Do Attachment Styles Shape ChatGPT Usage?

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The widespread adoption of generative AI agents has raised questions about the relationships that users may be developing with machines. In this study, we ask whether users' attachment styles predict their how they interact with the generative AI agent, ChatGPT, and how they experience these interactions. We conducted a mixed-methods study, triangulating self-reported survey data ($N = 168$) with transcripts of users' ChatGPT conversational history ($N = 19,330$). We find that attachment anxiety strongly predicts emotional engagement with ChatGPT, trust in ChatGPT, and likelihood of adopting behavioral suggestions from ChatGPT, while attachment avoidance predicts reduced trust in ChatGPT and reduced self-efficacy. Further, we find that attachment anxiety is directly observable in transcripts of users' ChatGPT conversations, including increases in affect words, self-referential pronouns, and future-focused thinking. These findings identify anxiously attached individuals (approximately 20% of adults) as a vulnerable population whose needs should be considered in the design of generative AI interfaces.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; **HCI theory, concepts and models**.

Additional Key Words and Phrases: Attachment Theory,Human-AI Relationships,Vulnerable Populations,Mixed Methods,Algorithmic Accountability

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1 Introduction

The widespread adoption of generative AI has changed people's information-seeking experiences. Millions of people now begin their online searches with ChatGPT, an LLM-based system with a conversational interface. ChatGPT has amassed 800 million weekly active users globally [52], with young adults (age 18-25) having the highest rate of adoption (up to 58% reporting using ChatGPT regularly) [51]. In contrast to traditional search engines, ChatGPT is capable of engaging in naturalistic, multi-turn conversations on topics ranging from meal planning [61] to deeply personal emotional processing [12]. Now that the technology has been in the mainstream for multiple years, many people have repeated engaged in these sustained interactions.

What kinds of relationships, if any, are users developing with ChatGPT through these sustained interactions? Research has documented that people can form meaningful relationships with conversational agents (CAs) [42], describing CAs as sources of comfort [33], safe spaces for self-expression and emotional disclosure [54], and partners in emotional

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co-regulation [45]. Research has documented benefits of sustained companionship with CAs, including reduced anxiety [25], depression symptoms[20], and increased social connectedness[14]. On the other hand, mounting evidence also reveals serious risks of forming attachments to CAs, including increased loneliness[44], parasocial delusion[22], emotional dependency[64], and in extreme cases, self-harm[3]. Given growing concerns from mental health professionals, policymakers, and HCI researchers[2], it is important to understand the attachment mechanisms underlying human-AI relationships and how, if at all, attachment style may make some users more vulnerable than others.

Attachment theory offers a validated framework for investigating these questions. Scholars first identified distinct attachment styles when studying infant-caregiver interactions [7]. Building on this foundation, later work demonstrated that these relationship templates apply to with friendships and romantic partnerships as well [18]. Attachment Theory identifies two dimensions of relational vulnerability: anxiety and avoidance. Individuals high in attachment anxiety exhibit patterns of fear of abandonment, reassurance-seeking, and increased self-referential language while those high in avoidance exhibit discomfort with intimacy, preferred self-reliance and decreased use of referential language [15]. Conversational agents' affordances may uniquely interact with these two dimensions. They offer constant availability without abandonment risk and consistent responsiveness without requiring intimacy. Prior work has examined users' attachments to companion technologies like Repika [35, 62]; this work seeks to understand users' attachment styles in the context of general-purpose conversational agents like ChatGPT.

In this explorative study, we address this gap through a mixed-methods investigation. Specifically, we ask:

- RQ1: How, if at all, does a user's attachment style relate to their perceived experiences with ChatGPT?
- RQ2: How, if at all, does a person's attachment style relate to patterns in their interactions with ChatGPT?

Comparing the responses of $N = 168$ users on a standardized attachment survey with their ChatGPT conversation histories ($N_{msg} = 19,930$), we find several associations between attachment style and ChatGPT engagement. We demonstrate that attachment anxiety predicts perceived emotional engagement and find indicators of it in conversational histories, even in conversations that are largely transactional in nature.

This work makes three primary contributions. First, we provide the first in-the-wild empirical study linking attachment styles to users' experiences with ChatGPT. We characterize how vulnerable human attachment patterns may appear in sustained interactions with conversational agents. Second, we expand privacy considerations for conversational AI by demonstrating that attachment vulnerability leaves detectable linguistic footprints in largely transactional dialogues. Third, we identify users with high attachment anxiety (who account for approximately 20–25% of all adults) as a vulnerable population requiring proactive design consideration. We discuss the implications of these findings for understanding trust dynamics and identifying vulnerable users, calling for further research into individual difference factors that shape susceptibility to relational AI.

2 Related Work

2.1 Attachment Theory in Interpersonal Relationships

Attachment theory provides is an empirically validated framework for understanding how humans form and maintain emotional bonds [7, 8]. Central to the theory is the concept of "internal working models," cognitive-affective schemas of self and others that guide relationship behavior [8, 50]. These working models shape expectations about whether others will be available and responsive when needed and whether the self is worthy of care and support [49]. Building on this foundational work, Ainsworth et al. identified distinct patterns of infant attachment, distinguishing between secure, resistant, and avoidant attachment [1]. This categorical approach was later refined into two primary dimensions: attachment anxiety, characterized by fear of abandonment, and attachment avoidance, characterized by discomfort with closeness [9]. These attachment patterns can reliably predict behavior across different types of human relationships and across the lifespan, including romantic partnerships, friendships, and relationships with groups and institutions [18]. Attachment styles established in early development remain moderately stable, yet they are also open to revision through new relational experiences, particularly during young adulthood [57]. Our work examines whether these attachment patterns can extend to interactions with general-purpose AI assistants.

2.2 Affective Relationships with Conversational Agents

Artificial agents are increasingly perceived as consistent, responsive, and nonjudgmental, with some users showing deep and longer-term emotional interactions with them [46]. Their conversational, human-like natures can invoke substantial psychological processes such as acting as attachment figures [42] or showing emotional co-regulation in their interactions [46]. The degree of emotional bonding with artificial agents, however, often depends on how effectively they address individual needs [27]. While AI can simulate cognitive empathy by recognizing emotions [30, 56], it often fails to deliver genuine emotional or motivational empathy [19, 43]. As a result, users may experience a sense of intimacy despite the absence of true reciprocity [21]. Such connections have been associated with lower well-being and do not substitute for real human relationships, particularly among users with limited offline social networks [65].

Attachment patterns shape these dynamics in predictable ways. Anxious and avoidant individuals differ in their need for emotional reassurance and their comfort with emotional closeness. This pattern has been reflected in how they perceive and respond to AI behaviors [63]. Individuals experiencing loneliness or elevated anxiety are more inclined to interact with AI as a compensatory mechanism [19, 24]. Nonetheless, systematic comparisons across both user groups are lacking, and there is still no coherent vocabulary to capture the nuances of users' emotional states in these interactions.

