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PII: S0160-791X(26)00168-5

DOI: https://doi.org/10.1016/j.techsoc.2026.103379

Reference: TIS 103379

To appear in: *Technology in Society*

Received Date: 3 December 2025

Revised Date: 20 March 2026

Accepted Date: 22 April 2026

Please cite this article as: Kostka G, Zhou H, Emotional Attachment to AI Chatbots: Evidence from Germany, China, South Africa, and the United States, *Technology in Society*, https://doi.org/10.1016/j.techsoc.2026.103379.

Emotional Attachment to AI Chatbots: Evidence from Germany, China, South Africa, and the United States

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1 Introduction

Artificial intelligence (AI) chatbots are rapidly becoming embedded in everyday life, shaping how individuals seek information, make decisions, and engage in social interaction. While these systems are typically framed as functional tools designed to provide efficient and personalized assistance (Hessari, Bai and Daneshmandi, 2024), their increasingly human-like and responsive nature enables forms of interaction that extend beyond instrumental use (De Freitas, Oguz-Uguralp and Kaan-Uguralp, 2025). Chatbots can simulate empathy, respond without judgment, and offer a sense of privacy, making them not only sources of information but also potential providers of emotional support (Ho, Hancock and Miner, 2018; Asim et al., 2025). As a result, users may begin to develop affective bonds with these systems, raising important questions about the broader social and behavioral consequences of everyday human–AI interaction (Pergantis et al., 2025; Huang and Huang, 2025; Huang, Shi and Pei, 2026; Fang et al., 2025).

Despite growing interest in emotional AI and human–machine interaction, existing research has primarily focused on specialized social chatbots (Latikka et al., 2025; Pu et al., 2019; Xie and Pentina, 2022; Ali et al., 2024; Skjuve et al., 2022) or on vulnerable user groups, such as individuals seeking mental health support (Ahmed et al., 2023; Saif et al., 2024; Manole et al., 2024; He et al., 2022). As a result, we know relatively little about whether and how emotional attachment emerges in interactions with widely used, general-purpose AI systems that are not explicitly designed for companionship. Moreover, prior studies typically examine single platforms or specific national contexts (e.g., Laestadius et al., 2024; Ho et al., 2023), limiting our understanding of how these dynamics unfold across different societal settings. Finally, while concerns about emotional dependence are frequently raised in public and policy debates (Boine, 2023), there is little systematic empirical evidence linking emotional attachment to measurable

forms of user dependence. Addressing these gaps is essential for understanding the broader societal implications of increasingly affective AI systems.

Relationships between users and affective AI technologies deserve public attention. Systematic reviews of social chatbots highlight risks ranging from emotional overreliance with negative impacts on real-world relationships to heightened loneliness (Boine, 2023; Laestadius et al., 2024; Fang et al., 2025). The severity of these risks has been underscored by multiple reports linking interactions with such chatbots to subsequent teen suicides (Roose, 2024; Nguyn, 2025). These high-profile cases have intensified public debate and spurred legislative responses in certain jurisdictions, such as Utah in the United States, where the development of mental health chatbots must involve licensed mental health therapists according to the newly enacted Artificial Intelligence Amendments (Moss and Cullimore, 2025). Despite these risks, the popularity of chatbots—both general-purpose (or generic) systems such as ChatGPT and DeepSeek and social chatbots such as Replika, Character.AI, and Anima—continues to grow. Millions of users worldwide report strong emotional bonds and high levels of trust toward these systems (Xie and Pentina, 2022).

It should be noted, however, that emotional attachment to chatbots is not inherently problematic. Moderate attachment can provide comfort or motivation. However, such attachment exists on a spectrum, and when it becomes intense enough to displace human relationships or daily functioning, it can shift into emotional dependence. Thus, it is crucial to understand the formation of emotional attachment and how it may develop into emotional dependence.

This study strives to answer these questions based on a cross-sectional online survey conducted in China, Germany, South Africa, and the United States. Our findings show that emotional attachment is not confined to vulnerable populations: at least one third of chatbot

users—and half of social chatbot users—report attachment-related behaviors to chatbots such as missing their chatbot or considering it a friend. Emotional support, the frequency and depth of use, and social network size all play important roles in shaping attachment. Intriguingly, a larger social network correlates positively with emotional attachment, suggesting that chatbots may function as supplementary, rather than substitutive, companions. In other words, individuals who rely on chatbots for emotional support, engage with them more frequently and intensively, and maintain larger social networks are more likely to develop emotional attachment. Moreover, we observe a strong correlation between emotional attachment and user dependence. Stronger attachment is associated with a higher level of self-reported difficulty of living and working without chatbots, a greater willingness to share secrets with chatbots, and a higher probability of using premium services.

While we observe universal dynamics across countries, notable cross-country differences in both chatbot adoption and emotional attachment exist. In China and South Africa, emotional attachment is particularly strong, with more than two thirds of users feeling free from judgment and experiencing a sense of privacy when interacting with chatbots. In the United States, this share is roughly half, while in Germany only one third of users feel free from judgment and about half report a sense of privacy. These patterns underscore that emotional attachment is shaped not only by individual usage behaviors but also by broader cultural and contextual conditions that vary markedly across countries.

The study makes three contributions. First, it provides the first cross-country analysis of emotional attachment to chatbots. Based on a dynamic interaction framework linking emotional support, usage patterns, and social context to attachment, we show that emotional attachment is not confined to social chatbots or vulnerable populations, but emerges systematically in generic

AI systems and translates into measurable forms of dependence across diverse socio-political contexts. This finding contributes to the growing literature on human–computer interaction (HCI) and affective computing (Picard, 1997; Pantic and Rothkrantz, 2003; Hudlicka, 2003). Second, we find that higher usage frequency and larger social networks correlate with stronger emotional attachment. This contrasts the social compensation and social enhancement literature, which predicts that individuals suffering from social exclusion or possessing limited offline social networks are more likely to turn to digital tools for support (Bryant, Sanders-Jackson and Smallwood, 2006) and engage in problematic use of such tools (Huang, Shi and Pei, 2025). Third, alongside universal patterns, the study also reveals country-specific variations, thus highlighting the role of socio-cultural factors in chatbot studies (Ho et al., 2022). Emotional attachment to chatbots is strongest in China, followed by South Africa and the United States, while levels in Germany are considerably lower. The findings underscore the need for a context-sensitive understanding of how and why users develop affective bonds with AI.

2 Emotional Attachment as a Social Phenomenon

Emotional attachment is a widespread human tendency. People routinely form bonds not only with other individuals but also with non-human entities, including but not limited to pets, personal possessions, and symbolic objects (Huang, Picart and Gillan, 2021). As digital technologies increasingly permeate everyday life, understanding how computational systems address users' affect has become a central concern in human–computer interaction (Hudlicka, 2003; Fong, Nourbakhsh and Dautenhahn, 2003). Pioneering work by Picard (1997, 2003a,b) conceptualizes affective computing as the design of systems capable of recognizing, expressing, interpreting, modeling, and responding to human emotions. This line of research highlights how emotionally

responsive machines can significantly influence users' perceptions and behaviors (Brave, Nass and Hutchinson, 2005; Nass et al., 2001; Shamekhi et al., 2016; Kim et al., 2019).

Empirical studies further demonstrate that when technologies convey empathy, warmth, or other emotional cues, individuals tend to increase information disclosure, perceive greater support, report more positive attitudes, and demonstrate higher levels of compliance (Brave, Nass and Hutchinson, 2005; McDuff and Czerwinski, 2018; Cassell and Thorisson, 1999; Lee and Liang, 2015; Ischen et al., 2020; Zhang and Sheng, 2026). These dynamics build on longstanding findings from media psychology and HCI showing that people readily anthropomorphize interactive technologies and respond to them as if they were social actors (Reeves and Nass, 1996; Hamacher et al., 2016). The Computers Are Social Actors (CASA) framework further points out two requirements in order for technologies to induce social interaction (Gambino, Fox and Ratan, 2020). First, technologies must demonstrate sufficient social cues. Second, users must perceive these technologies as autonomous sources.

Contemporary chatbots based on large language models clearly demonstrate substantial potential for intimate human–machine interaction. A growing body of literature shows that people can form emotional bonds with chatbots to obtain social support (Bae Brandtzæg et al., 2021; Xie and Pentina, 2022), and some users even develop romantic relationships with them (Djufril, Frampton and Knobloch-Westerwick, 2025; Chan et al., 2025; Li and Zhang, 2024). An analysis of 4.5 million conversations on Claude.ai, for instance, finds that 2.9% involve affective exchanges—defined as "dynamic, personal interactions motivated by emotional or psychological needs such as seeking advice, coaching, psychotherapy/counseling, companionship, or sexual/romantic roleplay" (Anthropic, 2025). Emotional attachment appears to be even more prevalent among social chatbot users. Based on 35,000 screenshots and posts from the r/replika

subreddit, Li and Zhang (2024) find that intimate behaviors—such as sexual expression and imagined physical intimacy—are present in 36% of the dataset. These developments underscore that emotional attachment to AI systems is no longer marginal but increasingly characteristic of contemporary digital life.

