Do Attachment Styles Shape ChatGPT Usage?

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The widespread adoption of general-purpose conversational agents (GPCAs) has raised questions about the relationships that users may be developing with these systems. In this study, we ask whether users' attachment styles predict how they interact with ChatGPT, a popular GPCA, 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 ($N = 19,930$ messages). We find that attachment anxiety 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 likelihood of reporting that ChatGPT improves users' self-efficacy. Furthermore, we find that attachment anxiety is associated with distinctive linguistic patterns in users' ChatGPT conversations, including increases in affect words, self-referential pronouns, and future-focused thinking. These findings suggest novel privacy risks, such as the risk of implicitly disclosing attachment style through conversational patterns, even when conversing with a non-intimate GPCA for banal purposes like homework help and information-seeking. These findings also point to implications for designers and policy-makers, including the need to recognize anxiously attached individuals as a vulnerable user group and the potential future need to regulate psychological profiling of users.

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 general-purpose conversational agents (GPCAs) has changed people's information-seeking experiences. Millions of people now begin their online searches with ChatGPT, a popular GPCA. ChatGPT has amassed 700 million weekly active users globally [93], with young adults (aged 18–25) having the highest rate of adoption (up to 58% of adults under 30 in the U.S. report prior use) [92].

Unlike traditional search engines, ChatGPT's anthropomorphic interface invites users to engage with it conversationally. As a GPCA, it is capable of carrying out naturalistic, multi-turn conversations on any topic, and it can retain a memory of its interactions with the user. The social feel of these interactions invites users to seek information via dialogue rather than simple queries. These extended, social-like interactions—ranging from meal planning [104] to deeply personal emotional processing [24]—often sound more like a collaborative brainstorming session with another human than a series of queries posed to a search engine.

To what extent, if at all, do these conversational interactions lead users to form relationships with ChatGPT? And what are these relationships like? Research has documented that people can form meaningful relationships with conversational agents (CAs) [80], particularly companion CAs; CAs can be sources of comfort [62], safe spaces for self-expression and emotional disclosure [95], and partners in emotional co-regulation [83]. Research has also documented benefits of sustained companionship with CAs, including reduced anxiety [53], reduced depression symptoms [45], and increased feelings of social connectedness [30]. However, mounting evidence also reveals serious risks of forming attachments to CAs, including increased loneliness [82], delusional experiences [9, 48], emotional dependence [108], and, in extreme cases, self-harm and suicide [9, 10]. Given growing concerns from mental health professionals, policymakers, and HCI researchers [1, 2, 8, 8, 67] and population-level adoption of GPCAs, it is important to understand the nature of the relationships, if any, that users are forming with GPCAs.

Attachment theory offers a validated framework for investigating how users relate to ChatGPT. The theory describes the ways in which individuals experience key relationships in their lives [6, 18, 72]. Originally developed in the context of infant-caregiving interactions, attachment patterns reliably predict relational behaviors in friendships [11], romantic partnerships [36], workplace relationships [43, 59], and relationships with institutions [66] and religious figures [69]. Attachment dimensions have also been applied to parasocial relationships—one-sided bonds with virtual figures [15, 47]—where they predict the intensity and quality of perceived connection [26, 28, 86]. Attachment theory identifies two patterns in the ways people relate to others: attachment anxiety and attachment avoidance. GPCAs' affordances may interact with these two dimensions. They offer constant availability without risk of abandonment and responsiveness without requiring intimacy. Prior work has examined users' attachments to the companion CA Replika [65, 105], finding that users can form attachment relationships with companion CAs and that these relationships can be both addictive [91] and harmful [56]. Our study contributes to this growing body of literature by examining users' attachment styles in the context of GPCAs like ChatGPT.

In this exploratory, mixed-methods investigation, we ask:

- RQ1: How, if at all, does a person'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, specifically, that: 1) individuals with high attachment anxiety show increased dependence and emotional engagement with ChatGPT, 2) individuals with high attachment avoidance are less likely to trust ChatGPT or see gains in self-efficacy as a result of their ChatGPT usage, and 3) users' attachment styles leave visible traces (potentially leaving them vulnerable to exploitation) in their prompts to ChatGPT.