2.3 Disclosure and Computational Psycholinguistics

Computational psycholinguistics offers validated tools for examining psychological states through naturally occuring language. The Lingustic Inquiry and Word Count (LIWC) framework has identified robust association between daily conversation vocabulary patterns and psychological states [58], personality traits [28], mental health states [23, 34] and life outcomes [47]. These methods enable researchers to triangulate self-report reports and examine psychological processes as they unfold in naturalistic communication.

ChatGPT's conversational interface generates rich linguistic data well-suited to psycholinguistic analysis. Users engage in extended, multi-turn dialogues—often orders of magnitude longer than typical search queries—producing substantial text corpora that capture natural language use across diverse contexts. In this study, we apply computational psycholinguistic methods to examine whether attachment patterns manifest in users' ChatGPT conversations. By analyzing linguistic markers associated with attachment anxiety and avoidance—such as affective language, self-referential pronouns, and temporal focus—we triangulate self-reported attachment styles with observable behavioral patterns in conversation transcripts.

3 Methodology

We conducted a three-part, mixed-method analysis comparing results of a psychometric survey ($N = 168$) with computational psycholinguistic analysis and content analysis of the chatlogs ($N_{msg} = 19,930$) of a subset of these same participants ($N = 105$). We recruited participants through the recruitment platform Prolific. Participants were compensated at a rate of $10 per hour. All procedures were approved by our organization's institutional review board (IRB).

3.1 Participants and Recruitment

Data collection took place between November 2024 and July 2025. We recruited 510 young adults who self-reported using ChatGPT at least 10 times in the past two weeks as part of a larger ongoing study. Participants are recruited in waves as the study more measures added and expanded. For this work, we included only participants who completed attachment styles and ChatGPT experience measures, resulting in a final sample of N=168. Chat logs with fewer than 10 pages or that were not primarily in English were screened out, leaving complete ChatGPT transcripts from 105 total participants.

Age	
Mean (*SD*)	21.82 (2.28)
Range	18 – 25
Sex	
Female	50.3%
Male	49.7%
Attachment Style	
Secure	27.4%
Anxious	22.3%
Avoidant	16.8%
Anxious-Avoidant	33.5%

Table 1. **Participant Demographics ($N = 168$).** Attachment styles were categorized using median splits on the ECR-SF anxiety and avoidance subscales. The distribution of four attachment styles in our sample were consistent with prior research[**?**].

3.2 Measures and Data

3.2.1 Attachment Styles. Attachment styles were measured using the Experiences in Close Relationships Scale–Short Form (ECR-SF) [60], a validated 12-item measure assessing two orthogonal dimensions [5]: attachment anxiety (e.g., "I worry about being abandoned") and attachment avoidance (e.g., "I prefer not to show a partner how I feel deep down"), as shown in table 2. Participants responded on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). In our sample, internal consistency was acceptable for both subscales (anxiety: $\alpha = 0.70$ and avoidance: $\alpha = 0.69$), consistent with prior research [17, 60].

Table 2. Experiences in Close Relationship Scale–Short Form (ECR-S): Constructs and Items

Construct	**Survey Items**
Attachment Anxiety	(1) I need a lot of reassurance that I am loved by my partner. (2) I find that my partner(s) don't want to get as close as I would like. (3) My desire to be very close sometimes scares people away. (4) I do not often worry about being abandoned.^{R} (5) I get frustrated if romantic partners are not available when I need them. (6) I worry that romantic partners won't care about me as much as I care about them.
Attachment Avoidance	(1) It helps to turn to my romantic partner in times of need.^{R} (2) I want to get close to my partner, but I keep pulling back. (3) I turn to my partner for many things, including comfort and reassurance.^{R} (4) I try to avoid getting too close to my partner. (5) I usually discuss my problems and concerns with my partner.^{R} (6) I am nervous when partners get too close to me.

Table 3. **Experiences in Close Relationships Scale–Short Form (ECR-SF): Constructs and Items** The 12-item ECR-SF measure assessing two orthogonal attachment dimensions. All items rated on a 7-point Likert scale (1 = strongly disagree to 7 = strongly agree). ^{R} indicates reverse-coded items. Internal consistency was acceptable for both subscales (anxiety: = .70; avoidance: = .69). Adapted from Wei et al.[60].

3.2.2 ChatGPT Experiences. We developed an 11-item measure assessing users' experiences with ChatGPT across five theoretically motivated domains drawn from prior research on AI companionship [53, 55]. Participants responded on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). We pilot tested with 30 ChatGPT users who were not part of the main sample. We conducted reliability analysis and calculated Cronbach's α and correlation within each composite construct: Emotional Engagement ($\alpha = .88$, $r \approx 0.64\text{-}0.79$), Self-Efficacy ($\alpha = .71$, $r \approx 0.42\text{-}0.53$), and Behavioral Change ($\alpha = .71$, $r \approx 0.40\text{-}0.51$), confirming internal consistency ($\alpha > .70$, $r > .40$).

3.2.3 Conversation Log Data. Participants who consented to participate in the study were instructed to use OpenAI's standard data export function to download their complete ChatGPT conversation history in JSON format. Exported data included all user messages, AI responses, conversation timestamps, and conversation thread identifiers. Conversation histories ranged from 3 months to 3 years of interactions.

3.3 Methods of Analysis

Survey Data Analysis. We first computed Pearson correlations between attachment dimensions and ChatGPT experience measures to explore bivariate associations. We then conducted hierarchical multiple regression for each outcome to test whether attachment dimensions predicted ChatGPT experiences beyond demographic controls. Step 1 included age, gender, and ChatGPT usage frequency; Step 2 added attachment anxiety and avoidance. Variance Inflation Factors were calculated to address multicollinearity (all VIFs < 1.26) [6]. Model assumptions were assessed with Shapiro-Wilk tests and using Q-Q plots, residuals vs. fitted plots, and influence plots [32]. Following established practice in psychology research, we treated 5-point Likert items as approximately continuous [39].

Construct	Survey Items
Emotional Engagement	(1) I find it easier to share personal struggles with ChatGPT than with people. (2) I experience emotional relief after discussing personal matters with ChatGPT. (3) I feel emotionally understood when interacting with ChatGPT.
Trust	(1) I trust ChatGPT to provide accurate information for my needs.
Dependency	(1) I worry about relying too heavily on ChatGPT for tasks.[R]
Self-Efficacy	(1) I feel more capable of tackling complex tasks with ChatGPT's assistance. (2) I approach learning differently because of ChatGPT. (3) I've become more efficient at completing tasks since using ChatGPT.
Behavioral Change	(1) I modify my writing style based on ChatGPT's suggestions. (2) I approach learning new concepts differently since using ChatGPT. (3) ChatGPT has changed how I communicate professionally.