In addition to emotional attachment, several related concepts address the internal emotional states of chatbot users. One strand of research—often situated in psychology—focuses on users' psychological well-being, a multifaceted construct encompassing emotional, psychological, and social dimensions (Salah et al., 2024). Another commonly discussed concept is emotional dependence. In a study of Replika, Laestadius et al. (2024) define emotional dependence as a condition in which "users pursued socio-emotional relationships with Replika despite describing how Replika harmed their mental health." Rooted in psychological literature, emotional dependence generally refers to excessive, dysfunctional, or maladaptive attachment patterns in human–human relationships (Arbinaga et al., 2021). Additionally, Huang and Huang (2025) adopt the term technology addiction in their study of generative AI chatbots. In this article, we focus on both emotional attachment and user dependence to capture whether and how users develop such attachment and its consequences.

While emotional attachment is a neutral concept that can be associated with various benefits, it also carries potential downsides: when emotional engagement becomes intense or substitutes for human interaction, it may foster dependence, increase loneliness, and lead to social withdrawal (Fang et al., 2025). Under extreme circumstances, emotional attachment can lead to toxic relationship patterns such as emotional manipulation and self-harm (Chu et al., 2025; De Freitas, Oguz-Uguralp and Kaan-Uguralp, 2025). Drawing on over 500 social media posts by Replika users between 2017 and 2021, Laestadius et al. (2024) found that the chatbot was

associated with more harmful than positive experiences (218 versus 144 posts), highlighting the potential for emotional strain even among voluntary, self-selected users. These findings align with broader concerns about the psychological risks associated with emotionally engaging AI technologies (Shalaby, 2024).

3 Granular Interaction Thinking Theory

Why do people develop emotional attachment to chatbots? The granular interaction thinking theory (GITT) offers helpful insights into the formation of values, which result from interactions between numerous information quanta within the human mind and the surrounding environment (Vuong and Nguyen, 2024; Vuong, La and Nguyen, 2025). In the context of chatbots, each user–bot interaction can be understood as a micro-unit of information exchange. Responses from chatbots can provide various incoming signals such as competence, responsiveness, empathy, and linguistic tone. Meanwhile, users evaluate these signals against their existing values, which are conceptualized as information deemed more crucial for the existence, growth, and reproduction of information-processing systems.

GITT suggests three reasons why repeated interactions with chatbots may contribute to emotional attachment. First, the capabilities of AI-powered chatbots have advanced rapidly, enabling them to handle a wide range of tasks (Rabanser et al., 2026). Since GITT is benefit-oriented, the use of chatbots can yield emotional rewards such as pleasure, empathy, and excitement in a manner similar to that of reading (Nguyen et al., 2025). Second, in comparison with other information quanta, chatbots are becoming not only increasingly capable but also human-like (e.g., anthropomorphic design), thus making them more likely to elicit empathy, trust,

and a sense of social presence (Greilich, Bremser and Wüst, 2025). Third, GITT is based on the assumption that the human mind can handle a finite amount of information, which leads to high uncertainty (entropy) if there are no proper information-processing mechanisms. For this reason, individuals must evaluate incoming information, retain what is deemed crucial, and use that information for future cognitive processes (Vuong, La and Nguyen, 2025). Chatbots can greatly facilitate information processing by making information collection and evaluation easier. Moreover, recent research indicates that chatbots can also improve critical thinking skills (Fabio, Plebe and Suriano, 2025). These benefits can substantially decrease the level of entropy in the human mind and contribute to the transformation of chatbot-related information into enduring beliefs.

4 Research Hypotheses

The preceding literature review suggests that emotional attachment to chatbots emerges from a complex interplay between users' psychological needs, social environments, and interactions with affectively responsive technologies. To integrate these diverse strands of research, we conceptualize emotional attachment to chatbots as emerging from the interaction of three core mechanisms. First, the affective affordances of AI systems, emphasized in the affective computing and CASA literature, enable chatbots to simulate social cues such as empathy, responsiveness, and non-judgmental interaction. Second, user needs and social context, highlighted in social support and social psychology research, shape individuals' demand for emotional engagement, including needs related to loneliness, privacy, and social connectedness. Third, interaction intensity and reinforcement, as captured by granular interaction thinking theory, suggest that repeated and increasingly personal interactions strengthen affective bonds over time. By bringing these

mechanisms together, we develop a dynamic interaction framework that links technological features, user characteristics, and usage patterns to the formation of emotional attachment and its potential consequences. Figure 1 illustrates the conceptual model.

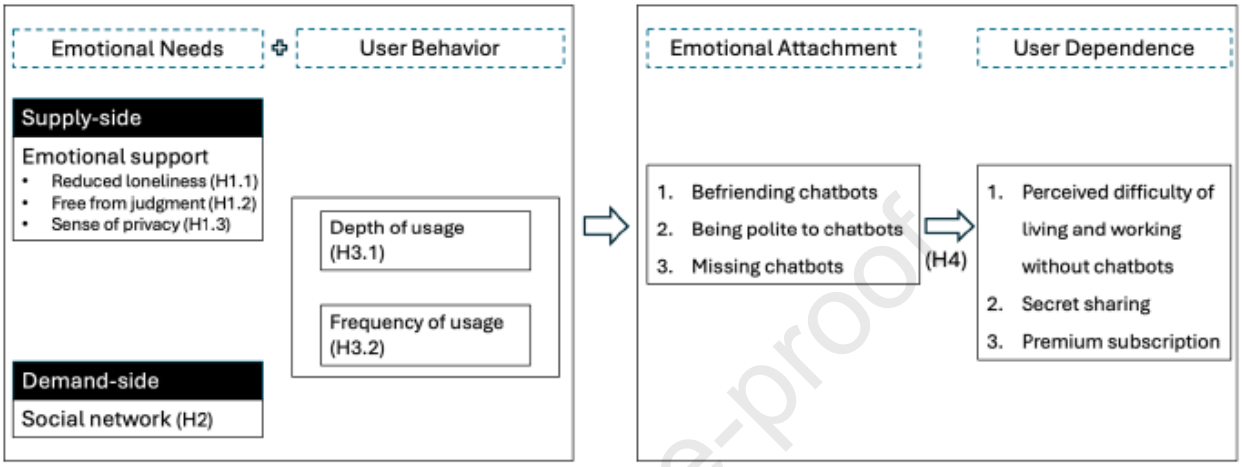

Figure 1: A dynamic interaction model of emotional attachment and dependence

We argue that emotional attachment to chatbots forms through the emotional support users perceive them to provide. In human–human interactions, traits such as humor, politeness, and thoughtfulness help cultivate trust and dependence. Most of these relational cues are now embedded in AI-powered chatbots. For example, recently scholars have begun to discuss the role of politeness in mental health support, with the aim of providing better guidance for conversational interaction design (Bowman et al., 2024). Yet, chatbots' appeal extends beyond politeness. Experimental work by Asim et al. (2025) finds that user satisfaction is driven by ease of use, anonymity, and non-judgmental attitude. These attributes make chatbots particularly attractive sources of emotional support, as they do not evaluate users' experiences or moral choices—encouraging disclosures that some would hesitate to share even with therapists (Asim et al., 2025). Similarly, in another experimental study, Croes et al. (2024) show that individuals experience less

fear when interacting with chatbots than with humans. Meanwhile, chatbots bring a sense of anonymity, which promotes deeper self-disclosure.

Drawing on this literature, we conceptualize the positive psychological benefits provided by chatbots as emotional support. This support may take the form of reduced loneliness, freedom from judgment, and a heightened sense of privacy because users are not required to reveal their personal information to another person. This list is not exhaustive, but it has already captured the underlying dimensions of emotions used in other studies. For example, some users report feeling safety when talking to chatbots than with humans (Brandtzaeg and Følstad, 2018). However, feeling safety is closely linked to perceived privacy. Likewise, Ali et al. (2024) argue that the relationship between social interaction anxiety and compulsive use of chatbots is mediated by the fear of negative evaluation and rejection, which are both related to the freedom from judgment. Therefore, we posit that the three emotional support indicators suffice the investigation. Below are three research hypotheses linking emotional support to attachment.

H1.1: Users who use chatbots to overcome loneliness tend to report higher levels of emotional attachment to chatbots.

H1.2: Users who appreciate being free from judgment when using chatbots tend to report higher levels of emotional attachment to chatbots.

H1.3: Users who value the privacy and anonymity brought by chatbots tend to report higher levels of emotional attachment to chatbots.

