SE: standard error; β: standardized coefficient. *$p < .05$; **$p < .01$; ***$p < .001$.

Table 2. Direct and Indirect Effects of Anthropomorphic Cues on AI Anxiety.

	Effect value	SE	95% bias confidence interval (CI)
Direct effects			
PCV → AA	−0.02	0.08	[−0.20, 0.13]
PRN → AA	−0.13	0.09	[−0.40, −0.03]
PMR → AA	0.13	0.06	[0.06, 0.28]
PWA → AA	−0.14	0.08	[−0.36, −0.06]
PCM → AA	−0.23	0.07	[−0.51, −0.22]
PEP → AA	0.17	0.06	[0.11, 0.33]
Specific indirect effects			
PCV → PH → AA	0.02	0.01	[0.01, 0.06]
PRN → PH → AA	−0.00	0.01	[−0.03, 0.01]
PMR → PH → AA	−0.02	0.01	[−0.06, −0.01]
PWA → PH → AA	−0.02	0.01	[−0.06, −0.01]
PCM → PH → AA	−0.00	0.01	[−0.02, 0.01]
PEP → PH → AA	−0.02	0.01	[−0.06, −0.01]
Indirect total effects			
HN → PH → AA	−0.05	0.03	[−0.12, −0.01]
HU → PH → AA	−0.01	0.01	[−0.03, 0.01]
APH → PH → AA	−0.06	0.03	[−0.13, −0.02]

Note. HN = Human nature, HU = Human uniqueness, APH = Anthropomorphism.

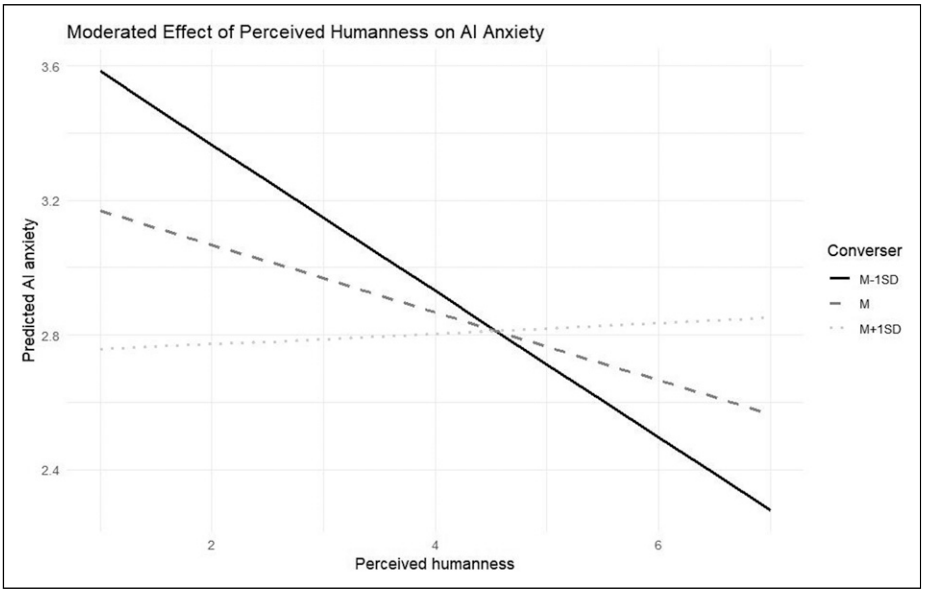

Figure 2. The interaction effect of perceived humanness and converser role on AI anxiety.

Discussion

This study, grounded in the dehumanization theory, explored the boundary turbulence between human and generative AI systems. The study found that human nature cues, especially warmth and empathy, played a key role in alleviating AI anxiety by enhancing machine humanness, while

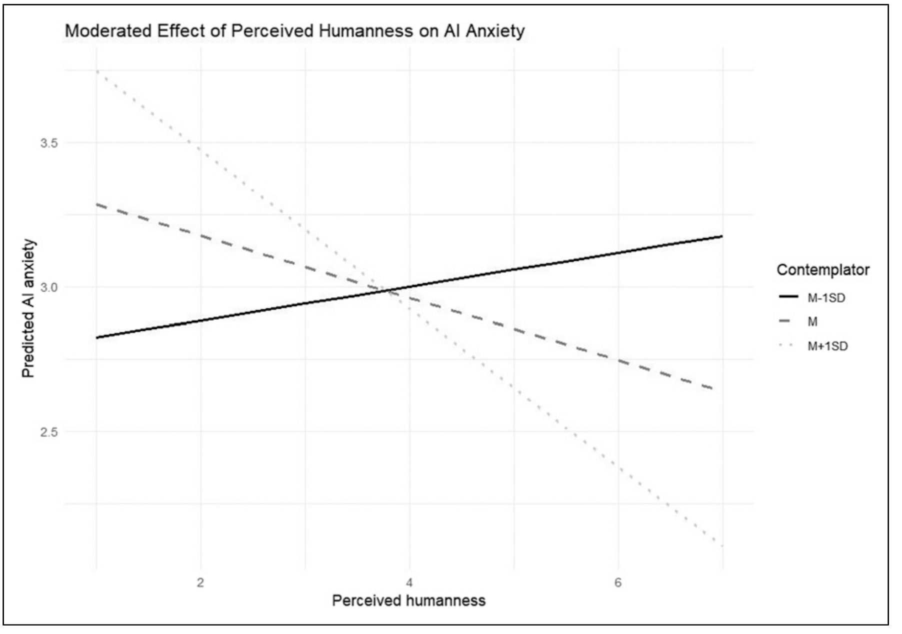

Figure 3. The interaction effect of perceived humanness and contemplator role on AI anxiety.