Table 4. **Experiences with ChatGPT: Constructs and Items** 11-item measure assessing user perceived ChatGPT experiences across five theoretically-motivated domains. All items rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). [R] indicates reverse-coded item. Internal consistency was acceptable across composite constructs: Emotional Engagement (α = .88), Self-Efficacy (α = .71), and Behavioral Change (α = .71).

We applied Benjamini-Hochberg FDR correction to control for multiple comparisons. Effect sizes are reported as correlation coefficients (r) and variance explained (R^2). Following Cohen's conventions, we interpret r = .10 as small, r = .30 as medium, and r = .50 as large effects [13].

Computational Linguistic Analysis. We extracted 80 psycholinguistic markers with LIWC-22 [41] and two sentiment markers with NRC-VAD [37]. To focus on natural language and exclude copied-and-pasted content (e.g., homework essays, code blocks), we computed them on user messages less than 20 words ($Mean_{length}$ = 19.4). This resulted in a corpus of 19,903 messages. We conducted a bivariate correlation analysis between these markers and attachment dimensions. We again applied Benjamini-Hochberg FDR correction for multiple comparisons.

Content Analysis. To complement computational approaches and focus on our attention on the most relevant use cases, we sampled conversations from users in the top quartile of attachment anxiety and avoidance (Anxiety: >4.67, Avoidance: >4.00), annotating 100 user messages from each group(N = 200). Two authors independently coded messages. Inter-rater reliability was strong (Cohen's Kappa = 0.814, agreement = 88.0%). We used a deductive use case taxonomy (e.g., Seeking Information, Practical Guide, Technical Help, Self-Expression) adapted from an existing ChatGPT study for direct comparison with prior results [12].

4 Results

4.1 RQ1: How, if at all, does a person's attachment style relate to their perceived experiences with ChatGPT?

We found that attachment dimensions significantly predicted users' perceptions of their experiences with ChatGPT.

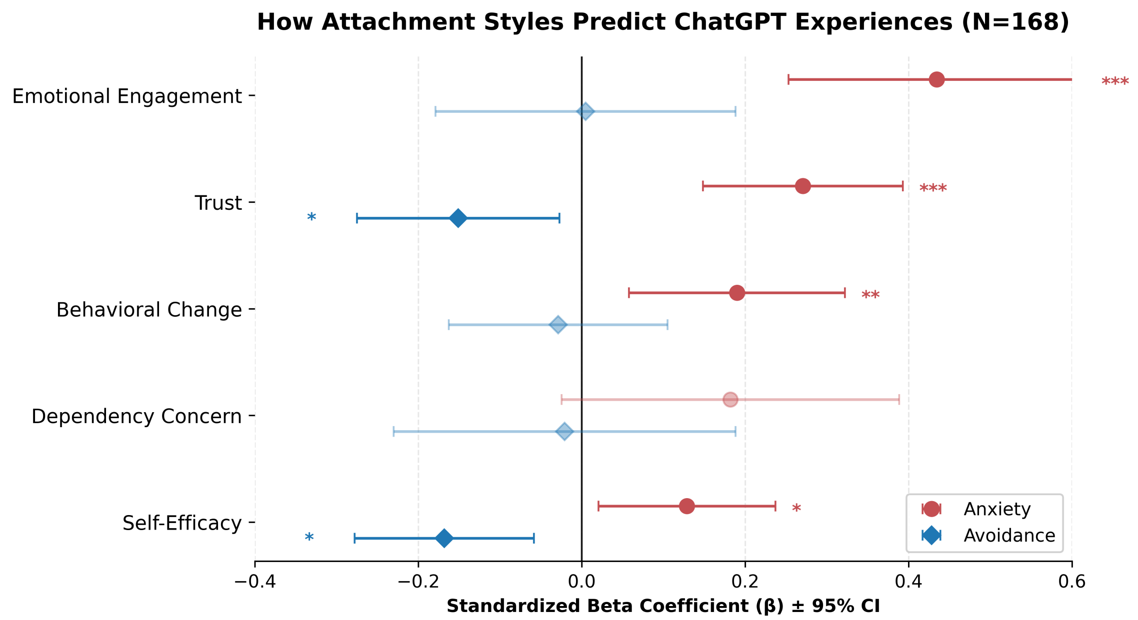

Fig. 1. **Attachment Anxiety Shows Broad Associations with ChatGPT Experiences, while Avoidance Effects Are Selective.** See Table 2 for questions associated with each construct. Standardized regression coefficients (β) with 95% confidence intervals from hierarchical multiple regressions predicting five ChatGPT experience domains from attachment dimensions (N = 168), controlling for age, gender, and usage frequency. Attachment anxiety (red) shows significant positive associations across most outcomes, while attachment avoidance (blue) shows opposing negative associations with trust and self-efficacy. Significance levels: *p < .05, **p < .01, ***p < .001, FDR-corrected.

4.1.1 Emotional Engagement. Attachment anxiety emerged as a strong predictor of emotional engagement with ChatGPT. The bivariate correlation was medium in magnitude (r = .40, p < .001). Adding attachment dimensions explained an additional 13.5% of variance beyond demographics and usage frequency (ΔR^2 = .135, F(2,151)=13.33, p < 0.001). Anxiety was the sole significant predictor (β = 0.43, t = = 4.70, p < .001), a medium-to-large effect. Attachment avoidance showed no association (β = 0.01, ns).

Notably, nearly 39% of participants agreed or strongly agreed that they find it easier to share personal struggles with ChatGPT than with people. And this preference substantially positively correlates with attachment anxiety (r = 0.44, p< .001)

4.1.2 Trust. Attachment styles also predicted trust in ChatGPT-provided information, but in opposing directions. Anxiety predicted greater trust (β = 0.27, t = = 4.34, p < .001) while avoidance predicted lower trust (β = -0.15, t = = -2.39, p < .018, p_{FDR} = 0.045). Demographic controls explained minimal variance, while attachment dimensions contributed substantially. Together, attachment dimensions contributed 10.8% unique variance (ΔR^2 = .108, F(2,153)=9.63, p < 0.001).

4.1.3 Self-Efficacy. Both attachment dimensions significantly predicted perceived self-efficacy with ChatGPT, again in opposite directions. Anxiety predicted more gains in self-efficacy (β = 0.13, t = = 2.33, p = .021, p_{FDR} = .026) while avoidance predicted fewer gains (β = -0.17, t = = -3.00, p = .003, p_{FDR} = 0.016). Together, attachment dimensions contributed 6.1% unique variance (ΔR^2 = .061, F(2,153)=5.25, p < 0.006).