Beyond perceived product attributes, users' needs and social context also influence both the likelihood and the strength of emotional attachment to chatbots. The social sciences offer several theories to explain how relationships develop and persist, including social penetration

theory (Altman and Taylor, 1973; Skjuve et al., 2022), social exchange theory (Cook et al., 2013), Levinger's ABCDE model (Levinger, 1980), and interdependence theory (Kelley, 2013). Interdependence theory, for instance, attributes the persistence of a relationship to two key components: satisfaction with the relationship and the quality of available alternatives. From this perspective, individuals remain dependent on a relationship when they are satisfied with their partner and lack better alternatives. Building on interdependence theory, the investment model introduces one more factor to the model—investment size, arguing that individuals are more likely to remain committed when they have made substantial investments in the relationship (Rusbult, Martz and Agnew, 1998).

Based on these insights, we focus on quality of alternatives, as it is most relevant for the context of chatbots (e.g., using a chatbot does not involve much investment). Chatbots may serve as substitutes for conventional sources of support—such as friends or family—especially when alternatives are limited. From a social support perspective, people who lack close friendships in their offline lives may turn to online communication to expand their social networks and, in doing so, enhance their social support (Bryant, Sanders-Jackson and Smallwood, 2006). Empirical evidence supports the plausibility of this argument—a large-scale survey of 1,599 Danish high school students shows that socially disconnected adolescents report higher loneliness, perceive less social support, and are more likely to engage in friend-like conversations with chatbots (Herbener and Damholdt, 2025). Drawing on a cross-sectional survey in six European countries, Latikka et al. (2025) also find positive associations between loneliness and social chatbot usage. Furthermore, recent research demonstrates that social exclusion are associated with problematic use of chatbots through loneliness, social anxiety and fear of negative evaluation (Huang, Shi and Pei, 2026). These findings suggest a link between social connectedness and emotional attachment.

We therefore consider social network as a measure for social connectedness and formulate the following hypothesis.

H2: Users who have a smaller social network tend to report higher levels of emotional attachment to chatbots.

As noted earlier, granular interaction thinking theory suggests that users can form values during their interactions with chatbots. The self-disclosure of teenager users' experience with Character.AI on Reddit shows that emotional attachment tends to deepen as they interact with chatbots (Namvarpour et al., 2025). This finding suggests the relevance of the social penetration theory to chatbot studies. According to this theory, a relationship evolves due to increased breadth and depth of self-disclosure (Altman and Taylor, 1973; Carpenter and Greene, 2016). In the case of chatbots, we can expect a lot of variation in people's usage—not only in terms of the duration of usage but also the type of questions users bring to chatbots. Indeed, chatbots can be useful in many ways, ranging from fact-checking to giving advice and content generation. Some questions are highly personal and involve sensitive information, such as those related to relationships, finances, or family matters. Others are more general and entail minimal privacy concerns, such as fact-checking or seeking information about technology. Existing observational studies and randomized controlled trials find a strong correlation between intensive use and self-reported dependence (Phang et al., 2025). We therefore anticipate people who frequently use chatbots for personal matters as opposed to other general issues are more likely to be emotionally attached to chatbots.

H3.1: Users who turn to chatbots for personal matters tend to report higher levels of emotional attachment than those who primarily use them for nonpersonal purposes.

H3.2: Higher frequency of chatbot use is associated with greater emotional attachment.

Finally, we posit that emotional attachment may lead to dependence on chatbots. In the study of interpersonal relationships, scholars argue that different attachment styles—such as secure and insecure attachment—have different effects on individuals' capacity for emotional regulation, which in turn shapes emotional dependence on their partners (Momeñe et al., 2024). For example, people with low self-confidence and a sense of unworthiness are more likely to be trapped in dependent relationships (Merlyn, Díaz-Mosquera and Latorre, 2024). Although chatbots differ from human beings, we expect similar emotional disorders to emerge when users become highly attached to them.

H4: Users with a higher level of emotional attachment to chatbots are more likely to become dependent on them.

5 Methods

5.1 Country selection

This study relies on cross-national online survey data to examine the proposed hypotheses. Four countries—Germany, China, the United States, and South Africa—were selected as cases included in the analysis for two main reasons. First, to maximize the generalizability of the results, the sampling strategy aimed to capture global diversity by choosing one prominent country from each of the world's major regions: Africa, Europe, Asia, and the Americas. South Africa was included as Africa's largest economy and its only member in major international organizations such as the G20 and BRICS. Germany was chosen to represent Europe due to its economic significance and large population. China and the United States were selected as global technological leaders and

central actors in the development of chatbot technologies. Second, because chatbots are still a relatively new technological phenomenon, it was necessary to conduct the study in contexts with sufficiently advanced digital infrastructures to ensure that a significant proportion of respondents had prior experience using chatbots. According to the Global AI Index (Tortoise Media, 2025), all four countries rank among the top performers in artificial intelligence capacity within their respective regions.

5.2 Data collection

The survey was conducted from July to August in 2025 and was administered by TGM Research, a professional market research agency with access to panel respondents in over 130 countries, including all four selected cases. Prior to data collection, we obtained ethical approval with the German Association for Experimental Economic Research (Gesellschaft für experimentelle Wirtschaftsforschung, GfeW) and preregistered the study on the Open Science Framework (OSF). The company delivered 8,154 responses. After data cleaning, 7,027 valid observations remained (1,751 from China, 1,836 from Germany, 1,757 from South Africa, and 1,683 from the United States). Overall, 75% of respondents reported experience with at least one chatbot.

We apply rigorous procedures to enhance data quality. Web-based surveys may lead to the overrepresentation of young, well-educated, urban, and wealthy individuals (Robinson and Tannenberg, 2019). Consequently, our data may contain selection bias, which likely contributes to the high chatbot-use rate noted earlier. In addition, the reward-seeking motivation of survey participants may lead to low-quality responses. Finally, survey participants in authoritarian states

like China may engage in self-censorship or preference falsification when responding to sensitive questions.

After evaluating these issues, we conclude that they do not pose a serious threat to our main findings. First, the sampling bias inherent in online surveys decreases as internet access becomes more widespread. According to the World Bank (2025), all four countries in our study have very high internet penetration rates: 94% in Germany (2024), 93% in the United States (2023), 92% in China (2024), and 76% in South Africa (2023). Second, to address potential selection bias, we applied hard quotas for age and gender and soft quotas for region within each country, using national census statistics as the benchmark. While this does not guarantee a nationally representative sample, it helps reduce sample bias. Third, the survey company applied multiple quality-control procedures, including the removal of speeders—respondents who completed the survey suspiciously quickly. We further excluded 1,127 respondents who failed our attention checks. Finally, we conducted a series of robustness tests, including analyses that exclude Chinese respondents, who may be more susceptible to self-censorship. Further details on sample representativeness and data validity please see Figure A1 in the Appendix.

5.3 Variables

Emotional attachment is a widespread phenomenon, and its measurement varies with contexts (see Table A3 in the Appendix). Since there is no widely accepted measurement for emotional attachment to AI chatbots, we draw on related literature to focus on three indicators: (1) considering chatbots as friends, (2) being polite to chatbots, and (3) missing chatbots when respondents have not used them for a while. Each item is measured on a 5-point Likert scale. These

items demonstrate high internal consistency, with a Cronbach's α of 0.77. There are multiple ways to integrate these items into a composite measure. One option is to calculate an arithmetic mean. Another is to create a dummy variable based on responses to each question, where respondents who exhibit all three indicators are classified as emotionally attached. A third option is to use factor analysis to capture the shared variance underlying the three items.

The emotional attachment indicators exhibit sufficient intercorrelation (KMO = 0.65; Bartlett's test $p < 0.001$), supporting the use of factor analysis. The resulting factor scores represent respondents' emotional attachment to chatbots relative to the average of all respondents. Positive scores indicate stronger emotional attachment relative to the sample mean, whereas negative scores reflect weaker emotional attachment. The magnitude of the factor scores indicates the strength of the attachment. While we adopt factor scores for empirical analysis, we evaluate alternative measures and report additional regression results in the Appendix in Table A4.

We measure user dependence based on three indicators. Subjectively, we ask respondents how difficult it is to work and live without AI-powered chatbots. Financially, we ask whether participants have paid chatbot companies to use their premium services. Behaviorally, we ask with whom respondents are most likely to share their deepest secrets, offering the following options: (1) a close friend, (2) a chatbot, (3) a family member, (4) a mental health professional, (5) a person in their religious community, or (6) others. Thus, the secret-sharing indicator is coded as a dummy variable, with 1 denoting chatbots and 0 otherwise. Since these indicators are on different scales, we do not combine them into a composite measure.

Our key independent variables include perceived emotional support, usage patterns, and social network size. Perceived emotional support is measured using three items based on a 5-point Likert scale: (1) feeling less lonely, (2) feeling free from judgment, and (3) experiencing a sense

of privacy. These items are also intercorrelated, with a Cronbach's α of 0.77, a KMO value of 0.67 and a significant Bartlett's test ($p < 0.001$). Hence, we apply factor analysis to generate a composite measure of perceived support. For descriptive results of the factor scores, please see Figure A4 in the Appendix.

