

The Impact of Anthropomorphizing Large Language Models-based Chatbots: A Scoping Review

Ylenia D'elia

ylenia96@gmail.com

University of Southern California

Nicole Caballa

University of Southern California

Caitlin Nguyen

University of Southern California

Xuege Tong

University of Southern California

Akila Kadambi

University of Southern California

Lisa Aziz-Zadeh

University of Southern California

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Abstract

Large language model (LLM)-based chatbots are increasingly integrated into various sectors of people's lives, including education, healthcare, and retail. As they become more ubiquitous, safety concerns have emerged, among them the tendency to ascribe human-like qualities to these systems — a phenomenon known as anthropomorphism. Anthropomorphism can shape not only interpersonal dynamics and affective responses but also foster overreliance and raise privacy concerns. This scoping review synthesizes empirical evidence on the impact of perceived anthropomorphism in LLMs and the system- and user-level factors that modulate this perception. Thematic synthesis revealed that LLM anthropomorphism affects psychological outcomes — including trust, emotional engagement, attachment, and perceptions of competence and warmth — as well as behavioral outcomes such as intention to use and social dynamics. Among system-level factors, conversational style and tone, emotional expressive language, and contextual responsiveness were identified as factors shaping anthropomorphic perception. User-level factors, including loneliness, emotional needs, motivational factors, prior experience with LLMs, as well as individual differences in personality traits, further shaped the degree of perceived anthropomorphism. Although effects were highly context-dependent, anthropomorphism generally enhanced user experience in social or supportive contexts, whereas excessive anthropomorphism sometimes reduced trust or elicited discomfort in formal or task-oriented settings. This review also highlights ongoing methodological challenges and underscores the need for continued research to inform the contextually and ethically sensitive design of LLMs.

1. Introduction

Recently, generative artificial intelligence (AI) tools, particularly large language model chatbots (LLM), such as ChatGPT by OpenAI (OpenAI, n.d.) or Gemini by Google have become increasingly integrated into people's lives (Blut et al., 2021). LLMs are used for complex text-processing tasks, including summarization, translation, and dialogue generation (Khan et al., 2023). Nevertheless, their emergence has also sparked significant concerns and debate regarding their safety. To date, one highly discussed concern is the tendency to anthropomorphize AI tools, that is, attributing human-like qualities to AI (Peter et al., 2025). Indeed, as LLMs become more sophisticated, their outputs have in many ways become more human-like (Abercrombie et al., 2023; Cheng et al., 2024), to a degree that makes it difficult for users to distinguish between human and AI-generated text (Jakesch et al., 2023). Such anthropomorphism of LLMs may further impact trust (Colombatto et al., 2025; Waytz et al., 2014), emotional engagement, and attachment (Maples et al., 2023; Pentina et al., 2023). Further, it can lead to overreliance and privacy risks (Akbulut et al., 2024; Deshpande et al., 2023).

Recent studies show that users may treat LLMs as friends, mentors, and even romantic partners (Croes & Antheunis, 2021; Pentina et al., 2023). These interactions are influenced by both system-level factors (design and functional characteristics inherent to the LLM system itself, such as its interface, language style, and built-in capabilities), and user-level factors (e.g., loneliness, prior experience with AI, and affective traits (Jacobs et al., 2022; Leichtmann et al., 2025). However, despite the increasing prevalence

of anthropomorphic design elements in LLMs, empirical evidence on their effects remains fragmented, context-dependent, and often inconsistent (Kühne & Peter, 2023; Li & Suh, 2022). Moreover, anthropomorphism in AI development, deployment, and use remains vastly understudied and underspecified (Li & Suh, 2022).

This scoping review addresses this gap by synthesizing recent empirical findings on the impact of perceived anthropomorphism in interactions with LLMs. It specifically focuses on text-based LLM-based chatbots, rather than robots or voice-based agents, because they have become the most widely adopted form of generative AI in everyday life. Specifically, we examine: (1) the psychological and behavioral outcomes associated with anthropomorphic perception, and (2) the system- and user-level factors that influence this perception. By exploring these questions, this scoping review aims to better understand human-LLM interaction and offers evidence-based insights for responsible design, development, and regulation of LLMs.

1.1 Anthropomorphism and LLMs

Anthropomorphism refers to the attribution of human-like qualities — including mental states, emotions, intentions, and social roles — to non-human entities (Epley et al., 2007). It is a pervasive human tendency, often occurring unconsciously when non-human entities exhibit cues that resemble human traits, emotions, or intentions (Epley et al., 2007; Waytz et al., 2019). From an evolutionary perspective, it is considered an adaptive mechanism for predicting and interpreting behaviors in uncertain environments (Waytz et al., 2010). Even when individuals explicitly deny that computers have mental capacities, empirical studies show that users continue to interact and respond to them as if they do (Airenti, 2015; Akbulut et al., 2024; Araujo, 2018; Epley et al., 2007; Y. Kim & Sundar, 2012; Nass & Moon, 2000). Two theoretical frameworks are particularly useful in the context of Human-AI interaction: the CASA paradigm (Reeves & Nass, 1996), which proposes that users apply social rules to any system displaying minimal social cues, and Epley et al.'s (2007) three-factor theory, which identifies elicited agent knowledge, effectance motivation, and sociality motivation as key determinants of anthropomorphic attribution.

Within the broad definition of anthropomorphism, the literature identifies several conceptually distinct dimensions. First, attributed qualities may be experiential (e.g., the capacity to feel; Barandiaran & Almendros, 2025; Colombatto et al., 2025) or agentic (e.g., the capacity to think or decide; Proudfoot, 2011). Second, the source of anthropomorphic perception may be interactional — arising from communicative behaviors such as warmth and conversational responsiveness — or functional, rooted in perceptions of competence and task performance (Zhang et al., 2025). Third, anthropomorphism can be conceptualized as a user-side tendency (an individual difference in the propensity to attribute human-like qualities; Waytz et al., 2010) or as a system-level property elicited by design features (Araujo, 2018). Given this heterogeneity, the present review adopts an inclusive approach, encompassing studies that explicitly addressed anthropomorphism in the context of user interaction with LLM-based chatbots.

Moreover, anthropomorphism in text-based LLM-based chatbots emerges primarily through linguistic cues, such as conversational style, empathy simulation, and memory, rather than physical embodiment. Indeed, qualitative analyses revealed a disconnect between theory-driven anthropomorphism constructs and the interactional features that users prioritize when evaluating AI systems (Schimmelpfennig et al., 2025, *preprint*). While prior literature emphasizes abstract attributes such as consciousness or intentionality, participants primarily relied on applied, interactional cues, such as conversational flow, responsiveness, authenticity, and perspective-taking, when judging human-likeness. Concepts such as “having a soul” or “moral agency” were rarely mentioned (less than 1%), suggesting that anthropomorphism in LLM interactions is grounded in conversational dynamics rather than metaphysical beliefs (Schimmelpfennig et al., 2025, *preprint*).

Moreover, in the context of LLMs, anthropomorphism is particularly salient. These systems can simulate empathy, reference prior conversation, and adopt personalized tones—features that may lead users to attribute to them both experiential qualities and agentic qualities (Barandiaran & Almendros, 2025; Proudfoot, 2011). Consequently, users may compromise their privacy or become susceptible to AI-enabled manipulation and coercion (Akbulut et al., 2024). At a psychological level, they may also develop emotional attachment to LLMs (Akbulut et al., 2024), with implications for wellbeing and relational behavior. Moreover, anthropomorphism of LLMs is not uniform. It is shaped by design characteristics such as capabilities, autonomy, conversational style, tone, response variability, and human-like naming, as well as conversational sociability including warmth, empathy, and relational cues (Rzepka & Berger, 2018; Zhao et al., 2025; Kumar et al., 2025; Luther et al., 2024; Pham et al., 2024; Xi et al., 2024).