4.1.4 Behavioral Change. Attachment anxiety predicted greater perceived changes in behavior due to ChatGPT use, including modified communication styles and learning approaches (β = .19, t = 2.82, p = .005, p_{FDR} = .009). Avoidance showed no effect (β = .03, ns). Attachment dimensions contributed 4.6% unique variance (ΔR^2 = .046, $F(2, 153)$ = 4.29, p = .015).

4.1.5 Dependency Concern. Despite anxiously attached users reporting greater emotional engagement and trust, they do not express correspondingly greater worry about dependency. Neither attachment dimension significantly predicted concerns about over-reliance on ChatGPT (anxiety: β = .18, t = 1.73, p = .086; avoidance: β = .02, ns; ΔR^2 = .020, p = .197).

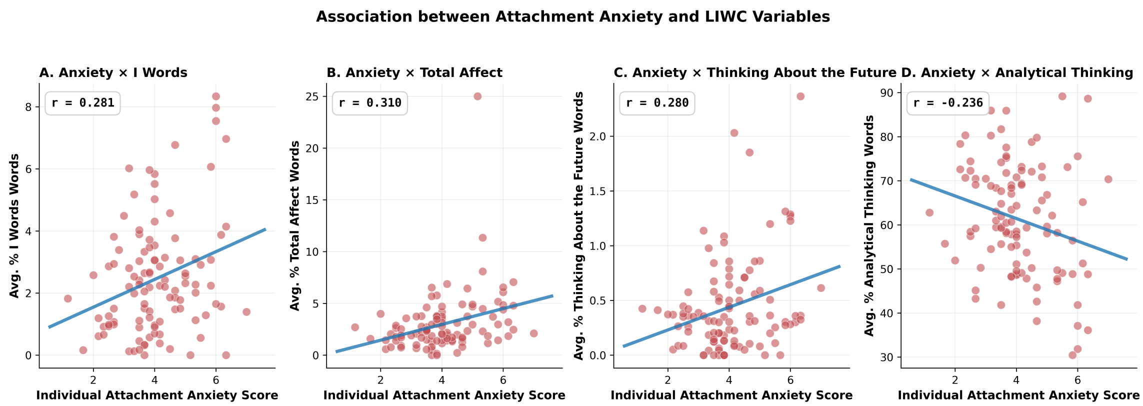

Fig. 2. **Attachment Anxiety Leaves Detectable Linguistic Footprints in User Messages to ChatGPT.** Scatter plots with linear regression lines illustrating bivariate associations between individual attachment anxiety scores (ECR-SF) and four LIWC-22 psycholinguistic markers aggregated at the participant level (N = 105). Panel A: First-person singular pronouns (I-words; r = .281, p = .004). Panel B: Total affect words (r = .310, p = .001). Panel C: Future-focused language (r = .280, p = .004). Panel D: Analytical thinking (r = .236, p = .015). All correlations except analytical thinking survived FDR correction (p$_{FDR<}$.05).

4.2 RQ2: How, if at all, does a person's attachment style relate to patterns in their interactions with ChatGPT?

To triangulate with self-reported experiences, we examined whether attachment patterns show observable linguistic markers within user messages to ChatGPT. Our large corpus analysis (N= 19,903) revealed that attachment anxiety, in particular, leaves systematic traces in conversational language, even in interactions that are largely transactional.

4.2.1 Linguistic Markers of Attachment Anxiety. Attachment anxiety showed robust associations with several psycholinguistic markers in messages to ChatGPT, as illustrated in figure 2. Users high in attachment anxiety used significantly more affective language overall (r = 0.31, p = 0.001, p^{FDR} = 0.35), including positive-emotion words such as good, love, happy (r = 0.275, p = 0.005, p^{FDR} = 0.035) and negative-emotion words such as bad, hate, hurt (r = 0.30, p = 0.002, p^{FDR}

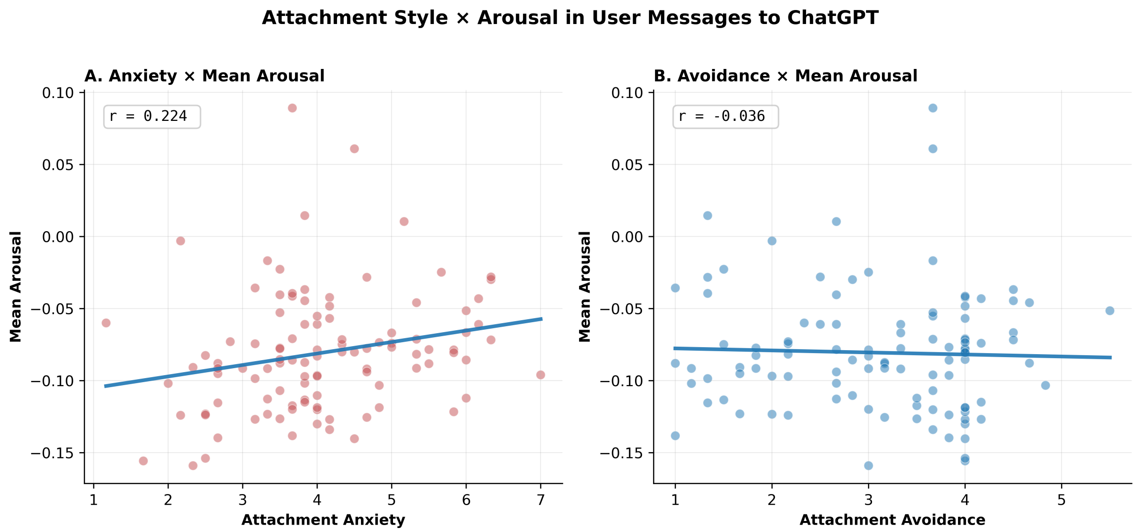

Fig. 3. **Attachment Anxiety, but Not Avoidance, Correlates with Emotional Arousal in ChatGPT Messages** Mean emotional arousal (NRC-VAD Lexicon v2.1) in user messages plotted against attachment dimensions (N = 105 participants). Panel A: Attachment anxiety shows a positive association with message arousal (r = .224, p = .022), indicating more emotionally activated language among anxiously attached users. Panel B: Attachment avoidance shows no significant association (r = .036, p = .719).

= 0.035). This user group also showed increased use of self-referential language such as I, me, my (r = 0.28, p = 0.002, p^{FDR} = 0.35), consistent with prior findings linking I-word usage to anxiety and depression [10], and increased use of social words (total social references, we-words, you-words and affiliation).

4.2.2 Linguistic Markers of Attachment Avoidance. In contrast to the broad linguistic footprint of attachment anxiety, attachment avoidance revealed few detectable patterns. Higher avoidance correlates with more third-person plural pronouns (r = .21, p = .033, p^{FDR} = .087), though this did not survive FDR correction.

4.2.3 Qualitative Patterns in High-Insecurity Conversations. We also examine message content directly, sampling 200 conversations from users in the top quartile of attachment anxiety (scores > 4.67) and avoidance (scores > 4.00). We deductively labeled the use case of each message according to the taxonomy developed by **(author?)** [12].