This work makes three primary contributions. First, we provide an in-the-wild empirical study linking attachment styles to users' interactions with a GPCA, ChatGPT. Second, we identify correlations between attachment dimensions and psycholinguistic patterns in users' ChatGPT messages, suggesting that CAs may accumulate implicit psychological information even in predominantly transactional interactions. Third, we distill the privacy risks and design implications that these findings point to, such as the need to recognize anxiously attached individuals as a vulnerable user group, the promise of drawing on evidence-based therapies for insecure attachment in the design of CAs, and the potential need for future regulation to limit AI companies' ability to psychologically profile users via latent information embedded in their conversational habits.

2 Related Work

2.1 Attachment Theory Across Relational Contexts

Attachment theory provides an empirically validated framework for understanding how humans form and maintain emotional bonds [17, 19]. Building on foundational observations of infant-caregiver interactions [5, 18], Bartholomew and Horowitz refined young people's attachment patterns into two primary dimensions: attachment anxiety, characterized by fear of abandonment and reassurance-seeking, and attachment avoidance, characterized by discomfort with closeness and preferred self-reliance[11]. Individuals low on both dimensions are described as securely attached, comfortable with intimacy and confident in others' availability [19, 88, 90]. These dimensions can be measured on continuous scales [103] and have proven robust across cultures, age groups, and measurement approaches[34, 35, 70, 71].

A key property of attachment dimensions is their generalizability across relational contexts. In friendships, attachment anxiety predicts greater jealousy, while avoidance predicts lower intimacy and self-disclosure [11]. In the workplace, attachment anxiety has been linked to worry about collegial relationships, while avoidance predicts reduced help-seeking [43, 59]. At broader scales, attachment dimensions predict trust in institutions [66] and the intensity of perceived relationships with religious figures [69]. In parasocial relationships with virtual figures[15], attachment anxiety predicts perceived connection despite the absence of reciprocity, while avoidance does not[26, 86]. Attachment styles established in early development remain moderately stable, yet they are also open to revision through new relational experiences, particularly during young adulthood [100]. This suggests both that users may bring pre-existing attachment styles to their interactions with GPCAs and that interactions with GPCAs might shape users' attachment styles.

2.2 Attachment with Conversational Agents

Conversational agents (CAs) are perceived to be consistent, responsive, and nonjudgmental conversational partners [20, 50, 57, 96–98]. Their conversational, human-like interfaces elicit users' social[68, 76, 77, 107] and emotional responses [56, 84, 95]. The extent to which a user bonds with a CA depends on how effectively the CA addresses the individual's needs [54]. Although CAs can simulate cognitive empathy by recognizing emotions [58, 99], they cannot, arguably, deliver the geninue reciprocity of human relationships [42, 46, 81]. As a result, studies have found that these connections have been associated with lower well-being, particularly among users with limited social networks [63, 110].

A growing body of work has documented risks arising from attachment with CAs. Laestadius et al. [56] identified emotional dependence as a risk of sustained Replika use. Phang et al. [82] found an association between increases in loneliness and increases in affective ChatGPT use. Shen and Yoon [91] documented addictive design patterns in CAs. Zhang et al. [109] outlined a taxonomy of harmful algorithmic behaviors in human-AI relationships, categorizing agents as perpetrators, instigators, facilitators, or enablers of harm. This collective work demonstrates the potential risks and harms of attachment with CAs.

Attachment theory expands on these prior findings by adding precision to how an individual's attachment style may affect the extent to which they are vulnerable. For example, Xie and Pentina [105] found that individuals with attachment anxiety are more likely to have an emotional bond with the CA. Yang et al. found that anxiously attached individuals seek more reassurance from CAs [106]. We build on this foundation by investigating attachment styles in the context of users' experiences with GPCAs, tools that are not explicitly designed for companionship purposes.

2.3 Privacy, Disclosure, and Computational Psycholinguistics

Current privacy frameworks for LLM-based CAs focus on protecting personally identifiable information that users explicitly share, such as names, locations, and contact information [60, 73, 89]. However, these frameworks treat sensitive information as residing in *what* users say. The psycholinguistics literature suggests that psychologically meaningful information may also reside in *how* users say it. The Linguistic Inquiry and Word Count (LIWC) framework has identified robust associations between the vocabulary patterns in users' everyday conversations and their emotional states [102], personality traits [55], mental health [51, 64], and life outcomes [85]. GPCAs' conversational interface elicit rich linguistic data well-suited to psycholinguistic analysis. Users engage in extended, multi-turn dialogues producing substantial text corpora that capture natural language use across diverse contexts. In this study, we use LIWC to examine whether attachment patterns manifest in users' ChatGPT conversations, testing the premise that how users prompt ChatGPT may reveal sensitive information alongside what they say in their prompts.