Furthermore, anthropomorphic perceptions and its relational consequences are shaped by user-level characteristics, such as social motivations, emotional needs (Pentina et al., 2023), and demographic background (Jacobs et al., 2022; Uysal et al., 2023). Anthropomorphism can also have opposite psychological effects depending on cultural context. For instance, one study showed that Brazilian participants had increased trust, engagement, and perception of the AI as a social partner, whereas Japanese participants exhibited reduced trust and lower willingness to continue interaction under more anthropomorphic conditions (Schimmelpfennig et al., 2025, *preprint*).

Taken together, anthropomorphism of LLMs is inherently context-dependent; the same LLM’s behavior may be interpreted differently across situations or user groups (Abercrombie et al., 2023). As Gambino et al., (2020) note, users do not apply a fixed “sociality script” to all technologies. Instead, users dynamically adjust their engagement based on the cues presented and their own interaction goals. However, research on anthropomorphism in LLMs remains fragmented, with inconsistent definitions, various measurement tools, and mixed findings.

The present scoping review therefore seeks to explore how LLM anthropomorphism impacts users’ perception and experience, including psychological (e.g., trust, emotional engagement, and attachment) and behavioral outcomes (e.g., intention to use), under what conditions it emerges, and how system- and user-level factors influence the perceived anthropomorphism.

1.2 Research Questions

This scoping review was guided by the following research questions:

1. How does anthropomorphism of LLMs influence specific psychological outcomes (e.g., trust, emotional engagement, and attachment) and behavioral outcomes (e.g., intention to use)?
2. Which design and functional characteristics of LLMs (e.g., conversational style, memory) influence the perception of anthropomorphism?
3. Which human user characteristics (e.g., personality traits, emotional needs, prior experience) are associated with the tendency to anthropomorphize LLMs?

By reviewing the empirical literature, we aim to identify findings across contexts, highlight methodological trends and limitations, and provide evidence-based recommendations for the ethical and context-sensitive design of anthropomorphic LLMs.

2. Methods

Our methodology followed the Joanna Briggs Institute (JBI) methodology for scoping reviews (Peters et al., 2020) and was reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR: (Tricco et al., 2018). This scoping review was designed to map the existing literature on the given topic, with the aim of synthesizing findings within a broader field (Daudt et al., 2013).

2.1 Information Sources and Search Strategy

The search strategy, including all identified keywords and index terms, was adapted for each included database and/or information source. Searches were conducted across the following databases: PubMed (<https://pubmed.ncbi.nlm.nih.gov/>), Google Scholar (<https://scholar.google.com/>), PsycInfo (<https://psycinfo.apa.org>), Scopus (<https://www.scopus.com>), Web of Science (<https://www.webofscience.com>), IEEE Xplore (<https://ieeexplore.ieee.org>), ACM Digital Library (<https://dl.acm.org/>), arXiv (<https://arxiv.org>), and Centre for Reviews and Dissemination (<https://www.york.ac.uk/crd/>). Google Scholar was searched in incognito mode to remove the influence of past search histories. The reference lists of all included studies were screened for additional documents. The following advanced searches were done: (Anthropomorphism OR Anthropomorphization OR "human-likeness" OR "mind attribution") AND ("Large Language Models" OR LLM OR chatbot* OR "Generative AI" OR "Conversational AI" OR GPT). We additionally tested a broader combined string to ensure no studies were missed: (Anthropomorphism OR Anthropomorphization) AND ("Large Language Models" OR LLM OR chatbot* OR "Generative AI" OR "Conversational AI" OR GPT) AND ("affective empathy" OR "cognitive empathy" OR warmth OR competence OR "self-similarity" OR "perceived similarity" OR personality).

The last search was conducted in January 2026.

2.2 Study Selection

Eligibility criteria were determined prior to study selection. Specifically, this review included only peer-reviewed and empirical studies (quantitative, qualitative, and mixed-methods) that explicitly addressed anthropomorphism, either as a primary focus or as a key variable shaping user perception and experience. Further, studies had to involve LLMs using a text-based interface; those employing voice-based or multimodal interactions were excluded. Additional inclusion criteria included publication in English and from 2020 onward to mark the rapid development and deployment of LLMs. Studies were excluded if they were non-empirical (e.g., theoretical papers, opinion pieces, editorials, or literature reviews), focused on robotic or embodied agents, or examined non-LLMs such as rule-based systems. Research that did not explicitly address anthropomorphism or that assessed only technical outcomes like accuracy or response time, without examining psychosocial or experiential aspects, was also excluded. Search results were imported into Covidence (www.covidence.org) for screening. After automatic duplicate removal, three reviewers (*blind*) independently screened titles and abstracts against inclusion criteria. Full-text articles of potentially eligible studies were then assessed. Disagreements were resolved through discussion until consensus was reached.

2.3 Data Extraction

Data extraction was performed utilizing Covidence. The following fields were extracted for each included study: title, authors, country where the study was conducted, characteristics of the study (methods, aim of the study, study design, participants, chatbots used, and results). Two reviewers (*blind*) independently extracted data and disagreements were resolved through discussion. Each extraction was checked by a third reviewer (*blind*) to ensure reliability. All extracted data was securely stored within Covidence's cloud-based system, which complies with data protection standards. The platform's automated backup system ensures data safety throughout the review process. After the data extraction, the dataset was exported from Covidence into Excel for synthesis.

2.4 Data synthesis

A narrative thematic analysis was conducted to identify patterns, themes, and insights across the included studies, consistent with JBI scoping review methodology (Peters et al., 2020). Extracted data were organized into a structured summary table, including study aims, design, population, LLM type, and key findings. Extracted findings were organized into three categories: i) impact of perceived anthropomorphism on users; ii) system-level factors influencing anthropomorphism; and iii) user-level factors influencing anthropomorphism.

3. Results

The literature search yielded a total of $n = 2978$ studies ($n = 2899$ from database searching and $n = 79$ from citation searching), as shown in the PRISMA flow diagram in Fig. 1. After duplicates were removed, 1780 studies remained. Following title and abstract screening, further 1332 studies were removed as not

compliant with the eligibility criteria for a total of 448 studies in the full-text screening. Following the full-text screening an additional 403 studies were excluded, yielding a total of 45 publications included in the review.