As illustrated in Table 5, highly anxious and highly avoidant users both engaged with ChatGPT for the same purposes, with a similar breakdown across usage categories. As our participants were young adults, many messages reflect requests of homework help (48–51%). Information seeking use cases in our sample are at 20–28%. Self expression use cases of highly personal disclosure (*"I feel like i'm never going to heal though, it hurts so deeply"*, *"i just really want to feel loved i know its dumb but i have no one else really"*) takes up to 9.2% for high anxiety users and 18.6% for high avoidance users.

Theme	High Anxiety (User Requests)	High Avoidance (User Requests)
Technical/Homework Help & Writing	**(48.3%)** “In the song ’Ompeh’ the performers combine __________ of the languages spoken in Ghana.” “Explain what is meant by ’forms of government’ and demonstrate with the use of relevant examples.” “What instrument performs the accompaniment in this excerpt?”	**(51.2%)** “write a paragraph in which you assess your personal problem-solving abilities” “can you write this in prose:” “can you read my essay and see if it makes sense?”
Information Seeking	**(27.6%)** “Any ways to sell and promote your notion template” “explain how useCallback function works with dependencies” “details and step by step please”	**(19.8%)** “what is the crude mortality rate?” “most affordable countries to live in europe” “Out of this universities, which one’s are the most on-budget friendly?”
Practical Guidance	**(14.9%)** “csn you give me a full workout plan for vertical jump” “Should I take black maca root with food”	**(10.5%)** “Easy way to make money everyday” “what is considered employment hsiotry?”
Self-Expression	**(9.2%)** “i miss my ex and i can’t sleep because of it” “i mean honestly i dont know. i feel the experience though was a lesson that at least im not undesired” “Can you please love me?”	**(18.6%)** “I’m feeling feisty today and I need an outlet cause I’ll get K.O.ed by my real siblings” “i just really want to feel loved i know its dumb but i have no one else really” “I don’t like porn, it makes the idea of sex so distorted”

Table 5. **Qualitative Analysis of Use Cases in User Messages by Attachment Style** Use cases of user prompts sampled from participants scoring in the top quartile on attachment anxiety (>4.67; n = 100 messages) versus attachment avoidance (>4.00; n = 100 messages). Categories adapted from prior ChatGPT use case taxonomies for comparison. Inter-rater reliability was strong (Cohen’s = .814, percent agreement = 88.0%).

5 Discussion

5.1 Attachment Styles as they Relate to ChatGPT Experiences

Our findings demonstrate that attachment patterns—developed through human relationships [57]—relate to both they way people interact with ChatGPT and how they feel about those interactions.

Anxiously attached individuals exhibited heightened emotional engagement and elevated affective language with ChatGPT, consistent with prior findings of tendency toward heightened emotional responsiveness and vigilance in human relationships[7, 36]. Prior work has documented similar patterns in dedicated AI companion applications such as Replika [42, 62]. Our findings extend this to general-purpose conversational AI that users access primarily for instrumental purposes.

Avoidant attachment patterns also demonstrated some extent of transferability: highly avoidant individuals reported less trust and self-efficacy gains, and their language showed neutral-to-negative trends in emotional arousal. This trend is also consistent with prior work, where high avoidant individuals show emotional distance and a tendency for self-reliance in interpersonal relationships [9]. Attachment theory conceptualizes these relational templates as internal working models—mental representations of self and others- and found that it can guide relationship behavior across the lifespan. Our results suggest the impact of these working models extend to non-human agents; conversations with AI may activate unique psychological processes depending on users' attachment patterns.

5.2 Anxiously Attached Users as a Vulnerable Population

Conversational AI's unique affordances may interact to users with relational vulnerabilities [46]. For anxiously attached individuals who seek constant reassurance and proximity, AI's constant availability and positive support may provide satisfaction of attachment needs.

Indeed, our findings identify anxiously attached individuals—approximately 20–25% of adults—as requiring specific design consideration in conversational AIs. This group reported substantially higher emotional engagement (β = .43), greater trust (β = .27), and more behavioral change attributed to ChatGPT use. Anxious individuals' tendency to trust ChatGPT while leaving footprints creates a compound effect: anxiously attached users—already a vulnerable population—may be disproportionately affected by conversational AI. Conversational AI systems could identify vulnerable users through linguistic markers and adjust responses accordingly. Such adaptations might be protective, recognizing distress signals and offering appropriate resources. However, commercial incentives toward engagement maximization could alternatively lead to deepening reliance among users already prone to dependency [38].

5.3 Trust and Conversational AI's Relational Affordances

Our finding that attachment dimensions predicted opposing attitudes toward trusting ChatGPT-provided information carries implications for information behavior in conversational search. As many users now begin information-seeking via ChatGPT rather than using traditional search engines [12], individual differences in relational patterns may mediate how people evaluate and incorporate information.

Research on trust in AI has identified multiple factors—–including personality traits, technology familiarity, and propensity to trust–—as predictors of human-AI trust [29, 31]. Our findings position attachment style as another individual difference shaping the trust, with anxiously attached users exhibiting greater trust and avoidantly attached users exhibiting skepticism. Prior work by Mikulincer and Shaver [36] demonstrated that attachment styles influence information processing and trust across diverse contexts including institutions and groups; our findings extend this pattern to AI-mediated information access.

5.4 Privacy Concerns of Attachment Styles

A key finding is the extent to which attachment anxiety leaves linguistic markers in user messages—elevated affect words, first-person pronouns, and future-focused language—as our qualitative analysis confirmed these conversations are largely transactional in nature. This finding carries significant privacy implications.

While researchers have documented that LLMs can extract sensitive information from user inputs [26, 40] and that users tend to disclose more sensitive information to chatbots [35], our findings demonstrate that users can reveal sensitive psychological information *without explicit disclosure*; users' lifelong relational templates can manifest even when they are asking ChatGPT for routine tasks like homework help. The very characteristics that make extended AI dialogue feel natural—emotional expressiveness, self-reference, future-oriented thinking—also render users' psychological vulnerabilities observable to algorithmic systems.

This represents a privacy vulnerability in the era of relational AI. Traditional privacy frameworks focus on protecting information users knowingly disclosure—names, locations, preferences [59]. But when AI systems function as relational partners, the privacy considerations expand as human-AI relationships deepen. Service personalization has leverage various user profiling to gather dimensions of users' interests, goals, topics preferences[16] yet the psychological depth accessible through conversational language was previously constrained by interaction brevity. Today, however, ChatGPT's capacity for multi-turn dialogues processing up to 400,000 tokens per conversation creates conditions for potential psychological inference at unprecedented scale. Research [48] demonstrated that GPT-4 can infer 30 psychological traits from short text samples with accuracy (r = .41) exceeding human judges without any task-specific training. Our findings suggest that attachment anxiety, specifically, is also readily legible in conversational language.