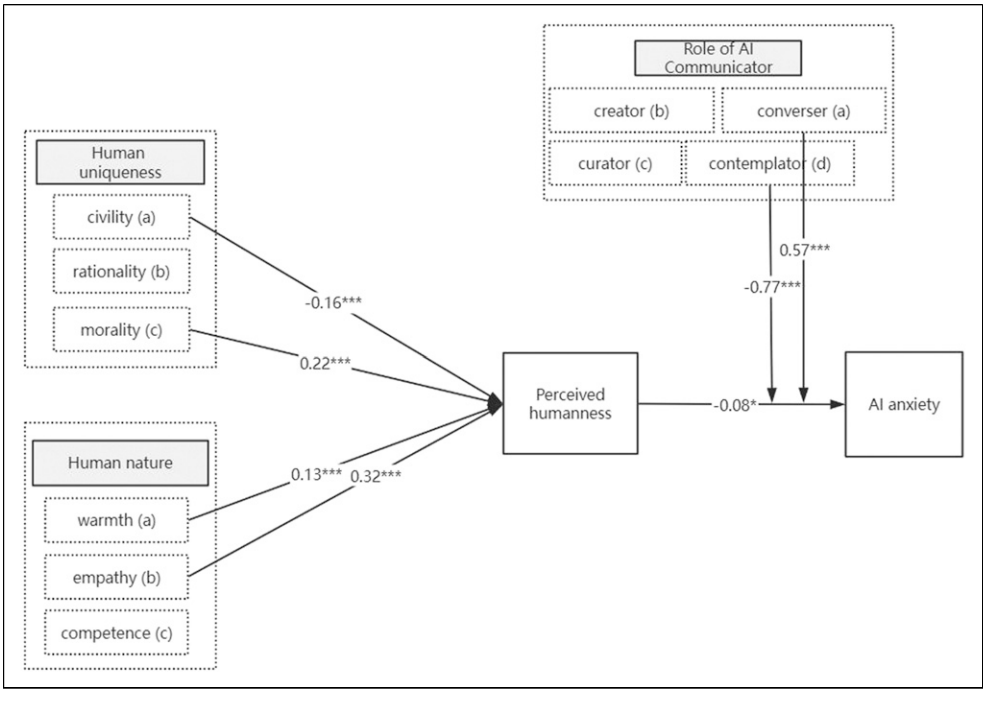

Figure 4. Overall results of hypotheses testing. Note: *p < 0.05, **p < 0.01, ***p < 0.001.

human uniqueness, due to the contrasting effect of morality and civility, did not. Additionally, the role of the chatbot—whether as a converser or contemplator—moderated the impact of humanness on anxiety, with conversers weakening and contemplators enhancing the anxiety-reducing effect. These findings reveal the complex relationship between anthropomorphic traits, humanness, and AI anxiety in HMI.

Warmth and empathy, key human nature traits, fostered emotional responsiveness and relational closeness (Liu & Sundar, 2018; Skjuve et al., 2021). Seeing AI as compassion-driven enhances its perceived empathy, reliability, and social fit, reinforcing its image as emotionally engaged rather than purely cognitive (Pataranutaporn et al., 2023). In our data, warmth not only promoted humanness but also reduced AI anxiety through both direct and mediated pathways, while empathy—despite enhancing humanness—paradoxically heightened anxiety. This pattern underscores the ambivalent role of emotional cues in AI design: while fostering social connectedness, they may also destabilize users' sense of control when perceived as excessively autonomous.

Similarly, morality signals ethical accountability and autonomy, positioning AI as a self-governing social entity rather than a mere tool (Kahn et al., 2007; Willems et al., 2022). This duality was evident in our findings, where morality both enhanced humanness and contributed to increased anxiety. Conversely, rationality and competence did not enhance humanness perceptions, likely because their "superhuman" precision violates expectations of human fallibility. Prior research shows that minor errors or hesitation can increase perceived humanness by suggesting imperfection (Jones-Jang & Park, 2023; Yao & Xi, 2024). Without social embeddedness, competence and rationality provide functional reassurance but fail to evoke a distinctly human-like presence (Fahnenstich et al., 2024).

The most unexpected finding was the negative effect of civility on perceptions of humanness. Although civility has traditionally been viewed as a positive trait that fosters social attachment (Chaves & Gerosa, 2021), its negative impact in this context may be attributed to its potential to create psychological distance. LLM-mediated conversations reshape users' expectations of authenticity and spontaneity (Shin, 2024). In conversational contexts, humans often interpret politeness not merely as a normative social good, but as a discursive performance—something that must feel unscripted and contextually grounded to be considered authentically human (Bowman et al., 2024). Over-formalized or overly civil LLM responses, however, are read as algorithmic simulations of courtesy rather than genuine social presence, thus disrupting users' sense of epistemic trust and conversational realness.

The mediation results highlighted the nuanced role of anthropomorphic traits in shaping AI anxiety through perceived humanness. Warmth exerted a dual influence, both indirectly by enhancing humanness and directly through immediate affective responses, aligning with research on affective empathy in robots (Liu & Sundar, 2018; Skjuve et al., 2021). In contrast, empathy and morality trigger anxiety because they represent the very value-laden qualities that confer autonomy onto AI (Xi et al., 2024). This repositioning shifts the AI from a subordinate executor to a quasi-equal participant in human normative domains. As users perceive LLMs to be not merely responding to human values but actively evaluating and enacting them, the relational hierarchy becomes destabilized. This generates a subtle but profound psychological tension: users must contend with an entity that not only mimics but claims participation in the moral-emotional order. This blurring of normative boundaries contributes to the erosion of epistemic and moral asymmetry between humans and machines. The result is a cognitive discomfort from its apparent success in entering the domains once thought uniquely human (Stein & Ohler, 2017).

Equally counterintuitive was the negative effect of civility on perceived humanness and its subsequent positive effect on AI anxiety. Excessive politeness in AI, devoid of emotional expression, created cognitive uncertainty and emotional emptiness, making its intentions unpredictable and causing users to feel alienated (Bowman et al., 2024; Nass & Moon, 2000). This mismatch between AI's formal politeness and human expectations for emotionally resonant interactions intensified discomfort. While politeness typically reduces anxiety in human interactions (Chaves & Gerosa, 2021; Ribino, 2023), AI's mechanical politeness failed to provide the expected emotional connection, heightening anxiety due to the lack of authenticity and unpredictability.