[Figure 1]

3.1 Sample and Study Characteristics

As shown in Fig. 2, the majority of publications were from 2024 ($n = 21$), followed by 2025 ($n = 18$), 2023 ($n = 6$) and 2022 ($n = 1$). Regarding the geographical distribution, some studies were conducted across multiple countries; therefore, each country was counted separately. Accordingly, the majority of studies were conducted in Asia ($n = 26$; China = 17, South Korea = 4, India = 2, United Arab Emirates = 1, Turkey = 1, Vietnam = 1), followed by North America ($n = 9$; United States = 8, Canada = 1) and Europe ($n = 12$; Germany = 3, The United Kingdom = 3, Italy = 3, The Netherlands = 1, Norway = 1). For details on the number of studies published per year in each country, see Fig. 3. Methodologically, the included studies employed different designs, with some studies adopting more than one methodological approach. Most studies used a cross-sectional quantitative design ($n = 20$), followed by mixed-methods approaches combining qualitative and quantitative approaches ($n = 9$). Other studies employed experimental designs, including between-subjects ($n = 9$) and within-subjects ($n = 1$) designs. In addition, 5 studies employed qualitative designs, including grounded theory, and autoethnographic approaches. Finally, one study adopted a longitudinal design. Moreover, the 45 included studies in this review employed different types of LLMs which differed in their capabilities, including reasoning abilities, memory of prior interactions, real-time responsiveness, and multimodal input processing. A subset of studies did not specify the exact LLMs used, limiting comparability across findings. For example, in some studies, data were collected through online questionnaires in which participants reported general use of LLMs without references to a specific model. Nevertheless, several studies employed LLMs powered by OpenAI, including ChatGPT (Susnjak & McIntosh, 2024), GPT-3.5 (OpenAI, 2023), GPT-3 (OpenAI, 2022), and GPT-4 (Sanderson, 2023).

[Figure 2]

[Figure 3]

3.2 Impact of Perceived Anthropomorphism

3.2.1 Psychological outcomes

Trust. Across studies, perceived anthropomorphism of LLMs was often linked to users' trust. Trust was commonly defined as the degree to which users perceive the information provided by technology as reliable, capable, and credible. Several studies found a positive relationship between perceived anthropomorphism and users' trust (Choi et al., 2023; Y. Li & Lee, 2025; Luther et al., 2024; Pham et al., 2024; Skjuve et al., 2022; Zhao et al., 2025). Importantly, the strength and direction of this relationship

varied across contexts. For instance, Skjuve et al., (2022) showed that while anthropomorphic perceptions were related to trust, this relationship was indirect and contingent on relational factors such as perceived social presence and interaction quality. Similarly, Zhao et al., (2025) demonstrated that anthropomorphic communication cues (e.g., conversational tone and cultural tailoring) increased trust only indirectly by enhancing perceived friendliness and credibility. In the context of online grocery shopping, Chakraborty et al., (2024) found that perceived anthropomorphism did not directly influence trust in the system. Instead, anthropomorphism acted as a moderating factor, strengthening the relationships between interaction quality, credibility, perceived threat, and users' attitudes toward the chatbot, which in turn shaped trust formation.

Importantly, some studies differ in conceptualizing trust, some treating it as a unidimensional construct, while others distinguish between cognitive-based trust (i.e., confidence in task accuracy and functionality) and emotional-based trust (as the degree to which one feels secure and comfortable relying on the trustee). For instance, Y. Li & Lee, (2025) found that anthropomorphism significantly increased both cognitive and emotional trust, with a stronger effect on emotional trust. In contrast, Luther et al., (2024) showed that in collaborative writing contexts, anthropomorphism was primarily associated with cognitive trust rather than affective trust.

Finally, other studies highlighted potential negative effects of anthropomorphism. Ding et al., (2023) found that students who had less anthropomorphism of ChatGPT exhibited higher levels of trust, whereas those with strong anthropomorphism were more likely to express skepticism. Similarly, in clinical contexts, Spatscheck et al., (2024) found that increased anthropomorphism reduced physicians' trust and led to lower levels of cognitive engagement, which in turn increased the risk of inappropriate reliance on the system.

Taken together, these findings suggest that the relationship between perceived anthropomorphism and trust is not uniform. Its direction and strength appear to vary as a function of the domain of use, the type of trust considered (cognitive vs. emotional), and the mediating role of relational factors such as social presence and credibility.

Emotional Responses and Engagement. Across studies, perceived anthropomorphism was found to play a role in shaping users' emotional responses and levels of engagement with LLMs. For instance, in child-LLM interactions, Seo et al., (2024) showed that children developed strong emotional engagement with the system, frequently perceiving it as a close friend with whom they could share personal experiences and emotions. Qualitative evidence further illustrates how perceived anthropomorphism increased emotional involvement and relational interpretations of LLMs. For example, Depounti et al., (2023) found that users frequently attributed emotions, intentions, and relational qualities to Replika, leading to strong affective engagement and perceived intimacy. Similarly, Folk et al., (2025) reported that higher levels of perceived anthropomorphism were associated with stronger feelings of social connection toward the LLM and, consequently, greater relational engagement during the interaction. Another study found that the relationship between anthropomorphism and emotional responses is not

always direct, but mediated by effort expectancy (the degree to which using LLMs are perceived as easy or requiring little effort; Mutlu, 2024).

Several studies also highlight that perceived anthropomorphism can give rise to adverse emotional outcomes. In a large-scale study of 2,026 Chinese undergraduates, C. Wang & Yin, (2025) found that higher levels of perceived anthropomorphism were associated with a greater likelihood of perceiving LLMs as a burden or obstacle rather than a resource, and in turn, with lower learning productivity. Similarly, Laestadius et al. (2024), in a grounded theory analysis of Replika users, found that emotional dependence on the chatbot frequently gave rise to negative emotional experiences — including guilt, anxiety, and distress — particularly in two contexts: when users disclosed sensitive mental health concerns to the system, and when the chatbot failed to meet their relational expectations. Other studies also indicate that anthropomorphic perceptions may elicit fear, anxiety, and discomfort when LLM behavior appears unpredictable or incoherent (Rapp et al., 2025; T. Zhang & Tong, 2025), which was associated with more negative attitudes toward the system and, in some cases, discontinuation of use (T. Zhang & Tong, 2025).

Overall, these findings suggest that anthropomorphism shapes emotional responses through both positive and negative pathways. While it may foster engagement and relational involvement, its effects are contingent on interaction context, user vulnerability, and the degree to which the LLM meets relational expectations.

Emotional Attachment. Across studies, perceived anthropomorphism was frequently associated with the development of users' emotional connection and attachment toward LLMs (Giudici et al., 2025; Krapp et al., 2024; Laestadius et al., 2024; Liu et al., 2025; Maples et al., 2023; Pentina et al., 2023; Zhou & Zhang, 2024). However, several studies showed that emotional attachment emerged only through sustained social interaction and perceived relational engagement with the LLM. For instance, Pentina et al., (2023) showed that anthropomorphism did not directly predict attachment to a social chatbot, rather it was fully mediated by social interaction (as the extent to which users engaged in reciprocal, emotionally meaningful exchanges with the system). Similarly, Skjuve et al., (2022) demonstrated that emotional attachment develops gradually over time. Although users described initial interactions as superficial or similar to meeting a stranger, longitudinal evidence showed that repeated interactions increased emotional attachment, particularly when interactions involved self-disclosure, perceived reciprocity, and consistent social engagement. In some cases, users came to perceive LLMs as possessing emotions or needs of their own, leading to perceived bidirectional relationships in which users felt Replika needed them (Laestadius et al., 2024).

At the same time, several studies highlighted potentially negative consequences of emotional attachment. Zhou and Zhang (2024) found that higher levels of emotional attachment to LLMs were associated with increased compulsive use and addiction-related symptoms. Similarly, Huang and Huang (2025) reported that perceived anthropomorphism positively predicted emotional attachment, which in turn was a predictor of technology addiction. In contrast, functional attachment, driven by system quality

and information quality, did not significantly predict addictive use, suggesting the central role of affective mechanisms in driving problematic engagement with LLMs.