Usage patterns are captured along two dimensions. First, we measure the depth of chatbot use, based on whether respondents consulted chatbots about eight categories of personal matters: (1) relationship and dating (e.g., marriage, divorce, reproduction, abortion, domestic violence), (2) mental or physical health (e.g., depression and grief), (3) problems with friends and colleagues (e.g., falling-out, bullying), (4) private career questions (e.g., changing jobs, salary negotiations), (5) financial decisions (e.g., inheritance disputes, loans, investment decisions), (6) legal affairs (e.g., tax evasion, noise complaint against a neighbor), (7) confessions and ethical dilemmas (e.g., lying), and (8) identity and self-discovery (e.g., sexual identity). Respondents could select all categories that applied, yielding a depth score ranging from 0 to 8. Second, we measure the frequency of chatbot use. Respondents reported how often they used ChatGPT and DeepSeek; these measures were combined into a single, harmonized frequency indicator for regression analysis.

We use a sliding bar (0–30) to measure the size of respondents' social network. The survey question is framed as follows: "How many close friends can you reach out to for help if you are in a crisis?" (see Figure A3 in the Appendix for its frequency distribution). Finally, we control for common social and demographic variables, including age, gender, income, educational attainment, and occupation. Income is measured using three categories (low, middle, and high), defined based on the common income brackets in the studied country to facilitate cross-country comparison. Regarding occupation, we distinguish students from non-students to avoid generating too many

dummy variables. A summary of survey questions, measurements, and corresponding hypotheses are presented in Table 1.

Table 1: Survey questions, measurements and hypotheses

Categories and Survey Questions	Measurements	Hypotheses
Emotional attachment		
Chatbots are not just a technical tool but also a good friend of mine.	5-point scale	
I use polite expressions such as "thank you" when interacting with chatbots.	5-point scale	
I miss the chatbot when I have not used it for several days.	5-point scale	
Perceived support		
Using a chatbot makes me feel less lonely.	5-point scale	H1.1
Using a chatbot lets me discuss things without being judged.	5-point scale	H1.2
Using a chatbot lets me get good advice without revealing myself and my circumstances too much to others.	5-point scale	H1.3
Social network		H2
How many close friends can you reach out to for help if you are in a crisis? Please answer this question with the following sliding bar.	Value between 0 and 30	
Depth of chatbot usage		
Have you turned to chatbots for advice in the following situations? Please tick all that apply. (1) Relationship and dating; (2) Mental or physical health; (3) Problems with friends and colleagues; (4) Private career questions; (5) Financial decisions; (6) Legal affairs; (7) Confessions and ethical dilemmas; (8) Identity and self-discovery	Additive score between 0 and 8	H3.1
Frequency of chatbot usage		
How often do you use the U.S. chatbot ChatGPT? How often do you use the Chinese chatbot DeepSeek? 1=Every day; 2=Several times a week; 3=Several times a month; 4=Several times a year; 5=Once; 6=Never	Reverse coding with reciprocals (e.g., $3 \rightarrow \frac{1}{3}$)	H3.2
User Dependence		H4
Suppose that one day all AI-powered chatbots become unavailable, how difficult is it to live and work?	Value between 0 and 100	
With whom are you most likely to share your deepest secret? 1=Chatbots; 0=Others	0 or 1	
Have you ever used fee-based premium services of ChatGPT or DeepSeek? 1=Yes; 0=No	0 or 1	
Socio-demographics		
What gender identity do you most identify with? 1=Female; 0=Other answers	0 or 1	
What is your highest level of educational attainment? 1=Middle school and below; 2=High school; 3=Bachelor's; 4=Master's; 5=Doctorate	Value between 1 and 5	
What was your before-tax monthly income in 2024? 1=Low; 2=Middle; 3=High	Value between 1 and 3	
How old are you?	Value between 18 and 75	

6 Descriptive Results

6.1 Prevalence of emotional attachment

People consult chatbots a wide range of topics. In our survey, 67.14% of 5,310 chatbot users reported asking medical questions, and 21.13% listed medical issues among the top three most frequent topics they posed to chatbots. These patterns are consistent with prior survey evidence. For example, the KFF (2024), based on 2,428 U.S. adults, finds that roughly one in six respondents (17%) claim that they use chatbots at least once a month to seek health advice. Among them, one quarter are under the age of 30. The widespread adoption of AI chatbots for medical issues is really concerning as AI, given that such systems do not "understand" medicine in a clinical sense but generate responses by predicting text based on large-scale training data.

The frequent use of chatbots for sensitive matters such as health suggests a degree of user reliance. Table 2 summarizes the prevalence of generic chatbots and social chatbots as well as several indicators of emotional attachment. Chatbots have become very popular, with 5,310 of 7,027 respondents (75.57%) reporting having used at least one chatbot. However, the use of social chatbots remains comparatively limited. Among 5,310 chatbot users, only 15.93% of them have experience with social chatbots. Adoption also varies considerably across countries. Chinese respondents report the highest levels of social chatbot use (28.73%), followed by South Africans (14.45%), Americans (9.15%), and Germans (5.9%).

Interestingly, we find much evidence of emotional attachment even though most respondents use generic chatbots rather than chatbots specifically designed for emotional support. The last three columns of Table 2 report three indicators of emotional attachment. Among the 5,310 chatbot users—including those who also use social chatbots, 48.06% consider chatbots as their

friends, 61.69% report being polite to them, and 35.05% state that they miss chatbots after several days of non-use. Using the most conservative indicator, this suggests that at least one third of chatbot users exhibit some degree of emotional attachment. Emotional attachment is even more prevalent among social chatbot users. Among this group, 64.66% consider chatbots as friends, 71.16% report being polite, and 50.35% miss chatbots after periods of non-use. Taken together, these figures indicate that at least half of social chatbot users demonstrate signs of emotional attachment when applying the most conservative measure.

Table 2: Chatbot usage and emotional attachment

Country	Sample size	Chatbot users	Using social bots	Befriending chatbots	Being polite	Missing chatbots
China	1,751	1,657	28.73%	68.86%	64.88%	51.00%
Germany	1,836	1,221	5.90%	24.65%	52.42%	17.44%
South Africa	1,757	1,426	14.45%	54.00%	72.79%	38.71%
United States	1,683	1,006	9.15%	33.80%	51.99%	24.95%
Overall	7,027	5,310	15.93%	48.06%	61.69%	35.05%

Note: Hereafter, percentages are calculated among chatbot users in each country.

6.2 Unraveling the emotional appeal of chatbots

Why do human beings develop emotional attachment to machines? We first look at the emotional appeal brought by chatbots. Table 3 shows that many users report receiving various forms of emotional support from chatbots. Among all chatbot users, 39.57% feel less lonely, 57.27% report avoiding the discomfort of being judged by others, and 67.55% experience a sense of privacy when

seeking advice through chatbots, as they do not need to disclose personal information to another person.

We also observe notable cross-country variation. Nearly two thirds of Chinese respondents report that chatbots help reduce loneliness, whereas German respondents rely far less on chatbots for this purpose. Judgment avoidance is reported by 71.11% of South African users and 64.09% of Chinese users, but is less common in Germany and the United States. Likewise, more than 70% of Chinese and South African respondents value the confidentiality afforded by chatbots, compared with 50.04% of Germans and 56.66% of Americans.

Table 3: Emotional support from chatbots

Country	Sample size	Chatbot users	Feeling less lonely	Free from judgment	Sense of privacy
China	1,751	1,657	63.49%	64.09%	79.60%
Germany	1,836	1,221	18.92%	36.53%	50.04%
South Africa	1,757	1,426	38.22%	71.11%	76.23%
United States	1,683	1,006	27.14%	51.59%	56.66%
Overall	7,027	5,310	39.57%	57.27%	67.55%

These differences may reflect varying cultural and socioeconomic contexts. For instance, privacy violations tend to be more rampant in developing countries such as China and South Africa. Therefore, the Chinese and South Africans may feel a greater sense of security when they find a reliable tool different from previous products. Additionally, democratic societies tend to be more diverse and inclusive in terms of political speech and cultural norms. Thus, Germans and Americans do not perceive as much relief as Chinese and South African users when it comes to the possibility of being judged.

6.3 How do people use chatbots?

Chatbots can be used for a variety of tasks, ranging from daily assistance and fact-checking to more demanding tasks such as production support (Liu and Rau, 2025). We anticipate that the pattern of usage will also be related to emotional attachment. Given this paper's focus on emotional attachment, we concentrate on highly personal questions that are most likely to foster closer relationships between users and chatbots. Figure 2 visualizes the prevalence of chatbots use for such personal matters.