Moreover, although competence and rationality did not significantly mediate AI anxiety via perceived humanness, they directly reduced anxiety, suggesting that these traits offer functional reassurance rather than evoking a distinctly human-like presence. This aligns with research showing that, in high-stakes interactions, users prioritize efficiency and reliability over anthropomorphic features (Fahnenstich et al., 2024). Competence offers reassurance through predictable task performance, while rationality provides cognitive stability by reducing uncertainty. These findings highlight the distinction between anthropomorphic trust and functional trust, emphasizing that AI acceptance does not always depend on human-like attributes.

Finally, the significant moderation effects observed in the converser and contemplator roles further illuminate how interactional context shapes user experience. The converser role, which typically fosters psychological closeness, was found to weaken the anxiety-buffering effect of humanness. In contrast, the contemplator role amplified the protective effect of humanness, especially in decision-oriented contexts where the AI's cognitive authority might otherwise exacerbate user anxiety. While creators and curators primarily function as task-oriented AI agents, operating in relatively transactional or assistive capacities, conversers and contemplators engage in more direct and immersive interactions, making them more influential in shaping users' affective responses and existential concerns about AI. These results suggest that not all AI roles evoke the same degree of psychological and social significance, and that humanness interacts with these roles in non-uniform ways (Guzman & Lewis, 2020; Lombard & Xu, 2021).

The converser role, characterized by emotional engagement and natural conversational flow, typically fosters psychological closeness and alleviates uncertainty (Rapp et al., 2021). However, the perception of AI as "too emotionally human" can trigger feelings of insecurity and loss of control, as users may feel unable to regulate the AI's empathetic responses (Seitz, 2024). This tension reflects a deeper boundary awareness in the emotional realm, where human vulnerability is more exposed than in functional interactions, thus amplifying anxiety (Xi et al., 2024). In contrast, the contemplator role heightens anxiety through two main mechanisms: its superior cognitive abilities, which evoke insecurity and inadequacy in users, and its opaque decision-making process, which leads to cognitive overload and a perceived loss of control. This "black-box" effect exacerbates uncertainty as users struggle to reconcile the AI's reasoning with their own limitations (Salah et al., 2024). However, the contemplator's ability to provide logical explanations and human-like imperfections, such as errors or hesitations, enhances transparency, relatability, and trust (Jones-Jang & Park, 2023). The infusion of warmth and social awareness also softens the cold, mechanical nature of automated decision-making, creating a more emotionally resonant interaction (Liu & Insua, 2020).

Theoretical and Practical Implications

This study advanced the theoretical understanding of machine humanness in HMI by applying the dehumanization framework. Our findings revealed that affective and social traits—specifically warmth, empathy, and morality—were more effective in triggering perceptions of humanness than cognitive traits like competence and rationality. This challenges existing models that primarily focus on low-level perceptual features (Breazeal, 2003; Złotowski et al., 2016) or high-level cognitive attributions (Go & Sundar, 2019; Kühne & Peter, 2023). By highlighting the importance of emotional and relational markers in determining social agency, our results emphasized that AI humanness is more shaped by social resonance than by functional attributes.

Second, this study offered new theoretical insights into the application of dehumanization theory in the HMI domain by challenging the assumption that perceptions of AI humanness evolve primarily toward higher-order uniqueness traits (Haslam, 2006; Haslam et al., 2008). However, our findings suggest that the activation of humanness is not strictly tied to trait complexity, but instead reflects a typological pattern encompassing affective, moral, and intellectual dimensions, aligning with Hume's (1739/2007) conceptualization of humanness. This indicates that dehumanization theory should be viewed less as a hierarchical progression toward uniqueness traits, and more as a dimensional model wherein different AI attributes elicit distinct forms of humanness recognition.

Third, our findings fuse the Media Evocation Paradigm with the Uncanny Theory of Mind into a single tension-based account, while adding a diagnosticity lens that explains why the tension spikes (Shin, 2024). Media Evocation holds that AI becomes thought-provoking when human and machine cues clash (Van Der Goot & Etzrod, 2023). We locate that clash in the affective–intellectual divide: an LLM that is cognitively deft yet affectively blank merely intrigues, but one that also displays empathy and morality dissolves the machine–human distinction that normally keeps interactional boundaries intact. These value-laden cues signal a level of autonomous agency that prompts users to recalibrate their relational stance toward the AI. The Uncanny Theory of Mind predicts anxiety when a system appears to harbor a near-human psyche (Stein & Ohler, 2017); our data refine this claim by showing that anxiety depends not only on the presence of moral and emotional cues, but on how they align with the AI's role. Specifically, in emotionally intimate converser roles, heightened humanness perception amplifies anxiety by destabilizing normative boundaries; conversely, in high-stakes contemplator roles, humanness perception mitigates anxiety by fostering a sense of social alignment and collaborative agency. Thus, it is the friction between desired cognitive realism and unsettling, diagnostically potent emotional realism—not realism per se—that renders highly human-like AI both compelling and disquieting. This emotional-cognitive tension may also echo broader societal anxieties, as AI's increasing capacity to simulate moral and emotional agency blurs the normative boundaries that structure labor roles, ethical accountability, and human autonomy (Xi & Mai, 2025).

This study also offered practical insights for designing and governing LLM chatbots in social robotics. From a design perspective, achieving an optimal balance between anthropomorphic cues requires making chatbots more socially resonant in the domain of cognitive intelligence, while deliberately constraining the depth of emotional intelligence. In cognitive interactions, competence and rationality cues can be designed to foster a sense of collaborative reasoning rather than mechanical information delivery. This involves embedding social framing into explanations—for example, positioning responses as part of a shared reasoning process rather than issuing authoritative statements. Language should reflect dialogic openness, using soft hedging where appropriate and incorporating signals of perspective-taking, so that users perceive the chatbot as an engaged cognitive partner rather than a detached knowledge source.