These findings suggest that emotional attachment to LLMs is not an automatic consequence of anthropomorphic perception, but an outcome that develops gradually through sustained relational engagement. While attachment can support positive outcomes such as continued use and social connection, it also carries risks of compulsive use and dependency, particularly when affective rather than functional mechanisms drive engagement.

Perceived competence and warmth. In some studies, anthropomorphism was associated with users' perceptions of LLM competence (perceived skill, intelligence, and efficacy) and warmth (caring, trustworthy, and emotionally engaging; (Kumar et al., 2025; Luther et al., 2024; Pham et al., 2024; Xi et al., 2024). For instance, Kumar et al., (2025) demonstrated that anthropomorphic characteristics of LLMs enhanced perceived competence which, in turn, positively predicted perceived authenticity. Nevertheless, in task-oriented contexts, Laestadius et al., (2024) found that users perceived ChatGPT as highly competent despite low levels of perceived warmth, indicating that perceived competence can also emerge independently of anthropomorphic perceptions.

Taken together, these findings suggest that perceived competence and warmth function as distinct mediating pathways through which anthropomorphism influences user experience. Warmth may be more closely tied to relational and affective outcomes, whereas competence may be more relevant in task-oriented contexts – and may emerge independently of anthropomorphic perception when users prioritize functional accuracy.

3.2.2 Behavioral Outcomes

Intention to use. Across studies, perceived anthropomorphism has been frequently associated with users' intention to use and continued use of LLMs. However, evidence suggests that this relationship is often mediated by cognitive, affective, and motivational factors. In educational settings, perceived anthropomorphism has been shown to shape students' attitudes toward LLMs, which in turn predict their intention to use them for learning purposes (Al-Emran et al., 2024; Polyportis & Pahos, 2025). Choi et al., (2023) and Liu et al., (2025) found that anthropomorphism positively predicted students' intention to continue using LLMs by enhancing perceived enjoyment, usefulness, and emotional satisfaction. Similar results were found in professional contexts. For example, Gupta (2024) found that entrepreneurs' perceptions of anthropomorphism in ChatGPT increased perceived ease of use, enjoyment, and usefulness which, in turn, increased positive emotions and adoption intentions. Finally, S. Li et al., (2025) found that perceived anthropomorphism increased adolescents' intention to use mental health LLMs, by enhancing emotional engagement and reducing psychological distance.

Several studies found trust as a mediator in the relationship between perceived anthropomorphism and usage intention or reliance (D. Kim et al., 2024; Pham et al., 2024; Spatscheck et al., 2024;). Y. Li & Lee (2025) found that anthropomorphism did not directly drive adoption intentions, but instead influenced

adoption intention through emotional and cognitive trust. In line with this, Chen et al. (2025) demonstrated that anthropomorphic cues in LLM-based medical tools facilitated trust repair after service failures by increasing perceived social support, which subsequently predicted continuance usage intentions. Moreover, X. Li et al., (2025) showed that anthropomorphic features such as perceived warmth and empathy increased users' intention to adopt LLMs indirectly by enhancing self-efficacy. Accordingly, M. Zhang et al., (2025) demonstrated that interactional anthropomorphism (defined as the extent to which an AI exhibits human-like communicative behaviors such as warmth, empathy, and conversational responsiveness) plays a compensatory role by reducing psychological distance and increasing relational trust, which, in turn, increased users' intention to continue using LLMs. In contrast, functional anthropomorphism, referring to perceptions of the AI's competence, intelligence, and task performance, did not produce the same effect. Zhou & Wu (2024) demonstrated that perceived anthropomorphism enhanced users' flow experience, which in turn increased migration intention from traditional Q&A platforms to LLM-based services. Similarly, Zhou and Li (2025) found an indirect effect of anthropomorphism on switching intention through user experience and dissatisfaction. In a study of online health consultation services, Y. Li et al., (2025) found that the relationship between anthropomorphism and behavioral intention was fully mediated by social presence and perceived source credibility. Further, several studies indicated that anthropomorphic design features enhanced users' satisfaction with LLMs, which in turn predicted continued usage intentions (Depounti et al., 2023).

However, findings across studies were not consistently positive. For example, C. Kim, (2025) reported only a modest effect of anthropomorphism on users' intention to use LLMs. Moreover, W. Kim et al., (2025) showed that higher anthropomorphism led to increased privacy concerns and lower purchase intention. Zhou and Wu (2025) showed that anthropomorphism also increased perceived affordance of the LLM (users' recognition of the system's possible utility), thereby increasing their intention to disclose information and, thus, their privacy risk.

Overall, these findings suggest that anthropomorphism influences behavioral intention primarily through indirect pathways, rather than through a direct effect on usage decisions. This mediated pattern, observed across diverse contexts, suggests that anthropomorphism may function as a relational facilitator rather than a direct driver of adoption.

Social relationships. Several studies examined how anthropomorphism in LLMs shapes social dynamics and interpersonal perceptions. For instance, Jacobs et al., (2024) showed that exposure to ChatGPT's responses increased individuals' self-perceived agency and experiential capacity while simultaneously reducing the belief that these traits are uniquely human, suggesting that exposure to anthropomorphic LLM output may alter perceptions of the self in relation to others. Similarly, Xi et al., (2024) found a differentiated effect of anthropomorphic cues: function-oriented traits (e.g., competence and rationality), reduced perceived identity threat, and, in turn, decreased user aggression. By contrast, value-oriented human-like traits (e.g., empathy and morality) increased identity threat, indirectly leading to higher levels of aggression toward LLMs.

Additionally, Maples et al., (2023) showed that users who attributed identity to Replika reported increased self-reflection and personal growth, which in turn was associated with improved communication and social engagement with other humans. Further, K. Wang et al., (2025) demonstrated that higher levels of AI anthropomorphism were associated with greater exercise motivation among adolescents, with this relationship being partially mediated by increased technology acceptance and enhanced self-efficacy. Furthermore, Ma et al., (2025) found that LLM use promoted international students' sociocultural adaptation via cognitive (positive reappraisal) and emotional (perceived empathy) mechanisms, with anthropomorphism strengthening these indirect effects by increasing perceived social support from the LLM.

Interestingly LLM anthropomorphism also appears to shape feelings toward LLM users. For example, Dang & Liu (2024) reported that LLM anthropomorphism mitigated dehumanization toward LLM users indirectly by reducing AI aversion, which in turn increased acceptance of LLM use and more positive social evaluations of LLM users.

Taken together, these findings extend the consequences of LLM anthropomorphism beyond the individual user to the broader social context. Anthropomorphic perception may influence how users understand themselves in relation to AI systems, with implications for identity, interpersonal dynamics, and social evaluation of AI use. These effects are not uniformly positive or negative, but depend on the type of anthropomorphic cues activated and the social context in which they occur.