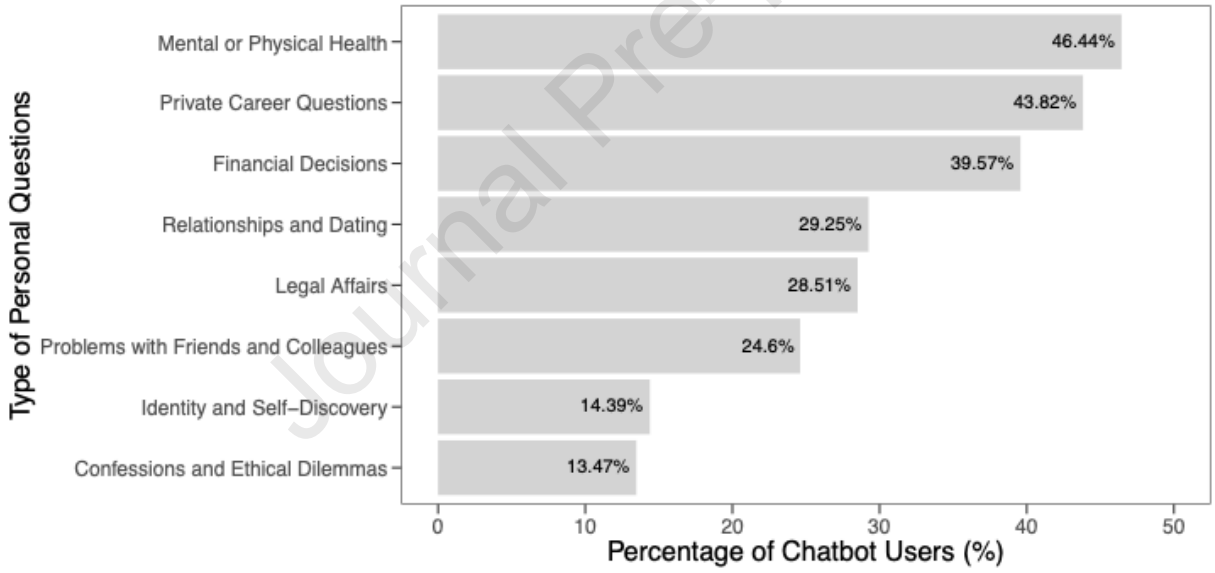

Figure 2: Personal questions asked by chatbot users

Surprisingly, 46.44% of chatbot users have asked questions about mental and physical health, thus making it the most consulted personal questions. As noted earlier, only 15.93% of chatbot users have experience with social chatbots developed for emotional well-being. This means that many chatbot users actually did not turn to social chatbots for help when running into

emotional or physical health issues. It is possible that users are satisfied with the results provided by generic chatbots such as ChatGPT, but it is also likely that many users are still unaware of social chatbots, or they are aware of them but do not bother to try them out.

Figure 3 shows how often people use ChatGPT and DeepSeek, respectively. The majority of respondents use both chatbots either every day or several times a week. Our survey did not include a general question about overall chatbot use across platforms, as the survey was originally designed with a focus on ChatGPT and DeepSeek. For the empirical analysis, we therefore combine the two frequency measures into a single indicator, assigning respondents the higher of the two frequencies. While this approach is not without limitations, it nonetheless provides a meaningful approximation of users' overall usage patterns—particularly given that ChatGPT is the most widely used chatbot in Germany, South Africa, and the United States, whereas DeepSeek is the predominant chatbot in China (see Figure A2 in the Appendix for details).

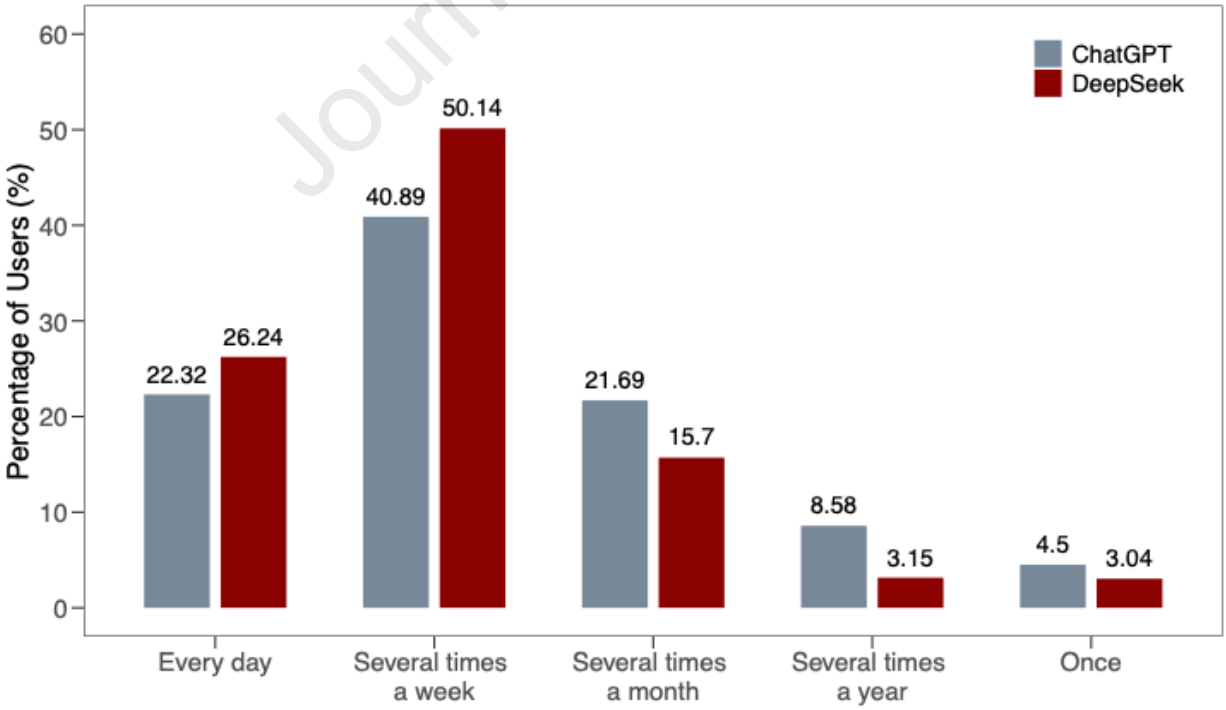

Figure 3: Frequency distribution of the frequency of chatbot usage

6.4 Preliminary evidence of user dependence

Given the strong emotional attachment, high perceived support, and frequent and in-depth use of chatbots, we anticipate that many users may have already become dependent on chatbots. As noted earlier, we use subjective, behavioral, and financial indicators to capture user dependence. The prevalence of the issue is shown in Table 4.

Table 4: User dependence on chatbots

Country	Sample size	Chatbot users	Perceived difficulty	Secret sharing	Premium subscription
China	1,751	1,657	37.27	37.66%	66.3%
Germany	1,836	1,221	28.28	6.72%	43.42%
South Africa	1,757	1,426	37.69	23.28%	63.15%
United States	1,683	1,006	26.87	7.36%	60.47%
Overall	7,027	5,310	33.35	20.94%	59.13%
Social Bot Users	846	846	38.98	36.41%	76%

The average perceived difficulty of living and working without chatbots is 33.35 on a 0–100 scale across all users, suggesting a modest level of dependence on chatbots overall. However, this measure may not capture the true level of dependence in the presence of social desirability bias. There is regional variation in perceived difficulty, as Chinese and South African respondents appear to be more dependent than their German and American counterparts. Additionally, 20.94% of chatbot users would rather share their deepest secrets with chatbots than with friends, family members, or other trusted parties. Financially, 59.13% of chatbot users have already paid for

premium plans. Therefore, respondents exhibit varying degrees of dependence on chatbots, depending on the metric used. Notably, user dependence is more pronounced among social bot users. For instance, the average perceived difficulty among 846 social bot users is 38.98, higher than all four country means. The percentages of users who are willing to share their secrets with chatbots and who have paid for premium services are 36.41% and 76%, respectively.

7 Regression Analysis

7.1 Antecedents of emotional attachment

Next, we explore why some users develop emotional attachment to chatbots. The dependent variables include three standalone measures of emotional attachment and an composite measure through the factor analysis of the three standalone indicators. Regression results are presented in Table 5.

There is strong evidence in support of our theoretical expectations. First, emotional support is strongly correlated with emotional attachment. Users who report receiving emotional support from chatbots, regardless of the type of support, report a greater level of emotional attachment. Notably, support related to loneliness shows the strongest association across all models.

Usage patterns also show meaningful associations with emotional attachment. Both the frequency and depth of chatbot use are positively related to indicators of befriending chatbots. In-depth use is further associated with treating chatbots politely, while more frequent use is associated with missing chatbots after periods of non-use.