In contrast, affective cues should be carefully moderated. While warmth remains a useful baseline for establishing relational comfort, deeper emotional cues such as empathy and morality require cautious handling. Chatbots should avoid phrasing that suggests privileged access to users' inner states or moral judgments; instead, expressions of support should adopt generalized or collective framings that respect interpersonal boundaries. Addressing civility in particular calls for moving beyond scripted politeness. Chatbots should adopt a conversational style shaped by adaptive turn-taking and informal acknowledgments that align with the user's tone. For instance, replacing repeated "Thank you for your understanding" with varied, lightweight responses such as "Sounds good" can make the interaction feel more authentic without overstepping affective boundaries.

At the governance level, the coordination of emotional and cognitive cues should be guided by the role- and trait-specific anxiety dynamics identified in this study. Governance instruments such as a trait–role expression matrix should specify which traits are appropriate for expression, in what form, and under which chatbot roles. For instance, in converser roles, traits like empathy and morality that increase user anxiety should be constrained, while in contemplator roles, humanness-enhancing traits such as warmth may be emphasized. To maintain relevance across evolving user contexts, this matrix should be regularly updated based on interaction data and user feedback. Design and moderation teams should be required to consult the matrix during key stages of the development cycle, including dialogue scripting, model tuning, and content review, in order to ensure consistent alignment between trait usage and user expectations. Moderation guidelines should incorporate these role-specific rules, linking risk levels to concrete review tasks, such as identifying unauthorized moral evaluations or excessive emotional mimicry.

Limitations and Future Research

While this study offered valuable insights into how LLM chatbot roles and anthropomorphic traits shape user perceptions of humanness and anxiety, several limitations need to be addressed in future research. First, the study primarily focused on general LLM chatbots without differentiating between various specialized types, such as health consultation or educational bots. This lack of specificity may have overlooked important nuances in how different chatbot types influence human perceptions. Future research could explore how specific types of AI chatbots interact with users in varied contexts, investigating how distinct human-like traits may trigger different types of human responses. This could be done by categorizing chatbots according to their intended purpose and analyzing how the perception of humanness varies across these categories.

Second, while the study incorporated user experience with the top ten LLM chatbots during the survey period, it did not distinguish between individual chatbot systems or model-specific interaction patterns. This design choice reflects the study's theoretical orientation toward perceived humanness as a socially constructed cognitive judgment, rather than a function of specific technical architectures. This generalization could introduce a limitation: different chatbot systems may foster distinct interaction norms, functional expectations, or cultural framings that could subtly shape how users interpret human-likeness. Although modeling chatbot identity as a covariate may not be feasible given overlapping use and user recall variability, future studies could benefit from narrowing the scope to one or two representative platforms to better isolate how interface design and contextual framing moderate anthropomorphic effects.

Third, although the survey employed robust statistical modeling, its cross-sectional and self-reported nature limits causal inference. To address this, future studies could adopt experimental designs where participants are randomly assigned to interact with chatbots that systematically vary in anthropomorphic traits (e.g., high vs. low empathy, warmth, or morality) and functional roles (e.g., contemplator vs. converser). Measuring changes in perceived humanness and anxiety before and after interaction would help isolate the causal impact of specific traits and contexts. Longitudinal data could also be used to test delayed effects or adaptation mechanisms, such as whether repeated exposure to emotionally expressive AI leads to habituation, reduced novelty perception, or growing unease. Such a design allows for within-person comparisons, improving sensitivity to psychological change while controlling for individual differences. These designs would not only strengthen causal interpretation but also illuminate how users cognitively and emotionally recalibrate to human-like AI over time.

Last, while this study focused on a predominantly Chinese context, future research should explore cross-cultural differences in how people perceive robots and their anthropomorphic traits. Cultural differences can significantly influence how people interpret human-like attributes in AI systems, as perceptions of warmth, empathy, and rationality may vary across cultural contexts. For instance, collectivist cultures might emphasize the social and relational aspects of human-robot interactions, while individualist cultures may focus more on cognitive and functional traits. Cross-cultural studies would offer valuable insights into whether and how anthropomorphic traits contribute to perceptions of humanness and technology anxiety in diverse global settings. This would further our understanding of the universal versus culture-specific dimensions of human-robot interaction and help tailor AI systems for a more global audience.

Appendix

Appendix for "From Assistants to Digital Beings: Exploring Anthropomorphism, Humanness Perception, and AI Anxiety in Large-Language-Model Chatbots"

I. Demographics of Respondents.

Table 1. Demographics of Respondents (N = 1000).

Category	Item	Frequency	Percentage
Gender	Male	753	75.3%
	Female	247	24.7%
Education	Senior high school and below	11	1.1%
	Associate degree	105	10.5%
	Bachelor's degree	768	76.8%
	Master's degree	111	11.1%
	Doctoral degree	5	0.5%
Age	18–25	98	9.8%
	26–35	668	66.8%
	36–45	228	22.8%
	46–55	6	0.6%
Annual income (RMB)	<10,000	28	2.8%
	10,000–50,000	592	59.2%
	50.000–200,000	307	30.7%
	200,000–500,000	66	6.6%
	500,000–1,000,000	6	0.6%
	>1,000,000	1	0.1%
Residence	Eastern China	554	55.4%
	Middle China	192	19.2%
	Western China	217	21.7%
	Northeastern China	37	3.7%
Frequency (per day)	Seldom use	6	0.6%
	0–1h	754	75.4%
	1–2h	167	16.7%
	3–4h	51	5.1%
	4–5h	20	2.0%
	5–6h	1	0.1%
	>6h	1	0.1%

II. Reliability and Validity of the Measurement.

Table 2. Confirmatory Factor Analysis of Model Variables (*N* = 1000).