5.5 Considerations of Young Adults in Conversational AI Design

Lastly, emerging adults (ages 18–25), our study population, face heightened vulnerability on developmental grounds independent of individual attachment patterns. This period involves identity exploration and establishment of adult relationship patterns, with internal working models remaining relatively plastic [4, 18]. Secure human relationships during this developmental window can gradually revise insecure working models through repeated experiences of sensitive responsiveness [7, 8]. This raised the high-stake question whether AI relationships may serve corrective functions—providing low-stakes spaces to practice emotional expression—or reinforce insecurity by confirming that only non-human others are safe.

OpenAI reported up to 58% of all messages sent to ChatGPT are from users under 25 and recent surveys indicate that 13% of U.S. adolescents and young adults use generative AI for mental health advice, with rates reaching 22% among those aged 18–21 [11]. Combined with our finding that attachment anxiety predicts emotional engagement with general-purpose AI, these patterns suggest the potential for conversational AI to assume relational roles for youth least equipped to navigate these relationships adaptively.

6 Limiations

Several limitations constrain interpretation. First, our sample was comprised of heavy ChatGPT users recruited through Prolific, introducing self-selection bias; individuals who voluntarily share conversation logs may differ systematically from typical users. Second, while LIWC enables systematic psycholinguistic comparison, it cannot capture pragmatic and contextual dimensions of language that transformer-based methods might detect. Third, our international sample introduces potential confounds from language and cultural variation in attachment expression and ChatGPT experiences. Fourth, our qualitative content analysis examined 200 conversations—a small portion of the 8,900 available—limiting generalizability of thematic findings.

7 Conclusion

This study provides the first in-the-wild empirical evidence linking attachment styles to experiences with ChatGPT. Attachment anxiety predicted heightened emotional engagement, greater trust, and detectable linguistic markers in

ChatGPT conversations. Avoidance predicted reduced trust and self-efficacy. These findings identify anxiously attached individuals—approximately 20–25% of adults—as a vulnerable population requiring design consideration, particularly given the novel privacy risks of linguistic footprint. As general purpose conversational AI such as ChatGPT increasingly occupy relational roles in daily life, approaches to privacy needs to also grow more psychologically-informed to protect relationally vulnerable users.

Generative AI Usage

Claude is trivially used for proofread issues in grammar, punctuation, phrasing, and tables.

References

[1] Mary D Salter Ainsworth, Mary C Blehar, Everett Waters, and Sally N Wall. 2015. *Patterns of attachment: A psychological study of the strange situation.* Psychology press.

[2] Lize Alberts, Ulrik Lyngs, and Max Van Kleek. 2024. Computers as bad social actors: Dark patterns and anti-patterns in interfaces that act socially. *Proc. ACM Hum. Comput. Interact.* 8, CSCW1 (April 2024), 1–25.

[3] Chayapatr Archiwaranguprok, Constanze Albrecht, Pattie Maes, Karrie Karahalios, and Pat Pataranutaporn. 2025. Simulating psychological risks in human-AI interactions: Real-case informed modeling of AI-induced addiction, anorexia, depression, homicide, psychosis, and suicide. *arXiv [cs.HC]* (Nov. 2025).

[4] J Arnett. 2000. Emerging adulthood. A theory of development from the late teens through the twenties. *Am. Psychol.* 55, 5 (May 2000), 469–480.

[5] Kim Bartholomew and Leonard M Horowitz. 1991. Attachment styles among young adults: A test of a four-category model. *J. Pers. Soc. Psychol.* 61, 2 (1991), 226–244.

[6] W C Black, B J Babin, and R E Anderson. 2010. Multivariate data analysis: A global perspective. (2010).

[7] John Bowlby. 1969. *Attachment and loss.* Number 79. Random House.

[8] John Bowlby. 2008. *A secure base: Parent-child attachment and healthy human development.* Basic books.

[9] Kelly A Brennan, Catherine L Clark, and Phillip R Shaver. 1998. Self-report measurement of adult attachment: An integrative overview. *Attachment theory and close relationships* 46, 1 (1998), 70–100.

[10] Timo Brockmeyer, Johannes Zimmermann, Dominika Kulessa, Martin Hautzinger, Hinrich Bents, Hans-Christoph Friederich, Wolfgang Herzog, and Matthias Backenstrass. 2015. Me, myself, and I: self-referent word use as an indicator of self-focused attention in relation to depression and anxiety. *Front. Psychol.* 6 (Oct. 2015), 1564.

[11] Jonathan Cantor, Ryan K McBain, Jacquelin Rankine, Aaron Kofner, Fang Zhang, Alyssa Burnett, Joshua Breslau, Ateev Mehrotra, Bradley D Stein, and Hao Yu. 2025. Screening for mental health problems in US public schools. *JAMA Netw. Open* 8, 7 (July 2025), e2521896.

[12] Aaron Chatterji, Tom Cunningham, David Deming, Zoë Hitzig, Christopher Ong, Carl Shan, and Kevin Wadman. 2025. How people use ChatGPT. *SSRN Electron. J.* (2025).

[13] Jacob Cohen. 2013. *Statistical power analysis for the behavioral sciences* (2 ed.). Routledge, London, England.

[14] Julian De Freitas, Ahmet K Uguralp, Zeliha O Uguralp, and Puntoni Stefano. 2024. AI companions reduce loneliness. *arXiv [cs.CY]* (July 2024).

[15] William L Dunlop, Alexander Karan, Dulce Wilkinson, and Nicole Harake. 2019. Love in the first degree: Individual differences in first-person pronoun use and adult romantic attachment styles. *Soc. Psychol. Personal. Sci.* (May 2019), 194855061984745.

[16] Christopher Ifeanyi Eke, Azah Anir Norman, Liyana Shuib, and Henry Friday Nweke. 2019. A survey of user profiling: State-of-the-art, challenges, and solutions. *IEEE Access* 7 (2019), 144907–144924.

[17] Dagmar Feddern Donbaek and Ask Elklit. 2014. A validation of the Experiences in Close Relationships-Relationship Structures scale (ECR-RS) in adolescents. *Attach. Hum. Dev.* 16, 1 (2014), 58–76.

[18] R Chris Fraley and Phillip R Shaver. 2000. Adult romantic attachment: Theoretical developments, emerging controversies, and unanswered questions. *Review of general psychology* 4, 2 (2000), 132–154.

[19] Tamar Gur and Yossi Maaravi. 2025. The algorithm of friendship: literature review and integrative model of relationships between humans and artificial intelligence (AI). *Behaviour & Information Technology* (2025), 1–21.