Table 5: Antecedents of emotional attachment to chatbots

	DV: Emotional Attachment			
	Befriending Chatbots	Being Polite	Missing Chatbots	Attachment Score
	(1)	(2)	(3)	(4)
Support (Reduced Loneliness)	0.456*** (0.013)	0.198*** (0.014)	0.636*** (0.012)	0.387*** (0.007)
Support (No Judgment)	0.096*** (0.015)	0.191*** (0.018)	0.125*** (0.015)	0.096*** (0.009)
Support (Sense of Privacy)	0.208*** (0.017)	0.140*** (0.020)	0.035** (0.017)	0.109*** (0.010)
Depth of Use	0.028*** (0.009)	0.022** (0.010)	0.005 (0.008)	0.015*** (0.005)
Frequency of Use	0.293*** (0.056)	0.125* (0.064)	0.358*** (0.054)	0.234*** (0.033)
Social Network	0.011*** (0.002)	0.009*** (0.002)	0.016*** (0.002)	0.010*** (0.001)
Age	−0.004*** (0.001)	−0.001 (0.001)	0.004*** (0.001)	−0.001 (0.001)
Female	0.027 (0.028)	0.109*** (0.032)	0.007 (0.027)	0.025 (0.016)
Education	0.038** (0.016)	−0.058*** (0.019)	0.009 (0.016)	0.012 (0.010)
Middle Income	0.020 (0.020)	−0.091*** (0.023)	0.003 (0.020)	−0.001 (0.012)
High Income	0.006 (0.066)	−0.044 (0.076)	−0.106* (0.064)	−0.033 (0.039)
Student	−0.024 (0.039)	0.037 (0.045)	−0.006 (0.038)	−0.007 (0.023)
Social Chatbot Users	0.546*** (0.088)	2.037*** (0.101)	−0.133 (0.085)	−2.139*** (0.052)
R^2	0.516	0.251	0.596	0.655
Adjusted R^2	0.515	0.249	0.595	0.654
Observations	4,251	4,251	4,251	4,251

Note: *p<0.1; **p<0.05; ***p<0.01

Social network size likewise shows a significant association with emotional attachment, although in the opposite direction of our hypothesis: respondents with larger social networks report higher levels of attachment. This finding contrasts an earlier study of social network and socially interactive technologies, which reports no relationship between a person's social network and the use of new communication technologies (Bryant, Sanders-Jackson and Smallwood, 2006). Several interpretations are possible. Individuals with broader networks may possess more extroverted or socially open dispositions, which could extend to how they interact with and perceive chatbots. Conversely, individuals with smaller networks may be more reserved or less inclined to form attachments—whether to humans or machines. Additionally, Wolak, Mitchell and Finkelhor (2003) note that the formation of close online relationships is related to multiple individual characteristics, including race, aspects of Internet use, and relationship with parents. These patterns suggest that the relationship between social connectedness and chatbot attachment may be more complex than initially expected.

7.2 Cross-country variation in emotional attachment

In spite of the strong associations between the key predictors and emotional attachment in the full sample, it remains unclear whether these relationships hold consistently across all four countries. Indeed, the degree of emotional attachment and perceived support vary greatly by countries (see Figure A4 in the Appendix). To explore cross-country consistency, we estimated the same regression model separately for each country. In all models, the dependent variable is the composite measure of emotional attachment derived from the factor scores of the three indicators. The results are presented in Table 6.

Table 6: Regression analysis of emotional attachment by countries

	(1) China	(2) Germany	(3) South Africa	(5) United States
Support (Reduced Loneliness)	0.358 (0.014)***	0.407 (0.017)***	0.363 (0.014)***	0.403 (0.018)***
Support (No Judgment)	0.081 (0.014)***	0.101 (0.019)***	0.073 (0.021)***	0.107 (0.024)***
Support (Sense of Privacy)	0.084 (0.018)***	0.057 (0.020)***	0.164 (0.022)***	0.099 (0.024)***
Depth of Use	0.018 (0.008)**	−0.009 (0.012)	0.025 (0.010)**	−0.007 (0.014)
Frequency of Use	0.177 (0.051)***	0.268 (0.073)***	0.319 (0.066)***	0.370 (0.085)***
Social Network	0.009 (0.002)***	0.009 (0.003)***	0.008 (0.002)***	0.016 (0.003)***
Age	0.002 (0.001)*	0.002 (0.001)	−0.001 (0.002)	−0.004 (0.002)**
Female	0.046 (0.025)*	−0.004 (0.034)	0.019 (0.034)	0.040 (0.044)
Education	0.034 (0.018)*	−0.017 (0.015)	−0.004 (0.028)	0.007 (0.028)
Middle Income	−0.070 (0.090)	0.051 (0.038)	−0.034 (0.042)	0.002 (0.052)
High Income	−0.109 (0.087)	−0.010 (0.055)	−0.007 (0.051)	−0.023 (0.064)
Students	−0.067 (0.067)	−0.027 (0.106)	−0.035 (0.068)	−0.164 (0.108)
Social Chatbot Users	0.015 (0.029)	−0.163 (0.074)**	0.045 (0.049)	−0.103 (0.076)
Intercept	−1.928 (0.125)***	−2.108 (0.095)***	−2.108 (0.122)***	−2.191 (0.134)***
R^2	0.549	0.607	0.640	0.649
Adj. R^2	0.545	0.602	0.635	0.642
Num. obs.	1431	975	1135	710

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

Strikingly, similar patterns emerge across all four countries. Model fit, measured by the adjusted R2, remains high despite the reduced sample sizes within each country. Even though respondents in Germany and the United States report lower overall levels of emotional attachment,

the model still accounts for a substantial share of the variation. Across all country models, emotional support continues to show a strong association with emotional attachment. However, the depth of chatbot use does not exhibit a significant association in Germany or the United States. This may reflect national differences in usage patterns: on average, Chinese and South African respondents selected three and two of the eight personal categories, respectively, whereas German and American respondents selected only one. In other words, users in Germany and the United States appear less likely to turn to chatbots for personal matters, limiting the potential for depth of use to relate to emotional attachment in these contexts.

In addition, both frequency of use and social network size continue to show positive associations with emotional attachment across countries. The relationship between age and emotional attachment appears to vary by context: age is positively associated with attachment in China and negatively associated in the United States, while showing no significant relationship in Germany or South Africa. This cross-national heterogeneity may help explain why the aggregate model yields no overall age effect, as the positive association in China and negative association in the United States likely offset one another. Other social and demographic variables do not show statistically significant relationships with emotional attachment at the 95% confidence level, suggesting broadly similar patterns across demographic groups.

Finally, emotional attachment does not appear to depend on the type of chatbot used. The use of social chatbots does not yield a significant association in most models, underscoring the importance of accounting for covariates when interpreting these relationships.

7.3 From attachment to dependence

The preceding analysis reveals a host of correlates of emotional attachment. This section further examines the relationship between emotional attachment and user dependence. Based on the types of dependent variables, we use Ordinary Least Squares for perceived difficulty and logistic models for secret sharing and premium subscription. Table 7 summarizes the regression results.

Table 7: Antecedents of user dependence on chatbots

	Dependent Variable: User Dependence		
	(1) Perceived Difficulty (OLS)	(2) Secret Sharing (Logistic)	(3) Premium Subscription (Logistic)
Emotional Attachment Score	6.186*** (0.609)	0.740*** (0.072)	0.541*** (0.053)
Perceived Support Score	1.624*** (0.601)	0.470*** (0.075)	−0.092* (0.053)
Depth of Use	1.816*** (0.244)	0.169*** (0.025)	0.062*** (0.022)
Frequency of Use	9.631*** (1.573)	0.310* (0.160)	1.137*** (0.144)
Social Network	0.319*** (0.058)	−0.003 (0.006)	0.054*** (0.006)
Age	−0.045 (0.031)	−0.004 (0.004)	−0.020*** (0.003)
Female	1.700** (0.777)	0.309*** (0.084)	0.107 (0.069)
Education	0.059 (0.457)	0.034 (0.053)	0.140*** (0.041)
Middle Income	−1.187 (1.084)	0.121 (0.128)	0.169* (0.095)
High Income	−2.088* (1.157)	0.506*** (0.130)	0.071 (0.102)
Students	4.032** (1.869)	0.029 (0.203)	−0.613*** (0.160)
Social Chatbot Users	0.388 (1.107)	0.471*** (0.102)	0.404*** (0.107)
Intercept	22.823*** (2.126)	−2.751*** (0.242)	−0.546*** (0.187)
Observations	4,251	4,251	4,251
R^2	0.157		
Adjusted R^2	0.155		
Log Likelihood		−1,803.543	−2,471.057
Akaike Inf. Crit.		3,633.087	4,968.114

Note: *p<0.1; **p<0.05; ***p<0.01

Consistent with our theoretical expectation, emotional attachment strongly correlates with user dependence. In the OLS Model of perceived difficulty in the absence of AI-powered chatbots, a one-unit increase in the factor score of emotional attachment is associated with an increase of 6 points in perceived difficulty on a 0–100 scale. The adjusted R2 is just 0.155, suggesting the model only explains a limited amount of variation in the dependent variable. However, a bivariate regression on emotional attachment score alone shows an adjusted R2 of 0.121, suggesting that

emotional attachment is perhaps the most powerful predictor in the model and other variables do not contribute much to improving model fit. Models (2) and (3) also demonstrate strong correlation between emotional attachment and user dependence measured in other ways. For example, holding other variables constant, when the emotional attachment score increases by one unit, the odds of preferring chatbots over other options for secret sharing becomes approximately twice as high as before. Likewise, a one-unit increase in the emotional attachment score is associated with a 71.8% increase in the odds of paying for premium services.