Items	Loading	M	SD	AVE	Sources
Perceived warmth (PWA) (α = 0.76)		5.42	0.97	0.53	Andrei and Zait (2014)
The LLM chatbot is kind	0.71				
The LLM chatbot is warm	0.76				
The LLM chatbot is sincere	0.70				
Perceived competence (PCM) (α = 0.83)		5.62	0.90	0.55	Belanche et al. (2021)
The LLM chatbot is capable	0.75				
The LLM chatbot is efficient	0.76				
The LLM chatbot is competent	0.71				
The LLM chatbot is effective	0.76				
Perceived empathy (PEP) (α = 0.88)		5.14	1.12	0.61	Yim (2023)
The LLM chatbot understands my anxiety	0.73				
The LLM chatbot shows emotional support	0.81				
The LLM chatbot seems to feel empathic	0.83				
The LLM chatbot seems to care for me	0.83				
The LLM chatbot seems to be open	0.69				
Perceived rationality (PRN) (α = 0.77)		5.60	0.85	0.53	Lelieveld and Hendriks (2021)
The LLM chatbot is reasonable	0.71				
The LLM chatbot is reliable	0.73				
The LLM chatbot is credible	0.74				
Perceived civility (PCV) (α = 0.76)		5.73	0.85	0.52	Kenski et al. (2020); Wang (2020)
The LLM chatbot is civil	0.69				
The LLM chatbot is polite	0.74				
The LLM chatbot respects me	0.74				
Perceived morality (PMR) (α = 0.89)		5.15	1.06	0.58	Banks (2019)
The LLM chatbot has a sense of what is right and wrong	0.76				
The LLM chatbot can think whether an action is moral	0.78				
The LLM chatbot may feel obligated to behave in a moral way	0.78				
The LLM chatbot is capable of being rational about good and evil	0.79				
The LLM chatbot behaves according to moral rules	0.73				
The LLM chatbot would refrain from doing things that have painful repercussion	0.70				
Perceived humanness (PH) (α = 0.87)		4.49	1.36	0.64	Jin and Youn (2023)
The LLM chatbot I use is human-like	0.71				
The LLM chatbot I use is natural	0.78				
The LLM chatbot I use is lifelike	0.85				
The LLM chatbot I use is conscious	0.83				
AI anxiety (AA) (α = 0.91)		2.87	1.41	0.72	Li et al. (2021)
I Have avoided LLM chatbot services because they are unfamiliar to me	0.86				
I Hesitate to use LLM chatbot services for fear of making mistakes I cannot correct	0.84				
I Have difficulty understanding most technological matters relating to LLM chatbot services	0.82				
I Am not able to keep up with important technological advances, such as the development of LLM chatbot services	0.86				

Table 3. Discriminant Validity: Correlation and Square Roots of the AVE.

	PWA	PCM	PEP	PCV	PMR	PRN	PH	AA
PWA	**0.72**							
PCM	0.64	**0.74**						
PEP	0.65	0.53	**0.78**					
PCV	0.59	0.66	0.54	**0.72**				
PMR	0.57	0.48	0.66	0.59	**0.76**			
PRN	0.65	0.68	0.64	0.68	0.63	**0.73**		
PH	−0.10	−0.22	0.02	−0.13	0.05	−0.10	**0.81**	
AA	−0.21	−0.28	−0.20	−0.17	−0.13	−0.23	0.43	**0.88**

Note. Diagonal elements reveal the square roots of the AVE. Off-diagonal elements are the correlation coefficients between the constructs.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the National Social Science Fund of China grant number (24CXW015)

ORCID iD

Yipeng Xi https://orcid.org/0000-0002-5060-4078

Data Availability Statement

Data could be shared with reasonable request. The full questionnaire used in the study is openly available and can be downloaded at the following OSF link: https://osf.io/u8zrm/?view_only=eb252d46f6a5459091f97a265b3d78e4.

Note

1. The "top 10 LLM chatbots" referenced in the screening question were identified based on the monthly user activity rankings published by Qimai Data, a leading mobile analytics platform in China, during the survey period. These top generative LLM chatbots included: ChatGPT, Ernie Bot, SparkDesk, Bard, Tongyi Qianwen, PanGu, 360 Smart Chatbot, SenseChat, Zidong Taichu, and TARS. Participants were screened to ensure they had interacted with at least one of these chatbots.

References

Andrei, A., & Zait, A. (2014). Perceptions of warmth & competence in online networking: An experimental analysis of a company launch. *Review of Economic and Business Studies*, *7*(1), 11–29.

Banks, J. (2019). A perceived moral agency scale: Development and validation of a metric for humans and social machines. *Computers in Human Behavior*, *90*(1), 363–371. https://doi.org/10.1016/j.chb.2018.08.028

Bartneck, C., Kulić, D., Croft, E., & Zoghbi, S. (2009). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International Journal of Social Robotics*, *1*(1), 71–81. https://doi.org/10.1007/s12369-008-0001-3

Becker, D., Rueda, D., Beese, F., Torres, B. S. G., Lafdili, M., Ahrens, K., & Wermter, S. (2023). The emotional dilemma: Influence of a human-like robot on trust and cooperation. In *2023 32nd IEEE* *international conference on robot and human interactive communication (RO-MAN)* (pp. 1689–1696). IEEE. https://doi.org/10.1109/RO-MAN57019.2023.10309321

Belanche, Casaló, L. V., Schepers, J., & Flavián, C. (2021). Examining the effects of robots' physical appearance, warmth, and competence in frontline services: The Humanness-Value-Loyalty model. *Psychology and Marketing*, *38*(12), 2357–2376. https://doi.org/10.1002/mar.21532

Borau, S., Otterbring, T., Laporte, S., & Fosso Wamba, S. (2021). The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI. *Psychology and Marketing*, *38*(7), 1052–1068. https://doi.org/10.1002/mar.21480

Bowman, R., Cooney, O., Newbold, J. W., Thieme, A., Clark, L., Doherty, G., & Cowan, B. (2024). Exploring how politeness impacts the user experience of chatbots for mental health support. *International Journal of Human-Computer Studies*, *184*, 103181. https://doi.org/10.1016/j.ijhcs.2023.103181

Breazeal, C. (2003). Toward sociable robots. *Robotics and Autonomous Systems*, *42*(3-4), 167–175. https://doi.org/10.1016/s0921-8890(02)00373-1