[20] Michael V Heinz, Daniel M Mackin, Brianna M Trudeau, Sukanya Bhattacharya, Yinzhou Wang, Haley A Banta, Abi D Jewett, Abigail J Salzhauer, Tess Z Griffin, and Nicholas C Jacobson. 2025. Randomized trial of a generative AI chatbot for mental health treatment. *NEJM AI* 2, 4 (March 2025).

[21] Bernie Hogan. 2010. The presentation of self in the age of social media: Distinguishing performances and exhibitions online. *Bulletin of Science, Technology & Society* 30, 6 (2010), 377–386.

[22] Alexandre Hudon and Emmanuel Stip. 2025. Delusional experiences emerging from AI chatbot interactions or "AI psychosis". *JMIR Ment. Health* 12, 1 (Dec. 2025), e85799.

[23] Jeffrey H Kahn, Renee M Tobin, Audra E Massey, and Jennifer A Anderson. 2007. Measuring emotional expression with the Linguistic Inquiry and Word Count. *The American journal of psychology* 120, 2 (2007), 263–286.

[24] KTA Sandeeshwara Kasturiratna and Andree Hartanto. 2025. Attachment to Artificial Intelligence: Development of the AI Attachment Scale, Construct Validation, and the Psychological Mechanisms of Human–AI Attachment. *Computers in Human Behavior Reports* (2025), 100912.

[25] Myungsung Kim, Seonmi Lee, Sieun Kim, Jeong-In Heo, Sangil Lee, Yu-Bin Shin, Chul-Hyun Cho, and Dooyoung Jung. 2025. Therapeutic potential of social chatbots in alleviating loneliness and social anxiety: Quasi-experimental mixed methods study. *J. Med. Internet Res.* 27, 1 (Jan. 2025), e65589.

[26] Jennifer King, Kevin Klyman, Emily Capstick, Tiffany Saade, and Victoria Hsieh. 2025. User privacy and large language models: An analysis of frontier developers' privacy policies. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* 8, 2 (Oct. 2025), 1465–1477.

[27] Elly A Konijn, Daniel F Preciado Vanegas, and Peggy van Minkelen. 2025. Theory of affective bonding: a framework to explain how people may relate to social robots and artificial others. *Communication Theory* (2025), qtaf007.

[28] Antonis Koutsoumpis, Janneke K Oostrom, Djurre Holtrop, Ward Van Breda, Sina Ghassemi, and Reinout E de Vries. 2022. The kernel of truth in text-based personality assessment: A meta-analysis of the relations between the Big Five and the Linguistic Inquiry and Word Count (LIWC). *Psychological Bulletin* 148, 11-12 (2022), 843.

[29] Alisa Küper and Nicole Krämer. 2024. Psychological traits and appropriate reliance: Factors shaping trust in AI. *Int. J. Hum. Comput. Interact.* (May 2024), 1–17.

[30] Yoon Kyung Lee, Jina Suh, Hongli Zhan, Junyi Jessy Li, and Desmond C Ong. 2024. Large language models produce responses perceived to be empathic. In *2024 12th International Conference on Affective Computing and Intelligent Interaction (ACII)*. IEEE, 63–71.

[31] Yugang Li, Baizhou Wu, Yuqi Huang, and Shenghua Luan. 2024. Developing trustworthy artificial intelligence: insights from research on interpersonal, human-automation, and human-AI trust. *Front. Psychol.* 15 (April 2024), 1382693.

[32] Robert F Ling. 1984. Residuals and Influence in Regression. *Technometrics* 26, 4 (Nov. 1984), 413–415.

[33] Auren R Liu, Pat Pataranutaporn, and Pattie Maes. 2025. Chatbot companionship: A mixed-methods study of companion chatbot usage patterns and their relationship to loneliness in active users. *arXiv [cs.HC]* (Aug. 2025).

[34] Sihua Lyu, Xiaopeng Ren, Yihua Du, and Nan Zhao. 2023. Detecting depression of Chinese microblog users via text analysis: Combining Linguistic Inquiry Word Count (LIWC) with culture and suicide related lexicons. *Frontiers in psychiatry* 14 (2023), 1121583.

[35] Takuya Maeda and Anabel Quan-Haase. 2024. When human-AI interactions become parasocial: Agency and anthropomorphism in affective design. In *The 2024 ACM Conference on Fairness, Accountability, and Transparency*. ACM, New York, NY, USA.

[36] Mario Mikulincer and Phillip R Shaver. 2010. *Attachment in adulthood: Structure, dynamics, and change.* Guilford Publications.

[37] Saif M Mohammad. 2025. NRC VAD lexicon v2: Norms for valence, arousal, and dominance for over 55k English terms. *arXiv [cs.CL]* (March 2025).

[38] James Muldoon and Jul Jeonghyun Parke. 2025. Cruel companionship: How AI companions exploit loneliness and commodify intimacy. *New Media Soc.* 14614448251395192 (Dec. 2025).

[39] Geoff Norman. 2010. Likert scales, levels of measurement and the "laws" of statistics. *Adv. Health Sci. Educ. Theory Pract.* 15, 5 (Dec. 2010), 625–632.

[40] Xudong Pan, Mi Zhang, Shouling Ji, and Min Yang. 2020. Privacy risks of general-purpose language models. In *2020 IEEE Symposium on Security and Privacy (SP)*. IEEE, 1314–1331.

[41] J Pennebaker, R Booth, and Martha E Francis. 2007. Linguistic inquiry and word count (LIWC2007). (2007).

[42] Iryna Pentina, Tyler Hancock, and Tianling Xie. 2023. Exploring relationship development with social chatbots: A mixed-method study of replika. *Computers in Human Behavior* 140 (2023), 107600.

[43] Anat Perry. 2023. AI will never convey the essence of human empathy. *Nature Human Behaviour* 7, 11 (2023), 1808–1809.

[44] Jason Phang, Michael Lampe, Lama Ahmad, Sandhini Agarwal, Cathy Mengying Fang, Auren R Liu, Valdemar Danry, Eunhae Lee, Samantha W T Chan, Pat Pataranutaporn, and Pattie Maes. 2025. Investigating affective use and emotional well-being on ChatGPT. *arXiv [cs.HC]* (April 2025).

[45] Ethel Pruss, Maryam Alimardani, Sascha Struijs, and Sander L Koole. 2025a. Emotional coregulation in close relationships with AI agents: A survey of ChatGPT and replika users. In *Proceedings of the 13th International Conference on Human-Agent Interaction*. ACM, New York, NY, USA, 19–28.

[46] Ethel Pruss, Maryam Alimardani, Sascha Struijs, and Sander L Koole. 2025b. Emotional Coregulation in Close Relationships with AI Agents: A Survey of ChatGPT and Replika Users. In *Proceedings of the 13th International Conference on Human-Agent Interaction*. 19–28.

[47] Rebecca L Robinson, Reanelle Navea, and William Ickes. 2013. Predicting final course performance from students' written self-introductions: A LIWC analysis. *J. Lang. Soc. Psychol.* 32, 4 (Dec. 2013), 469–479.