3.3 System-level characteristics

Across studies, anthropomorphic perceptions appear to emerge from an interplay between system-level design features and users' interpretative processes. Qualitative evidence indicates that emotionally expressive and socially oriented dialogue, such as the use of warmth, humor, or conversational tone, contributes to perceived anthropomorphism (Depounti et al., 2023; Pentina et al., 2023). Experimental evidence shows that interactional anthropomorphism can compensate for limited functional performance by increasing trust and reducing psychological distance (M. Zhang et al., 2025). This aligns with evidence that attributing emotional or human-like capacities to LLMs increases engagement even in the absence of objective performance improvements (Liu et al., 2025). For example, Dorigoni and Giardino (2025) demonstrated that perceived anthropomorphism emerges when LLMs use emotionally expressive language or a personalized tone. However, this perception collapses once users become aware that the message was generated by LLMs. Moreover, Zhao et al., (2025) showed that manipulating the LLMs' tone and communication style to align with culturally specific norms (i.e., levels of formality and social distance) may shape anthropomorphic perceptions. At the same time, evidence suggests that certain system behaviors, such as inconsistent, unsettling, or emotionally inappropriate responses, may lead users to attribute agency or internal states to the system, thereby increasing perceived anthropomorphism (Rapp et al., 2025). This, in turn, may give rise to maladaptive forms of anthropomorphism, in which users over-attribute emotions or intentions to the system (Laestadius et al., 2024). Similarly, when LLMs were perceived as too machine-like, (e.g., repeating scripts, glitching, lack of

contextual understanding and memory), users reported reduced engagement and dissatisfaction with the interaction (Depounti et al., 2023), suggesting a reduced anthropomorphic perception.

Overall, these findings suggest that anthropomorphic perception is not an inherent property of LLMs but an interactional outcome shaped by specific design features. Importantly, these system-level factors do not appear to operate in isolation but interact with users' interpretative tendencies and contextual expectations.

3.4 User-level characteristics

Several user-level characteristics emerged as relevant in shaping perceived anthropomorphism. First, users' social and emotional needs appear to play a role in shaping anthropomorphic interpretations, as individuals project expectations of emotional responsiveness and social presence onto chatbots, particularly in contexts of loneliness and relational seeking (Depounti et al., 2023; Laestadius et al., 2024; Skjuve et al., 2022). Extending this perspective, Pentina et al., (2023) showed that perceived social presence and relational continuity may function as drivers of emotional engagement with conversational agents, fostering attachment and sustained interaction. Similarly, Maples et al., (2023) report that users who experience loneliness, emotional distress, or major life transitions tend to interpret agents such as Replika as socially meaningful entities, describing them as friends, companions, or mirrors of the self .

Second, motivational factors indirectly shape how users engage with anthropomorphized chatbots. Pentina et al., (2023) showed that motivations such as social connection, curiosity, or entertainment moderate the relationship between perceived anthropomorphism and emotional attachment, with socially motivated users being more likely to develop stronger relational bonds with the chatbot. In contrast, users who approach chatbots primarily with technical or intellectual curiosity tend to develop weaker relational engagement over time, which is associated with lower levels of perceived anthropomorphism (Skjuve et al., 2022).

Third, affective traits such as fear of AI shape how anthropomorphic perceptions translate into behavioral outcomes. Liu et al., (2025) indicated that while anthropomorphism positively predicts the intention to continue usage, this effect was attenuated among users with higher levels of AI-related anxiety.

Fourth, individual differences in anthropomorphism and mind attribution moderated users' social responses to AI. Specifically, higher general anthropomorphic tendencies were associated with stronger feelings of social connection independent of interaction length or disclosure behavior (Folk et al., 2025).

Fifth, prior experience with and affinity toward LLMs also shape perceived anthropomorphism. In particular, higher familiarity and affinity for technology were associated with greater engagement, more frequent use of anthropomorphic language, and stronger perceptions of competence and collaboration, which may indirectly foster anthropomorphic interpretations of LLMs (Luther et al., 2024). Rapp et al., (2025) further suggest that limited familiarity with LLMs can lead users to anthropomorphize the system as a cognitive strategy to resolve ambiguity and unexpected responses, thereby increasing perceived

agency and social intentionality. In addition, user-level cognitive characteristics play a moderating role. Zhou & Wu (2025) showed that algorithm literacy shapes how users interpret anthropomorphic cues and system affordances, strengthening the effect of perceived anthropomorphism on perceived usefulness while reducing reliance on peripheral cues such as social influence or privacy concerns.

Lastly, demographic and experiential differences were found to moderate the effects of anthropomorphism. C. Wang & Yin (2025) showed that students from rural backgrounds and those in earlier years of study were more likely to experience anthropomorphic cues as hindering rather than supportive, whereas more experienced students appeared better able to integrate such cues into their learning.

Taken together, these findings suggest that anthropomorphic perception is not a uniform response to system design, but is shaped by users' psychological characteristics. These individual differences have important implications for the design of LLMs, as the same anthropomorphic features may elicit different responses across user populations.

4. Discussion and Conclusions

This scoping review aimed to synthesize empirical evidence on how perceived anthropomorphism of LLMs shapes users' psychological and behavioral responses, as well as the system- and user-level factors that modulate these effects. Building on the findings synthesized above, this section discusses their theoretical and practical implications, and identifies directions for future research. Overall, the evidence suggests that the effects of LLM anthropomorphism are neither uniform nor inevitable, but appear to emerge from the dynamic interplay between system design features, user characteristics, and interaction context.

A first theoretical implication concerns the nature of trust in human-LLM interaction. The reviewed evidence challenges the assumption that anthropomorphism straightforwardly increases trust. Across studies, the direction and magnitude of this relationship depended on the type of trust considered and the interaction domain. In relational and supportive contexts, anthropomorphic cues enhanced emotional trust by fostering perceived social presence and credibility. In task-oriented and professional settings, however, the same cues were associated with reduced cognitive trust and increased skepticism — suggesting that anthropomorphism may interfere with users' evaluation of functional accuracy when this is prioritized over relational engagement (Ding et al., 2023; Spatscheck et al., 2024). This pattern is consistent with dual-process accounts of technology acceptance, in which affective and cognitive evaluations operate through distinct pathways (Y. Li & Lee, 2025; M. Zhang et al., 2025). These findings align with a large-scale study (N = 3,500) indicating that increased anthropomorphism did not lead to higher trust at the aggregate level. In an incentivized trust game, participants did not allocate more resources to more human-like AI systems. This suggests that anthropomorphism alone may be insufficient to increase behavioral trust, which appears to depend more strongly on perceived competence and goal alignment (Schimmelpfennig et al., 2025).

A second major theme concerns the temporal dynamics of emotional attachment (Depounti et al., 2023; Folk et al., 2025; Seo et al., 2024). The reviewed evidence suggests that emotional attachment to LLMs is not an immediate response to anthropomorphic design, but an outcome that develops gradually through sustained relational engagement involving self-disclosure, perceived reciprocity, and interaction consistency (Pentina et al., 2023; Skjuve et al., 2022). Notably, this attachment was disrupted when LLM behavior violated relational expectations – through inappropriate responses, lack of memory, or unexpected updates (Dorigoni & Giardino, 2025; Skjuve et al., 2022). These findings suggest that affective engagement appears to depend on the consistency and coherence of the interaction over time rather than exclusively perceived anthropomorphism. This may be because affective commitment tends to build gradually over time, whereas cognitive dissonance can emerge quickly, leading to immediate behavioral changes. This discrepancy may reflect the asymmetric temporal dynamics of affective and cognitive processes: while emotional attachment develops gradually through repeated interaction, violations of expectations may trigger rapid cognitive re-evaluation, prompting quicker behavioral disengagement. This temporal asymmetry has important design implications: anthropomorphic features that foster early relational engagement may generate dependency without the robustness needed to sustain it under conditions of system failure or behavioral inconsistency. Some evidence also highlights risks of overdependence and addiction, with affective mechanisms – rather than functional ones – appearing to play a more prominent role in problematic engagement (Huang & Huang, 2025; Zhou & Zhang, 2024). Taken together, these findings underscore the need to consider the potential negative psychological consequences of anthropomorphic design, particularly in contexts where sustained or emotionally intensive interaction is expected.