Carpinella, C. M., Wyman, A. B., Perez, M. A., & Stroessner, S. J. (2017). The robotic social attributes scale (RoSAS): Development and validation. In *Proceedings of the 2017 ACM/IEEE international conference on human-robot interaction* (pp. 254–262). IEEE. https://doi.org/10.1145/2909824.3020208

Chaves, A. P., & Gerosa, M. A. (2021). How should my chatbot interact? A survey on human-chatbot interaction design. *International Journal of Human-Computer Interaction*, *37*(8), 729–758. https://doi.org/10.1080/10447318.2020.1841438

Cheung, M. W. (2007). Comparison of approaches to constructing confidence intervals for mediating effects using structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(2), 227–246. https://doi.org/10.1080/10705510709336745

Christoforakos, L., & Diefenbach, S. (2023). Technology as a social companion? An exploration of individual and product-related factors of anthropomorphism. *Social Science Computer Review*, *41*(3), 1039–1062. https://doi.org/10.1177/08944393211065867

Cuddy, A. J. C., Fiske, S. T., & Glick, P. (2007). The BIAS map: Behaviors from intergroup affect and stereotypes. *Journal of Personality and Social Psychology*, *92*(4), 631–648. https://doi.org/10.1037/0022-3514.92.4.631

Edwards, C., Edwards, A., Spence, P. R., & Westerman, D. (2016). Initial interaction expectations with robots: Testing the human-to-human interaction script. *Communication Studies*, *67*(2), 227–238. https://doi.org/10.1080/10510974.2015.1121899

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: A three-factor theory of anthropomorphism. *Psychological Review*, *114*(4), 864–886. https://doi.org/10.1037/0033-295X.114.4.864

Eyssel, F. (2017). An experimental psychological perspective on social robotics. *Robotics and Autonomous Systems*, *87*(1), 363–371. https://doi.org/10.1016/j.robot.2016.08.029

Eyssel, F., & Kuchenbrandt, D. (2012). Social categorization of social robots: Anthropomorphism as a function of robot group membership. *British Journal of Social Psychology*, *51*(4), 724–731. https://doi.org/10.1111/j.2044-8309.2011.02082.x

Fahnenstich, H., Rieger, T., & Roesler, E. (2024). Trusting under risk–comparing human to AI decision support agents. *Computers in Human Behavior*, *153*, 108107. https://doi.org/10.1016/j.chb.2023.108107

Fetterolf, E., & Hertog, E. (2023). It's not her fault: Trust through anthropomorphism among young adult Amazon Alexa users. *Convergence*, *31*(2), 559–576. https://doi.org/10.1177/13548565231200337

Fiske, S. T., Cuddy, A. J., & Glick, P. (2007). Universal dimensions of social cognition: Warmth and competence. *Trends in Cognitive Sciences*, *11*(2), 77–83. https://doi.org/10.1016/j.tics.2006.11.005

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

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

Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. *Science*, *315*(5812), 619. https://doi.org/10.1126/science.1134475

Guzman, A. L., & Lewis, S. C. (2020). Artificial intelligence and communication: A human–machine communication research agenda. *New Media & Society*, *22*(1), 70–86. https://doi.org/10.1177/1461444819858691

Harris-Watson, A. M., Larson, L. E., Lauharatanahirun, N., DeChurch, L. A., & Contractor, N. S. (2023). Social perception in Human-AI teams: Warmth and competence predict receptivity to AI teammates. *Computers in Human Behavior*, *145*, 107765. https://doi.org/10.1016/j.chb.2023.107765

Haslam, N. (2006). Dehumanization: An integrative review. *Personality and Social Psychology Review: An Official Journal of the Society for Personality and Social Psychology, Inc*, *10*(3), 252–264. https://doi.org/10.1207/s15327957pspr1003_4

Haslam, N., Loughnan, S., Kashima, Y., & Bain, P. (2008). Attributing and denying humanness to others. *European Review of Social Psychology*, *19*(1), 55–85. https://doi.org/10.1080/10463280801981645

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Huang, G., & Wang, S. (2023). Is artificial intelligence more persuasive than humans? A meta-analysis. *Journal of Communication*, *73*(6), 552–562. https://doi.org/10.1093/joc/jqad024

Hume, D. (2007). In D. F. Norton & M. J. Norton (Ed.), *A Treatise of human nature: Volumn 1: Texts*. Clarendon Press. (Original work published in 1739).

Jin, S. V., & Youn, S. (2023). Social presence and imagery processing as predictors of chatbot continuance intention in human-AI-interaction. *International Journal of Human-Computer Interaction*, *39*(9), 1874–1886. https://doi.org/10.1080/10447318.2022.2129277

Jo, H., & Park, D. H. (2024). Effects of ChatGPT's AI capabilities and human-like traits on spreading information in work environments. *Scientific Reports*, *14*(1), 7806. https://doi.org/10.1038/s41598-024-57977-0

Jones-Jang, S. M., & Park, Y. J. (2023). How do people react to AI failure? Automation bias, algorithmic aversion, and perceived controllability. *Journal of Computer-Mediated Communication*, *28*(1), zmac029. https://doi.org/10.1093/jcmc/zmac029

Kahn, Jr., P. H., Ishiguro, H., Friedman, B., Kanda, T., Freier, N. G., Severson, R. L., & Miller, J. (2007). What is a human? Toward psychological benchmarks in the field of human-robot interaction. *Interaction Studies*, *8*(3), 363–390. https://doi.org/10.1075/is.8.3.04kah

Kenski, K., Coe, K., & Rains, S. A. (2020). Perceptions of uncivil discourse online: An examination of types and predictors. *Communication Research*, *47*(6), 795–814. https://doi.org/10.1177/0093650217699933

Kim, J., & Im, I. (2023). Anthropomorphic response: Understanding interactions between humans and artificial intelligence agents. *Computers in Human Behavior*, *139*, 107512. https://doi.org/10.1016/j.chb.2022.107512

Kim, Y., & Sundar, S. S. (2012). Anthropomorphism of computers: Is it mindful or mindless? *Computers in Human Behavior*, *28*(1), 241–250. https://doi.org/10.1016/j.chb.2011.09.006

Kline, R. B. (2023). *Principles and practice of structural equation modeling*. Guilford publications.