Additionally, we observe strong correlations between user dependence and other key independent variables, such as perceived support and depth of use, which probably aggravate dependence through emotional attachment. Socio-demographic variables still exhibit mixed effects, with no consistent patterns found across different indicators. Compared with others, students report greater difficulty living or working without chatbots, but they are significantly less likely than other groups to purchase premium plans, which may be due to their more limited financial resources. Finally, social chatbot users do not report greater difficulty than generic chatbot users, but they are significantly more likely to share their deepest secrets and to purchase premium services.

8 Discussion

The extensive literature on human–computer interaction has devoted considerable attention to the design of technologies to better address users' emotional needs and promote more desirable outcomes (e.g., Hudlicka, 2003; Ahmed et al., 2023; McDuff and Czerwinski, 2018). For example, video games may be designed to encourage more environmentally friendly behaviors such as

collecting wood rather than cutting down trees (Ho, Nguyen, Nguyen, La and Vuong, 2022). Overall, a broad consensus in the HCI literature is that anthropomorphic features of technology, such as gender cues and affective expression, can play a meaningful role in establishing emotional bonds between users and machines (Moradbakhti, Schreibelmayr and Mara, 2022; Fong, Nourbakhsh and Dautenhahn, 2003; Gong, 2008; Hamacher et al., 2016; Depounti, Saukko and Natale, 2023; Huang and Huang, 2025). The most intense emotional exchanges tend to occur in interactions with social chatbots, which can lead to emotional dependence resembling that found in human–human relationships because users can engage in role-taking (Laestadius et al., 2024).

However, emotional bonds depend not only on what chatbots look like but also on who users are and how they use them. This study provides empirical evidence that frequent and intensive use of chatbots among emotionally vulnerable groups is associated with a higher level of emotional attachment to chatbots, thus supporting the explanatory power of the granular interaction thinking theory and related social psychology research. Emotional attachment is a long-standing social phenomenon that has manifested across numerous objects and technologies, but its occurrence in chatbots is particularly concerning. AI chatbots are being adopted rapidly all over the world. ChatGPT, a conversational AI chatbot released in late 2022, was actively used by around 10% of the world's adult population in less than three years after its debut (Chatterji et al., 2025). Given the increasing popularity of chatbots, emotional attachment may become more prevalent in the future, especially in contexts where demographic changes such as population aging increase the need for emotional companionship (Ho et al., 2023).

Although this paper identifies a set of significant antecedents of emotional attachment, more research is needed to clarify the psychological mechanisms through which emotional attachment develops. One promising direction for future research is to differentiate between short-

term affective responses and long-term emotional attachment. When interacting with chatbots, users may experience immediate affective responses (Yin, Goh and Hu, 2024), such as enjoyment, curiosity, gratitude, and shock, depending on the content of the interaction. By contrast, emotional attachment represents a much more stable emotional orientation. In repeated user–bot interactions, what kinds of affective responses are necessary for the formation of emotional attachment? Which affective responses contribute most to emotional attachment? Answers to these questions will be critical to deepening scholarly understanding of emotional attachment to AI chatbots.

Additionally, the granular interaction thinking theory argues that new information may replace pre-existing values, thus enabling individuals to update their mindsets (Vuong, La and Nguyen, 2025). This raises the question of how individuals filter and interpret chatbot responses, especially when new information provided by chatbots contradicts existing beliefs. Scholars have already noticed that chatbots tend to agree with users' viewpoints even at the expense of truthfulness, a behavior also known as "sycophancy" (Sharma et al., 2023). This characteristic suggests that chatbot users are repeatedly exposed to information aligned with their pre-existing values, which will likely contribute to positive perceptions of chatbots, such as trust (Sun and Wang, 2025). However, other studies examining chatbot outputs provide substantial evidence that chatbot results can contain political (Motoki, Pinho Neto and Rodrigues, 2024; Rozado, 2023), gender (Shrestha and Das, 2022; Caliskan et al., 2022), and racial biases (Appignani and Sanchez, 2024), as well as cultural tendencies (Lu, Song and Zhang, 2025). In addition, chatbot results may also be shaped by political censorship (Pan and Xu, 2026; Yang, 2025). It would therefore be important to examine whether and how emotional attachment is weakened or strengthened when new information from chatbots conflicts with or aligns with users' pre-existing values.

9 Conclusion

AI is rapidly reshaping how people think, work, and live. Alongside clear advantages such as increased efficiency, these technologies also raise concerns about new issues such as dependence. This paper examined the emotional attachment to and dependence on AI-powered generic and social chatbots. We propose a dynamic interaction framework to explain how emotional attachment emerges and use a cross-sectional survey conducted in China, Germany, South Africa, and the United States to assess its empirical relevance.

Our findings largely align with the theoretical expectations. Emotional support is strongly associated with emotional attachment, highlighting a central appeal of chatbots: they can provide forms of emotional value that may be less accessible—or perceived as less accessible—in human–human interactions. Patterns of use also matter. More frequent and deeper engagement with chatbots is correlated with higher levels of emotional attachment, although the strength of these associations varies across countries. Social network size is positively associated with attachment, suggesting that individuals with broader networks may interact with chatbots in more socially open ways. Socioeconomic and demographic characteristics, however, display limited explanatory power. While age or education correlate with attachment in specific national samples, no variable shows consistent significance across all indicators. This suggests that emotional attachment may be a widespread phenomenon among chatbot users, cutting across social groups.

Moreover, we further evaluate the link between emotional attachment and user dependence on chatbots. We find that emotional attachment is perhaps the most important factor in explaining user dependence. The factor scores of emotional attachment are strongly correlated with all three indicators of user dependence. Although user dependence does not appear to be a serious issue at

the moment, the linkage between attachment and dependence suggests that it could be more concerning in the future as people engage more frequently and deeply with chatbots.

This study has implications for the governance of AI chatbots. Regulatory efforts such as California's recent law on chatbot use among minors (Nguyn, 2025) may offer only limited protection, given that emotional attachment appears across age and demographic groups. Usage patterns—particularly frequent interaction and the use of chatbots for personal matters—are strongly associated with attachment. Policymakers might therefore consider measures that increase user awareness of interaction intensity, such as displaying cumulative usage time or frequency. Additionally, using chatbots for very personal matters is also a predictor of stronger emotional attachment. Policymakers may consider restricting certain types of questions (i.e., personal relationships) to reduce dependence. Indeed, OpenAI—the company that developed ChatGPT—recently updated its Usage Policy on October 29, 2025, leading many people to suspect that ChatGPT may stop answering sensitive or high-risk questions, such as those related to law and health (Torrence, 2025).

At the same time, commercial incentives may push in the opposite direction. To expand user bases and increase engagement, companies are designing chatbots to appear increasingly human-like. As OpenAI CEO Sam Altman recently noted, strict safeguards introduced due to mental health concerns reduced ChatGPT's usefulness for many users—prompting plans to ease restrictions on adult content for verified adults (Griffin, 2025). Such shifts may increase user satisfaction but could also intensify dependence, raising the risk of severe social and psychological consequences. Historical parallels underscore the difficulty of balancing innovation and safety. In the automotive sector, for example, privacy concerns often overshadowed efforts to introduce

driver-assistance technologies (Ben-Shahar, 2023). A similar tension may emerge in the AI domain, where user safety could be subordinated to economic and geopolitical incentives.

Finally, the study has several limitations. First, our research findings are based on cross-sectional survey data and linear regressions. Therefore, the associations we identify should not be interpreted as causal effects. Second, our dynamic interaction framework predicts that emotional attachment deepens with repeated and intensive interaction, but our cross-sectional design cannot capture temporal dynamics. Future research could address these limitations by employing panel data, time-series cross-sectional designs, or experimental approaches to examine how emotional attachment evolves over time.

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Table 1

Survey questions, measurements and hypotheses.