Across behavioral outcomes, the effects of perceived anthropomorphism were mediated by cognitive, affective, and motivational factors such as trust (D. Kim et al., 2024; Y. Li & Lee, 2025; Pham et al., 2024; Spatscheck et al., 2024; M. Zhang et al., 2025), emotional engagement (S. Li et al., 2025), social support (Chen et al., 2025), and perceived empathy (Y. Li et al., 2025). Perceived competence and warmth also emerged as mediators, though with meaningful distinctions in how they functioned. In this regard, a notable distinction emerged between two forms of anthropomorphism. Interactional anthropomorphism – characterized by warmth, empathy, and conversational responsiveness – was found to reduce psychological distance and strengthen relational trust, which was associated with greater intention to continue engaging with LLMs. Functional anthropomorphism, by contrast, which relates to perceived intelligence and competence, did not directly predict behavioral intention. Instead, it operated as a cognitive mediator, shaping users' confidence in their ability to interact affectively with the system (M. Zhang et al., 2025). This distinction has important theoretical implications, suggesting that the social and instrumental dimensions of anthropomorphism exert influence through fundamentally different psychological pathways. These findings are supported by experimental evidence suggesting that anthropomorphism in LLM interactions is primarily driven by social and relational cues rather than by evaluations of system performance, functioning as a relational heuristic that shapes engagement, trust, and willingness to interact rather than reflecting beliefs about the AI's cognitive capacity (Schimmelpfennig et al., 2025, *preprint*).

Importantly, anthropomorphism also carries broader implications for how users perceive themselves and relate to others. Evidence suggests that anthropomorphic cues may influence self-other boundaries by reducing the belief that LLM traits are uniquely human (Jacobs et al., 2024). Thus, rather than anthropomorphising the system, it seems to induce users to reassess what it means to be human in relation to these increasingly human-like technologies. Moreover, the consequences of anthropomorphism appear to depend on the LLMs' traits. When anthropomorphic cues highlight more functional traits (e.g., competence and rationality), they tend to reduce perceived identity threat and user aggression, whereas value-oriented traits (e.g., empathy and morality) increase identity threat (Xi et al., 2024). At the social level, studies indicate that anthropomorphic perceptions can reduce dehumanization toward AI users and foster more positive social evaluations (Dang & Liu, 2024), while also supporting self-reflection and social engagement (Maples et al., 2023). Taken together, these findings underscore that the consequences of anthropomorphism are neither uniform nor inevitable. As the findings on system- and user-level factors suggest, the direction and magnitude of these effects depend on the conditions under which anthropomorphism is perceived and the characteristics of the users experiencing it.

At the system level, emotionally expressive language, socially oriented dialogue, and communication tone and style — including degrees of formality and social distance — appear to shape the extent to which users attributed human-like qualities to LLMs (Depounti et al., 2023; Dorigoni & Giardino, 2025; Pentina et al., 2023; Zhao et al., 2025). At the user level, anthropomorphic perceptions were further modulated by individuals' social and emotional needs (Depounti et al., 2023; Laestadius et al., 2024; Maples et al., 2023; Pentina et al., 2023; Skjuve et al., 2022), motivational orientations (Pentina et al., 2023), affective traits (Liu et al., 2025), individual differences in the propensity to anthropomorphize and attribute mental states (Folk et al., 2025), and prior experience with LLMs (Luther et al., 2024). Taken together, these findings align with previous work suggesting that anthropomorphism functions as a socially driven interpretative process through which individuals attribute human-like qualities to non-human agents in order to satisfy social, cognitive, and motivational needs (Epley et al., 2007; Waytz et al., 2014). The interplay of system design features and user dispositional factors suggests that this process is neither purely stimulus-driven nor trait-dependent, but emerges from the dynamic interaction between the characteristics of the system and the psychological state of the user. Moreover, findings suggested that depending on the context, anthropomorphism generally enhanced user experience in social or supportive contexts, whereas excessive anthropomorphism sometimes reduced trust or elicited discomfort in formal or task-oriented settings. This aligns with the emergence of an “uncanny valley” effect, in which entities that closely resemble a human appearance or behavior induce discomfort and even aversion. Indeed, in some studies excessive or poorly calibrated anthropomorphic cues were associated with discomfort, distrust, and reduced acceptance (W. Kim et al., 2025; S. Li et al., 2025; Spatscheck et al., 2024). While early work on disembodied conversational agents demonstrated that anthropomorphic perceptions can emerge even in the absence of physical embodiment (Araujo, 2018), recent LLMs further appear to introduce a new type of uncanny valley rooted in linguistic rather than

visual cues (Kirkeby-Hinrup & Stenseke, 2025). Consistent with this, uncanny valley effects have been shown to hinder technology adoption (Shin et al., 2019).

Moreover, anthropomorphism appears to influence user behavior through affective mechanisms. As predicted by the CASA paradigm (Reeves & Nass, 1996), the reviewed findings are consistent with the view that anthropomorphism can be understood not as a conscious attribution of humanness, but as a default cognitive response triggered by socially meaningful signals. Users frequently responded emotionally to LLMs, developed trust and attachment, and engaged in relational behaviors despite knowing that the system lacks intentionality — precisely the pattern the CASA framework anticipates when technological systems display minimal social cues. Extending this account, the present findings further suggest that in LLM interactions this default social response is activated primarily through linguistic rather than visual or physical cues, pointing to a distinctively textual form of social actor perception that warrants further theoretical elaboration.

Taken together, as LLMs become increasingly integrated into education, healthcare, and everyday digital communication, understanding the psychological and behavioral effects of anthropomorphism is important for supporting responsible and sustainable use. These findings have concrete implications for the design, deployment, and regulation of LLMs. At the design level, anthropomorphic features may benefit from being calibrated to the interaction context: interactional cues such as warmth and empathy may be particularly suited to relational and supportive settings, whereas in task-oriented contexts they may undermine confidence in system accuracy and should be used with restraint. Systems designed for sustained interaction should also incorporate mechanisms that make the artificial nature of the system transparent and manage users' relational expectations, given the risk of emotional dependency identified across multiple studies (Huang & Huang, 2025; Zhou & Zhang, 2024). At the policy level, domain-specific regulatory guidelines may be warranted, particularly in high-risk contexts such as mental health, caregiving, and education, where users may be especially vulnerable to overreliance and emotional attachment. Finally, user-facing literacy interventions may help individuals — particularly those with high social or emotional needs — develop more accurate mental models of LLM capabilities, reducing the risk of miscalibrated anthropomorphic attributions. More broadly, managing the psychological consequences of anthropomorphism is not merely a design challenge but a public interest concern that warrants sustained attention from researchers, developers, and policymakers.