Koban, K., & Banks, J. (2024). It feels, therefore it is: Associations between mind perception and mind ascription for social robots. *Computers in Human Behavior*, *153*, 108098. https://doi.org/10.1016/j.chb.2023.108098

Kteily, N., Bruneau, E., Waytz, A., & Cotterill, S. (2015). The ascent of man: Theoretical and empirical evidence for blatant dehumanization. *Journal of Personality and Social Psychology*, *109*(5), 901–931. https://doi.org/10.1037/pspp0000048

Kühne, R., & Peter, J. (2023). Anthropomorphism in human–robot interactions: A multidimensional conceptualization. *Communication Theory*, *33*(1), 42–52. https://doi.org/10.1093/ct/qtac020

Lee, J., & Lee, D. (2023). User perception and self-disclosure towards an AI psychotherapy chatbot according to the anthropomorphism of its profile picture. *Telematics and Informatics*, *85*, 102052. https://doi.org/10.1016/j.tele.2023.102052

Lee, J. G., & Lee, K. M. (2022). Polite speech strategies and their impact on drivers' trust in autonomous vehicles. *Computers in Human Behavior*, *127*, 107015. https://doi.org/10.1016/j.chb.2021.107015

Lee, S., Lee, N., & Sah, Y. J. (2020). Perceiving a mind in a chatbot: Effect of mind perception and social cues on co-presence, closeness, and intention to use. *International Journal of Human-Computer Interaction*, *36*(10), 930–940. https://doi.org/10.1080/10447318.2019.1699748

Lelieveld, G. J., & Hendriks, H. (2021). The interpersonal effects of distinct emotions in online reviews. *Cognition & Emotion*, *35*(7), 1257–1258. https://doi.org/10.1080/02699931.2021.1947199

Li, J., & Huang, J. S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society*, *63*, 101410. https://doi.org/10.1016/j.techsoc.2020.101410

Li, L., Lee, K. Y., Emokpae, E., & Yang, S. B. (2021). What makes you continuously use chatbot services? Evidence from Chinese online travel agencies. *Electronic Markets*, *31*(3), 1–2. https://doi.org/10.1007/s12525-020-00454-z

Li, X., & Sung, Y. (2021). Anthropomorphism brings us closer: The mediating role of psychological distance in User–AI assistant interactions. *Computers in Human Behavior*, *118*, 106680. https://doi.org/10.1016/j.chb.2021.106680

Liu, B., & Sundar, S. S. (2018). Should machines express sympathy and empathy? Experiments with a health advice chatbot. *Cyberpsychology, Behavior, and Social Networking*, *21*(10), 625–636. https://doi.org/10.1089/cyber.2018.0110

Liu, S., & Insua, D. R. (2020). An affective decision-making model with applications to social robotics. *EURO Journal on Decision Processes*, *8*(1-2), 13–39. https://doi.org/10.1007/s40070-019-00109-1

Lombard, M., & Xu, K. (2021). Social responses to media technologies in the 21st century: The media are social actors paradigm. *Human-Machine Communication*, *2*, 29–55. https://doi.org/10.30658/hmc.2.2

Malle, B. F., & Thapa Magar, S. (2017). What kind of mind do I want in my robot? Developing a measure of desired mental capacities in social robots. In *Proceedings of the companion of the 2017 ACM/IEEE international conference on human-robot interaction* (pp. 195–196). IEEE. https://doi.org/10.1145/3029798.3038378

Morewedge, C. K., Preston, J., & Wegner, D. M. (2007). Timescale bias in the attribution of mind. *Journal of Personality and Social Psychology*, *93*(1), 1–11. https://doi.org/10.1037/0022-3514.93.1.1

Mozafari, N., Weiger, W. H., & Hammerschmidt, M. (2022). Trust me, I'm a bot–repercussions of chatbot disclosure in different service frontline settings. *Journal of Service Management*, *33*(2), 221–245. https://doi.org/10.1108/josm-10-2020-0380

Nass, C., & Moon, Y. (2000). Machines and Mindlessness: Social Responses to Computers. *Journal of Social Issues*, *56*(1), 81–103. https://doi.org/10.1111/0022-4537.00153

O'Brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality and Quantity*, *41*(5), 673–690. https://doi.org/10.1007/s11135-006-9018-6

Pataranutaporn, P., Liu, R., Finn, E., & Maes, P. (2023). Influencing human–AI interaction by priming beliefs about AI can increase perceived trustworthiness, empathy and effectiveness. *Nature Machine Intelligence*, *5*(10), 1076–1086. https://doi.org/10.1038/s42256-023-00720-7

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Rai, T. S., Valdesolo, P., & Graham, J. (2017). Dehumanization increases instrumental violence, but not moral violence. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(32), 8511–8516. https://doi.org/10.1073/pnas.1705238114

Rajaraman, V. (2023). From ELIZA to ChatGPT: History of human-computer conversation. *Resonance*, *28*(6), 889–905. https://doi.org/10.1007/s12045-023-1620-6

Rapp, A., Boldi, A., Curti, L., Perrucci, A., & Simeoni, R. (2024). How do people ascribe humanness to chatbots? An analysis of real-world human–agent interactions and a theoretical model of humanness. *International Journal of Human-Computer Interaction*, *40*(19), 6027–6050. https://doi.org/10.1080/10447318.2023.2247596

Rapp, A., Curti, L., & Boldi, A. (2021). The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots. *International Journal of Human-Computer Studies*, *151*, 102630. https://doi.org/10.1016/j.ijhcs.2021.102630

Reeves, B., & Nass, C. I. (1996). The media equation: How people treat computers, television, and new media like real people and places. *Center for the study of language and information*. Cambridge University Press.