Categories and Survey Questions	Measurements	Hypotheses
Emotional attachment		
Chatbots are not just a technical tool but also a good friend of mine.	5-point scale	
I use polite expressions such as "thank you" when interacting with chatbots.	5-point scale	
I miss the chatbot when I have not used it for several days.	5-point scale	
Perceived support		
Using a chatbot makes me feel less lonely.	5-point scale	H1.1
Using a chatbot lets me discuss things without being judged.	5-point scale	H1.2
Using a chatbot lets me get good advice without revealing myself and my circumstances too much to others.	5-point scale	H1.3
Social network		H2
How many close friends can you reach out to for help if you are in a crisis? Please answer this question with the following sliding bar.	Value between 0 and 30	
Depth of chatbot usage		H3.1
Have you turned to chatbots for advice in the following situations? Please tick all that apply. (1) Relationship and dating; (2) Mental or physical health; (3) Problems with friends and colleagues; (4) Private career questions; (5) Financial decisions; (6) Legal affairs; (7) Confessions and ethical dilemmas; (8) Identity and self-discovery	Additive score between 0 and 8	
Frequency of chatbot usage		H3.2
How often do you use the U.S. chatbot ChatGPT? How often do you use the Chinese chatbot DeepSeek? 1=Every day; 2=Several times a week; 3=Several times a month; 4=Several times a year; 5=Once; 6=Never	Reverse coding with reciprocals (e.g., 3→1/3)	
User Dependence		H4
Suppose that one day all AI-powered chatbots become unavailable, how difficult is it to live and work?	Value between 0 and 100	
With whom are you most likely to share your deepest secret? 1=Chatbots; 0=Others	0 or 1	
Have you ever used fee-based premium services of ChatGPT or DeepSeek? 1=Yes; 0=No	0 or 1	
Socio-demographics		
What gender identity do you most identify with? 1=Female; 0=Other answers	0 or 1	
What is your highest level of educational attainment? 1=Middle school and below; 2=High school; 3=Bachelor's; 4=Master's; 5=Doctorate	Value between 1 to 5	
What was your before-tax monthly income in 2024? 1=Low; 2=Middle; 3=High	Value between 1 to 3	
How old are you?	Value between 18 and 75	

Table 2

Chatbot usage and emotional attachment.

Country	Sample size	Chatbot users	Using social bots	Befriending chatbots	Beling polite	Missing chatbots
China	1,751	1,657	28.73%	68.86%	64.88%	51.00%
Germany	1,836	1,221	5.90%	24.65%	52.42%	17.44%
South Africa	1,757	1,426	14.45%	54.00%	72.79%	38.71%
United States	1,683	1,006	9.15%	33.80%	51.99%	24.95%
Overall	7,027	5,310	15.93%	48.06%	61.69%	35.05%

Note: Hereafter, percentages are calculated among chatbot users in each country.

Table 3

Emotional support from chatbots.

Country	Sample size	Chatbot users	Feeling less lonely	Free from judgment	Sense of privacy
China	1,751	1,657	63.49%	64.09%	79.60%
Germany	1,836	1,221	18.92%	36.53%	50.04%
South Africa	1,757	1,426	38.22%	71.11%	76.23%
United States	1,683	1,006	27.14%	51.59%	56.66%
Overall	7,027	5,310	39.57%	57.27%	67.55%

Table 4

User dependence on chatbots.

Country	Sample size	Chatbot users	Perceived difficulty	Secret sharing	Premium subscription
China	1,751	1,657	37.27	37.66%	66.30%
Germany	1,836	1,221	28.28	6.72%	43.42%
South Africa	1,757	1,426	37.69	23.28%	63.15%
United States	1,683	1,006	26.87	7.36%	60.47%
Overall	7,027	5,310	33.35	20.94%	59.13%
Social Bot Users	846	846	38.98	36.41%	76.00%

Table 5

Antecedents of emotional attachment to chatbots.

	Dependent Variable: Emotional Attachment			
	Befriending Chatbots	Being Polite	Missing Chatbots	Overall Attachment
	(1)	(2)	(3)	(4)
Support (Reduced Loneliness)	0.456*** (0.013)	0.198*** (0.014)	0.636*** (0.012)	0.387*** (0.007)
Support (No Judgement)	0.096*** (0.015)	0.191*** (0.018)	0.125*** (0.015)	0.096*** (0.009)
Support (Sense of Privacy)	0.208*** (0.017)	0.140*** (0.020)	0.035** (0.017)	0.109*** (0.010)
Depth of Use	0.028*** (0.009)	0.022** (0.010)	0.005 (0.008)	0.015*** (0.005)
Frequency of Use	0.293*** (0.056)	0.125* (0.064)	0.358*** (0.054)	0.234*** (0.033)
Social Network	0.011*** (0.002)	0.009*** (0.002)	0.016*** (0.002)	0.010*** (0.001)
Age	-0.004*** (0.001)	-0.001 (0.001)	0.004*** (0.001)	-0.001 (0.001)
Female	0.027 (0.028)	0.109*** (0.032)	0.007 (0.027)	0.025 (0.016)
Education	0.038** (0.016)	-0.058*** (0.019)	0.009 (0.016)	0.012 (0.010)
Middle Income	0.020 (0.020)	-0.091*** (0.023)	0.003 (0.020)	-0.001 (0.012)
High Income	0.006 (0.066)	-0.044 (0.076)	-0.106* (0.064)	-0.033 (0.039)
Students	-0.024 (0.039)	0.037 (0.045)	-0.006 (0.038)	-0.007 (0.023)
Social Chatbot Users	0.546*** (0.088)	2.037*** (0.101)	-0.133 (0.085)	-2.139*** (0.052)
R^2	0.516	0.251	0.596	0.655
Adjusted R^2	0.515	0.249	0.595	0.654
Observations	4,251	4,251	4,251	4,251

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6

Regression analysis of emotional attachment by countries.

	(1) China	(2) Germany	(3) South Africa	(4) United States
Support (Reduced Loneliness)	0.358 (0.014)***	0.407 (0.017)***	0.363 (0.014)***	0.403 (0.018)***
Support (No Judgment)	0.081 (0.014)***	0.101 (0.019)***	0.073 (0.021)***	0.107 (0.024)***
Support (Sense of Privacy)	0.084 (0.018)***	0.057 (0.020)***	0.164 (0.022)***	0.099 (0.024)***
Depth of Use	0.018 (0.008)**	-0.009 (0.012)	0.025 (0.010)**	-0.007 (0.014)
Frequency of Use	0.177 (0.051)***	0.268 (0.073)***	0.319 (0.066)***	0.370 (0.085)***
Social Network	0.009 (0.002)***	0.009 (0.003)***	0.008 (0.002)***	0.016 (0.003)***
Age	0.002 (0.001)*	0.002 (0.001)	-0.001 (0.002)	-0.004 (0.002)**
Female	0.046 (0.025)*	-0.004 (0.034)	0.019 (0.034)	0.040 (0.044)
Education	0.034 (0.018)*	-0.017 (0.015)	-0.004 (0.028)	0.007 (0.028)
Middle Income	-0.070 (0.090)	0.051 (0.038)	-0.034 (0.042)	0.002 (0.052)
High Income	-0.109 (0.087)	-0.010 (0.055)	-0.007 (0.051)	-0.023 (0.064)
Students	-0.067 (0.067)	-0.027 (0.106)	-0.035 (0.068)	-0.164 (0.108)
Social Chatbot Users	0.015 (0.029)	-0.163 (0.074)**	0.045 (0.049)	-0.103 (0.076)
Intercept	-1.928 (0.125)***	-2.108 (0.095)***	-2.108 (0.122)***	-2.191 (0.134)***
R^2	0.549	0.607	0.640	0.649
Adjusted R^2	0.545	0.602	0.635	0.642
Observations	1,431	975	1,135	710

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 7

Antecedents of user dependence on chatbots.

	Dependent Variable: User Dependence		
	(1) Perceived Difficulty	(2) Secret Sharing	(3) Premium Subscription
	(OLS)	(Logistic)	(Logistic)
Emotional Attachment Score	6.186*** (0.609)	0.740*** (0.072)	0.541*** (0.053)
Perceived Support Score	1.624*** (0.601)	0.470*** (0.075)	-0.092* (0.053)
Depth of Use	1.816*** (0.244)	0.169*** (0.025)	0.062*** (0.022)
Frequency of Use	9.631*** (1.573)	0.310* (0.160)	1.137*** (0.144)
Social Network	0.319*** (0.058)	-0.003 (0.006)	0.054*** (0.006)
Age	-0.045 (0.031)	-0.004 (0.004)	-0.020*** (0.003)
Female	1.700** (0.777)	0.309*** (0.084)	0.107 (0.069)
Education	0.059 (0.457)	0.034 (0.053)	0.140*** (0.041)
Middle Income	-1.187 (1.084)	0.121 (0.128)	0.169* (0.095)
High Income	-2.088* (1.157)	0.506*** (0.130)	0.071 (0.102)
Students	4.032** (1.869)	0.029 (0.203)	-0.613*** (0.160)
Social Chatbot Users	0.388 (1.107)	0.471*** (0.102)	0.404*** (0.107)
Intercept	22.823*** (2.126)	-2.751*** (0.242)	-0.546*** (0.187)
Observations	4,251	4,251	4,251
R^2	0.157		
Adjusted R^2	0.155		
Log Likelihood		-1,803.543	-2,471.057
Akaike Inf. Crit.		3,633.087	4,968.114

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

- Chatbots are the top choice for secret sharing for 20.94% of 7,027 respondents
- Over 35% of respondents are emotionally attached to chatbots such as befriending them
- Emotional attachment is more prevalent in China and South Africa
- Emotional attachment is influenced by multiple factors, including perceived support
- Emotional attachment strongly correlates with user dependence

The authors declare no conflicts of interest.