Strength and Limitations

Despite its contribution, several limitations of this review should be acknowledged. First, the conceptual ambiguity surrounding anthropomorphism extends into the scope of this review. The search strategy employed the broad term "anthropomorphism" to capture relevant studies, and may have excluded work focusing on related but conceptually adjacent constructs such as social presence, human-likeness, or animacy. Second, it included only peer-reviewed articles published in English, thereby excluding preprints, abstracts, and publications in other languages. Third, the included studies vary considerably in design, sample characteristics, and cultural context, which limits the comparability of findings across the

review. The review includes cross-sectional surveys, between-subjects experiments, longitudinal studies, qualitative analyses, and autoethnographic accounts — methodological approaches that differ substantially in their assumptions, generalizability, and susceptibility to bias. Furthermore, the majority of quantitative studies relied on self-report measures collected from convenience samples, predominantly students, which may not reflect the experiences of broader or more diverse user populations. The geographic distribution of studies is also skewed, with a disproportionate concentration in Asia — particularly China — and in WEIRD populations, limiting the cross-cultural validity of the findings. Given this heterogeneity, the thematic synthesis presented here should be interpreted as an exploratory mapping of the field rather than a definitive account of the effects of LLM anthropomorphism. The predominance of cross-sectional designs and self-report measures further limits causal inference. Additionally, as a narrative thematic synthesis, this review does not provide quantitative estimates of effect sizes, and findings should be interpreted accordingly. Fourth, much of the reviewed literature focused on ChatGPT, overlooking behavioral variation in other LLMs, especially as newer models incorporate multimodal capabilities and emotionally expressive features. Similarly, contextual moderators such as interaction duration, intensity, and user goals (task-oriented vs. affective) remain underexplored, despite their potential influence on anthropomorphism's effects. Indeed, empirical evidence shows that anthropomorphic behaviors do not typically emerge immediately, but rather surface after multiple turns of interaction (2–5).

Future research should aim to clarify the boundaries between anthropomorphism and adjacent constructs, using precise theoretical definitions and validated multidimensional measures. Longitudinal studies are particularly needed to assess how anthropomorphic perceptions of LLMs evolve over time and whether they lead to enduring changes in user trust, dependency, or social dynamics. Further investigations are needed as to how these attachments are formed and maintained, and under what conditions they shift from supportive to maladaptive. Furthermore, cross-cultural investigations are needed to understand how sociocultural norms influence the tendency to anthropomorphize and engage with LLMs. Ethical guidelines and regulatory frameworks will be increasingly important in domains such as education, mental health, and caregiving, where emotional attachment and trust must be carefully managed. Moreover, there is still a lack of consensus within both academia and industry regarding the acceptability of anthropomorphic features in AI systems (Akbulut et al., 2024). Research should also explore the optimal degree of human-likeness in LLMs.

Declarations

Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

This article does not contain any studies with human participants performed by any of the authors.

Competing interests

The authors have no conflicts of interest to declare that are relevant to the content of this article.

Author Contributions

Author Contribution Conceptualization: [blind]; Methodology: [blind]; Literature search [blind]; Data extraction [blind]; Thematic analysis: [blind]; Writing original draft preparation: [blind]; Writing review and editing: [blind].

Author Contribution

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Data Availability

This study is a scoping review and produced no original human-subject data. All data are derived from published studies cited in the manuscript. The data supporting the findings of this scoping review are openly available as supplementary materials at: https://osf.io/hmzsr/?view_only=2bf8af15fb3b414481b92304400b6763. Materials include database search export files (.ris format for each database consulted), inclusion and exclusion records, data extraction table, and full search strategy documentation.

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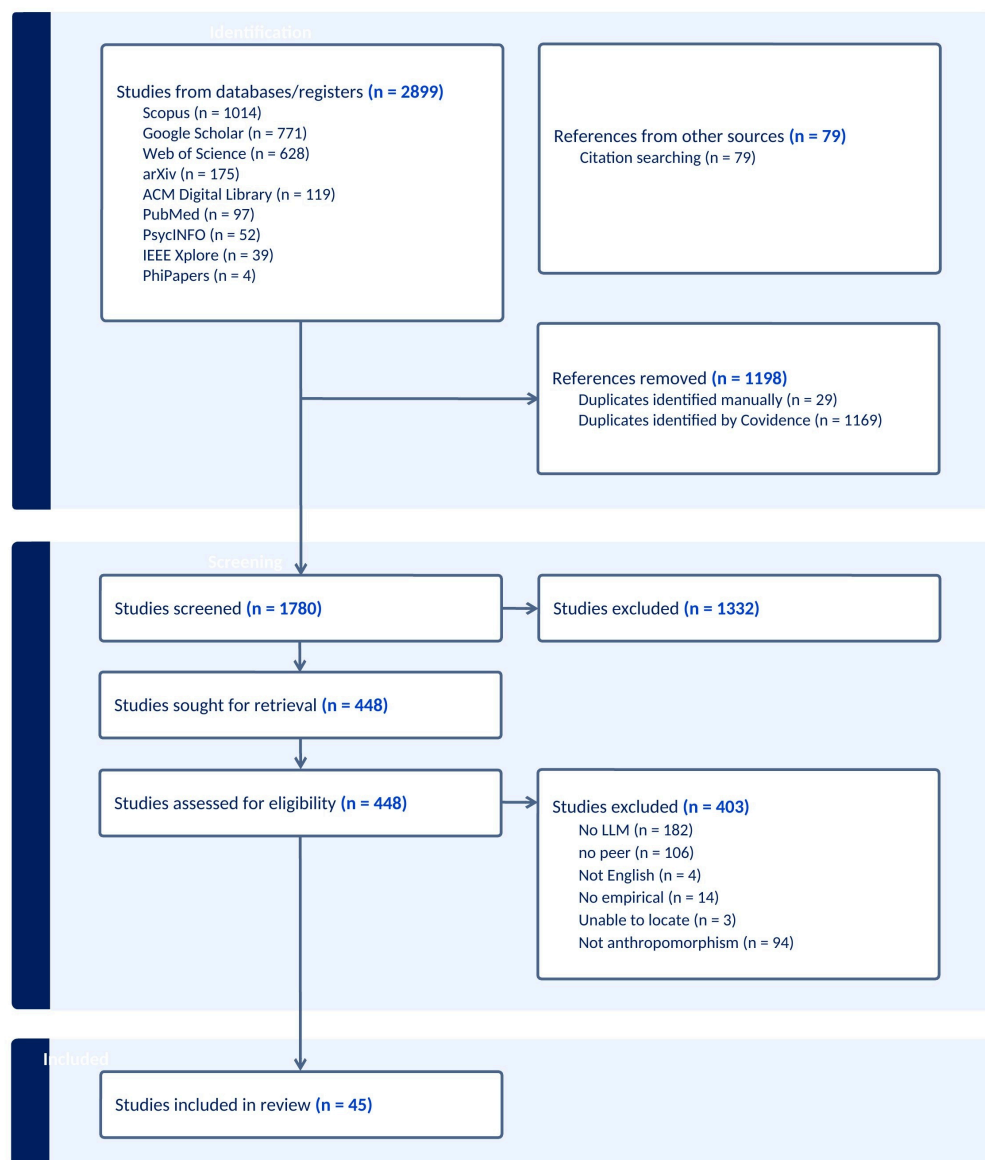
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Figures