Ribino, P. (2023). The role of politeness in human–machine interactions: A systematic literature review and future perspectives. *Artificial Intelligence Review*, *56*(Suppl 1), 445–482. https://doi.org/10.1007/s10462-023-10540-1

Salah, M., Abdelfattah, F., & Al Halbusi, H. (2024). The good, the bad, and the GPT: Reviewing the impact of generative artificial intelligence on psychology. *Current Opinion in Psychology*, *59*, 101872. https://doi.org/10.1016/j.copsyc.2024.101872

Seitz, L. (2024). Artificial empathy in healthcare chatbots: Does it feel authentic? *Computers in Human Behavior. Artificial Humans*, *2*(1), 100067. https://doi.org/10.1016/j.chbah.2024.100067

Shank, D. B., Graves, C., Gott, A., Gamez, P., & Rodriguez, S. (2019). Feeling our way to machine minds: People's emotions predict perceptions of sentience in robots. *Computers in Human Behavior*, *98*, 256–266. https://doi.org/10.1016/j.chb.2019.04.001

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Shin, D. (2024). *Artificial misinformation: Exploring human-algorithm interaction online*. Springer.

Skjuve, M., Følstad, A., Fostervold, K. I., & Brandtzaeg, P. B. (2021). My chatbot companion-a study of human-chatbot relationships. *International Journal of Human-Computer Studies*, *149*, 102601. https://doi.org/10.1016/j.ijhcs.2021.102601

Stein, J. P., & Ohler, P. (2017). Venturing into the uncanny valley of mind—the influence of mind attribution on the acceptance of human-like characters in a virtual reality setting. *Cognition*, *160*, 43–50. https://doi.org/10.1016/j.cognition.2016.12.010

Stroessner, S. J., & Benitez, J. (2019). The social perception of humanoid and non-humanoid robots: Effects of gendered and machinelike features. *International Journal of Social Robotics*, *11*(2), 305–315. https://doi.org/10.1007/s12369-018-0502-7

Sundar, S. S., & Lee, E.-J. (2022). Rethinking communication in the era of artificial intelligence. *Human Communication Research*, *48*(3), 379–385. https://doi.org/10.1093/hcr/hqac014

Ullrich, D., Butz, A., & Diefenbach, S. (2018). Who do you follow? Social robots' impact on human judgment. In *Companion of the 2018 ACM/IEEE international conference on human-robot interaction* (pp. 265–266). IEEE. https://doi.org/10.1145/3173386.3177014

Van Der Goot, M., & Etzrod, K. (2023). Disentangling two fundamental paradigms in human–machine communication research: Media equation and media evocation. *Human-Machine Communication*, *6*, 17–30. https://doi.org/10.30658/hmc.6.2

Wang, S. (2020). The influence of anonymity and incivility on perceptions of user comments on news websites. *Mass Communication & Society*, *23*(6), 912–936. https://doi.org/10.1080/15205436.2020.1784950

Wang, Y. Y., & Wang, Y. S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments*, *30*(4), 619–634. https://doi.org/10.1080/10494820.2019.1674887

Waytz, A., Cacioppo, J., & Epley, N. (2010). Who sees human? The stability and importance of individual differences in anthropomorphism. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, *5*(3), 219–223. https://doi.org/10.1177/1745691610369336

Waytz, A., Heafner, J., & Epley, N. (2014). The mind in the machine: Anthropomorphism increases trust in an autonomous vehicle. *Journal of Experimental Social Psychology*, *52*, 113–117. https://doi.org/10.1016/j.jesp.2014.01.005

Willems, J., Schmidthuber, L., Vogel, D., Ebinger, F., & Vanderelst, D. (2022). Ethics of robotized public services: The role of robot design and its actions. *Government Information Quarterly*, *39*(2), 101683. https://doi.org/10.1016/j.giq.2022.101683

Wilson, A., Stefanik, C., & Shank, D. B. (2022). How do people judge the immorality of artificial intelligence versus humans committing moral wrongs in real-world situations? *Computers in Human Behavior Reports*, *8*, 100229. https://doi.org/10.1016/j.chbr.2022.100229

Xi, Y., Ji, A., & Yu, W. (2024). Enhancing or impeding? Exploring the dual impact of anthropomorphism in large language models on user aggression. *Telematics and Informatics*, *95*, 102194. https://doi.org/10.1016/j.tele.2024.102194

Xi, Y., & Mai, L. T. N. (2025) (In press). Shifting tides: How public perceptions of GPT regulation evolved before and after GPT-4 on Quora. *Telecommunications Policy*, 103001. https://doi.org/10.1016/j.telpol.2025.103001

Yao, X., & Xi, Y. (2024). Pathways linking expectations for AI chatbots to loyalty: A moderated mediation analysis. *Technology in Society*, *78*, 102625. https://doi.org/10.1016/j.techsoc.2024.102625

Yim, M. C. (2023). Effect of AI chatbot's interactivity on consumers' negative word-of-mouth intention: Mediating role of perceived empathy and anger. *International Journal of Human-Computer Interaction*, *40*(18), 5415–5430. https://doi.org/10.1080/10447318.2023.2234114

Złotowski, J., Proudfoot, D., Yogeeswaran, K., & Bartneck, C. (2015). Anthropomorphism: Opportunities and challenges in human–robot interaction. *International journal of social robotics*, *7*(3), 347–360. https://doi.org/10.1007/s12369-014-0267-6

Złotowski, J., Sumioka, H., Nishio, S., Glas, D. F., Bartneck, C., & Ishiguro, H. (2016). Appearance of a robot affects the impact of its behaviour on perceived trustworthiness and empathy. *Paladyn, Journal of Behavioral Robotics*, *7*(1), 000010151520160005. https://doi.org/10.1515/pjbr-2016-0005

Author Biographies

Xintong Yao is a research assistant in the School of Media and Communication at Shanghai Jiao Tong University. Her research interests lie in human-computer interactions and health Communication.

Yipeng Xi is an assistant professor of communication in the School of Media and Communication at Shanghai Jiao Tong University. His research focuses on the psychological and social impacts of science and media technologies.