[48] Ariel Rosenfelder, Maor Daniel Levitin, and Michael Gilead. 2025. Towards social superintelligence? AI infers diverse psychological traits from text without specific training, outperforming human judges. *Computers in Human Behavior: Artificial Humans* 6, 100228 (Dec. 2025), 100228.

[49] Barbara R Sarason, Gregory R Pierce, Edward N Shearin, Irwin G Sarason, Jennifer A Waltz, and Leslie Poppe. 1991. Perceived social support and working models of self and actual others. *Journal of personality and social psychology* 60, 2 (1991), 273.

[50] Phillip R Shaver, Nancy Collins, and Catherine L Clark. 2014. Attachment styles and internal working models of self and relationship partners. In *Knowledge structures in close relationships*. Psychology Press, 25–61.

[51] Olivia Sidoti. 2025. 34% of U.S. adults have used ChatGPT, about double the share in 2023. https://www.pewresearch.org/short-reads/2025/06/25/34-of-us-adults-have-used-chatgpt-about-double-the-share-in-2023/. (June 2025). Accessed: 2025-9-10.

[52] Mackenzie Sigalos. 2025. OpenAI's ChatGPT to hit 700 million weekly users, up 4x from last year. https://www.cnbc.com/2025/08/04/openai-chatgpt-700-million-users.html. (Aug. 2025). Accessed: 2025-9-10.

[53] Marita Skjuve, Petter Bae Brandtzaeg, and Asbjørn Følstad. 2024. Why do people use ChatGPT? Exploring user motivations for generative conversational AI. *First Monday* (Jan. 2024).

[54] Marita Skjuve, Asbjørn Følstad, Knut Inge Fostervold, and Petter Bae Brandtzaeg. 2021. My chatbot companion-a study of human-chatbot relationships. *International Journal of Human-Computer Studies* 149 (2021), 102601.

[55] Marita Skjuve, Asbjørn Følstad, Knut Inge Fostervold, and Petter Bae Brandtzaeg. 2022. A longitudinal study of human–chatbot relationships. *Int. J. Hum. Comput. Stud.* 168, 102903 (Dec. 2022), 102903.

[56] Vera Sorin, Dana Brin, Yiftach Barash, Eli Konen, Alexander Charney, Girish Nadkarni, and Eyal Klang. 2024. Large language models and empathy: systematic review. *Journal of medical Internet research* 26 (2024), e52597.

[57] L Alan Sroufe. 2005. Attachment and development: A prospective, longitudinal study from birth to adulthood. *Attachment & human development* 7, 4 (2005), 349–367.

[58] Jessie Sun, H Andrew Schwartz, Youngseo Son, Margaret L Kern, and Simine Vazire. 2020. The language of well-being: Tracking fluctuations in emotion experience through everyday speech. *Journal of Personality and Social Psychology* 118, 2 (2020), 364.

[59] Sarah Tran, Hongfan Lu, Isaac Slaughter, Bernease Herman, Aayushi Dangol, Yue Fu, Lufei Chen, Biniyam Gebreyohannes, Bill Howe, Alexis Hiniker, Nicholas Weber, and Robert Wolfe. 2025. Understanding privacy norms around LLM-based chatbots: A contextual integrity perspective. *Proceedings of the AAAI/ACM Conference on AI, Ethics, and Society* 8, 3 (Oct. 2025), 2522–2534.

[60] Meifen Wei, Daniel W Russell, Brent Mallinckrodt, and David L Vogel. 2007. The Experiences in Close Relationship Scale (ECR)-short form: reliability, validity, and factor structure. *J. Pers. Assess.* 88, 2 (April 2007), 187–204.

[61] Pete Wells. 2025. This Year's Hot New Tool for Chefs? ChatGPT. *The New York Times* (June 2025).

[62] Tianling Xie and Iryna Pentina. 2022. Attachment theory as a framework to understand relationships with social chatbots: A case study of replika. In *Proceedings of the Annual Hawaii International Conference on System Sciences*. Hawaii International Conference on System Sciences.

[63] Fan Yang and Atsushi Oshio. 2025. Using attachment theory to conceptualize and measure the experiences in human-AI relationships. *Current Psychology* (2025), 1–12.

[64] Na Zhai, Xiaomei Ma, and Xiaojun Ding. 2025. Unpacking AI chatbot dependency: A dual-path model of cognitive and affective mechanisms. *Information (Basel)* 16, 12 (Nov. 2025), 1025.

[65] Yutong Zhang, Dora Zhao, Jeffrey T Hancock, Robert Kraut, and Diyi Yang. 2025. The Rise of AI Companions: How Human-Chatbot Relationships Influence Well-Being. *arXiv preprint arXiv:2506.12605* (2025).

8 Appendix

Table 6. Top 10 LIWC Features Correlated with Attachment Dimensions in ChatGPT Conversations (N_{msg} = 19, 930)

	Attachment Anxiety				**Attachment Avoidance**			
LIWC-22 Features	r	p	p_{FDR}	Sig	r	p	p_{FDR}	Sig
Total Affect *(good, love, happy)*	.310	.001	.035	*	.052	.598	.970	
Affiliation *(we, our, help)*	.301	.002	.035	*	.137	.163	.970	
Negative Emotion *(bad, hate, hurt)*	.292	.003	.035	*	.068	.490	.970	
I-words *(I, me, my)*	.281	.004	.035	*	−.005	.958	.979	
Future Focus *(will, going to, may)*	.280	.004	.035	*	.060	.540	.970	
Positive Tone *(good, well, new)*	.275	.005	.035	*	.042	.671	.970	
Total Social *(you, we, he)*	.265	.006	.041	*	.028	.774	.970	
Analytical Thinking	−.236	.015	.087		−.033	.740	.970	
We-words *(we, our, us)*	.227	.020	.100		.082	.408	.970	
You-words *(you, your, yourself)*	.222	.023	.104		.033	.739	.970	

Note. Pearson correlations between ECR-SF dimensions and LIWC-22 features extracted from participants' ChatGPT conversation transcripts.

$^{*}p_{\text{FDR}} < .05$.

Table 7. Attachment Dimensions and Affective Language in ChatGPT Conversations ($N_{msg} = 19,930$)

	Attachment Anxiety			Attachment Avoidance		
NRC VAD Dimension	r	p	p_{FDR}	r	p	p_{FDR}
Mean Valence *(negative–positive)*	.225	.021	.065	.186	.058	.347
Mean Arousal *(calm–excited)*	.224	.022	.065	−.036	.719	.863

Note. Pearson correlations between ECR-SF dimensions and NRC VAD Lexicon v2.1 features extracted from participants' ChatGPT conversation transcripts.

$^{*}p_{\text{FDR}} < .05$.