10th April 2026



Figure 1

PRISMA flow diagram for the study selected

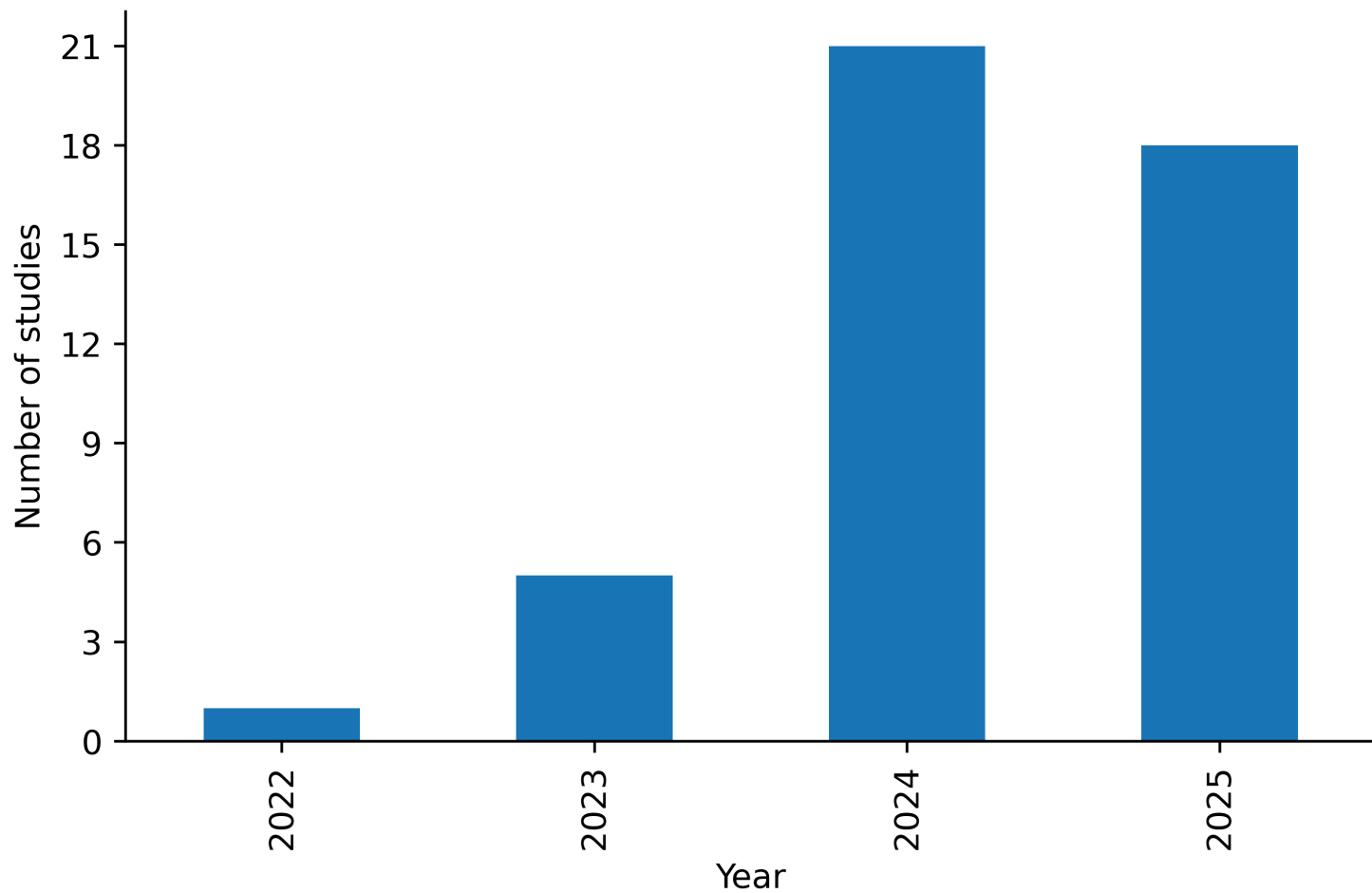


Figure 2

Number of included studies per publication year

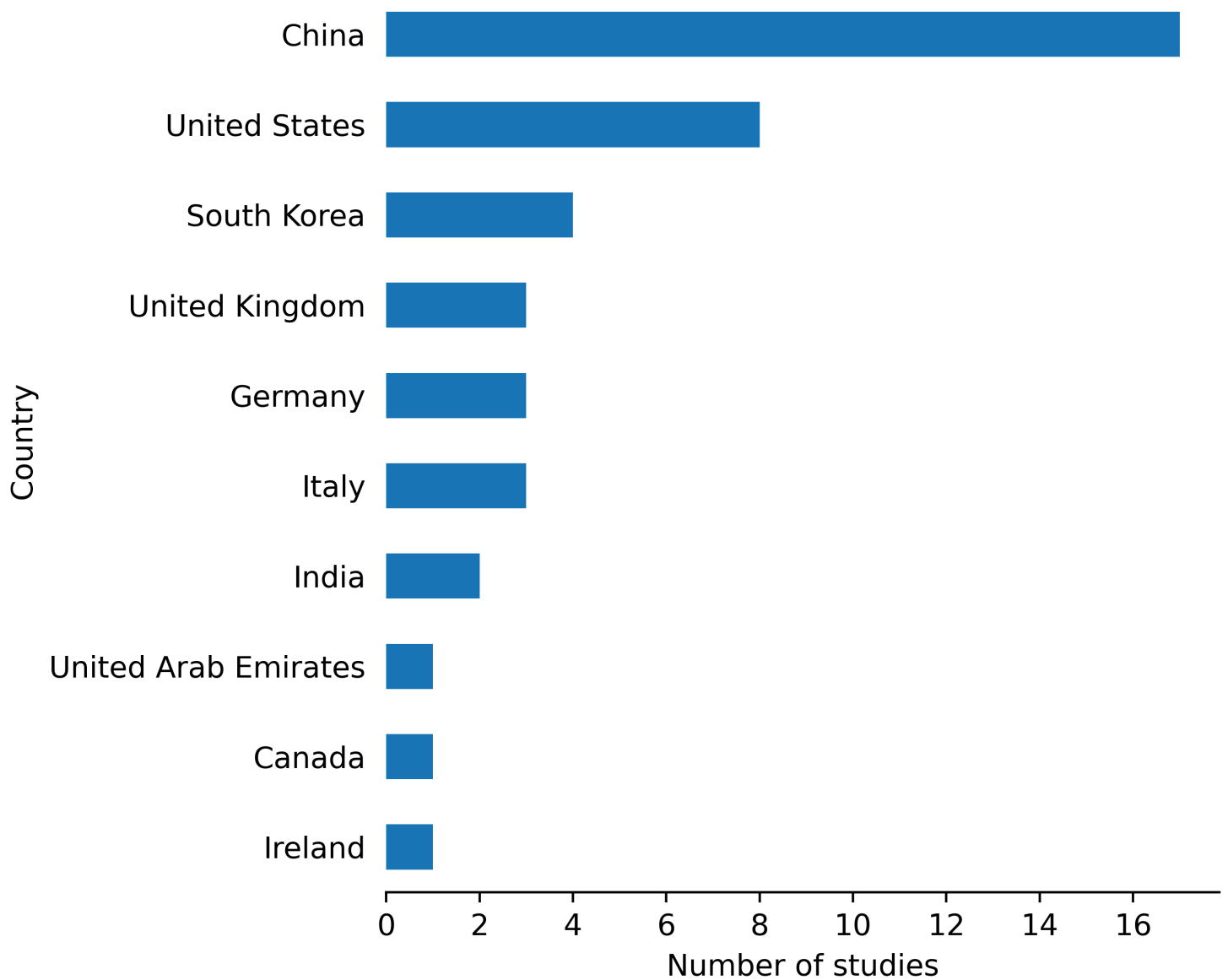


Figure 3

Number of included studies per year by country