3 Method

We conducted a three-part, mixed-methods analysis comparing results of a two-part psychometric survey ($N = 168$) with computational psycholinguistic analysis and content analysis of the ChatGPT chatlogs of a subset of these same participants ($N_{msg} = 19,930$). We recruited participants through the research platform, Prolific[1]. Participants were compensated at a rate of $10 per hour. All procedures were approved by our institutional review board.

3.1 Participants and Recruitment

Data collection took place between November 2024 and July 2025. As part of a larger ongoing study, we recruited 510 young adults who self-reported using ChatGPT at least 10 times in the past two weeks . For the current study, we included only participants who completed both parts of the survey we administered (one part on attachment styles and one part on experiences with ChatGPT, see more details below), resulting in a sample of $N_{participant}$=168. Chat logs containing fewer than 10 pages and those not primarily in English were screened out, leaving 105 meaningful ChatGPT transcripts.

[1]https://www.prolific.com/

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).** Participants were assigned to one of four attachment categories via median splits on the ECR-SF anxiety and avoidance subscales, following the four-category Bartholomew-Horowitz model [11]. Our sample distribution closely matches that reported by Gleeson and Fitzgerald who applied the same median-split procedure to ECR-R scores in a sample of 227 young adults (30.4% secure, 18.1% anxious-preoccupied, 16.3% avoidant-dismissing, and 35.2% anxious-avoidant) [38].

3.2 Materials

3.2.1 Measuring Attachment Styles. Attachment styles were measured using the Experiences in Close Relationships Scale–Short Form (ECR-SF) [103], a validated 12-item measure assessing two orthogonal dimensions [12]: 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: α = 0.70 and avoidance: α = 0.69), consistent with prior research [33, 103].

3.2.2 Measuring ChatGPT Experiences. We developed an 11-item measure assessing users' experiences with ChatGPT across five theoretically motivated domains: Emotional Engagement, Trust, Dependency Concern, Self-Efficacy, and Behavioral Change. Items were drawn from constructs identified in prior research on human-AI relationships [94, 97]. For example, Emotional Engagement items were informed by findings showing that users experience CAs as safe spaces sharing personal struggles [50, 68, 98] and emotional co-regulation [56, 83]; Self-Efficacy items drew on research linking CA use to perceived competence gains [16, 52]. Participants responded on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree).

We pilot-tested the initial item pool with 30 ChatGPT users not included in the main sample. Based on pilot results, we removed items with poor inter-item correlations (r < .30).[2] We conducted reliability analysis and calculated Cronbach's α and correlation within each composite construct on the main sample: Emotional Engagement (α = .88, $r \approx$ .64-.79), Self-Efficacy (α = .71, $r \approx$ .42-.53), and Behavioral Change (α = .71, $r \approx$ .40-.51), confirming internal consistency (α > .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

[2]The initial 15 item survey is provided in the supplementary materials.

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 2. **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.[103].

format. Exported data included all user messages, AI responses, conversation timestamps, and conversation-thread identifiers. Conversation histories ranged from three months to three years of interactions. Most ChatGPT responses were generated by GPT-4o (49.6%) and GPT-4o-mini (12.8%).

3.3 Data Analysis

Our analysis followed a convergent mixed-methods design [29]. We investigated RQ1 (users' perceived experiences) through hierarchical regression analysis of self-reported survey data. We investigated RQ2 (users' interaction patterns) through two methods: first, we used computational psycholinguistic analysis across the full corpus of ChatGPT transcripts to identify associations between attachment dimensions and linguistic features, and second, we used content analysis of high-anxiety and high-avoidance users' messages to contextualize what these linguistic patterns look like in practice.

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 assess multicollinearity (all VIFs < 1.26) [14]. Model assumptions were assessed using Shapiro-Wilk tests, Q-Q plots, residuals vs. fitted plots, and influence plots [61]. Following established practice in psychology research, we treated 5-point Likert items as approximately continuous [78].

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 [27].

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 3. **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).

Computational Linguistic Analysis. We extracted 80 psycholinguistic markers with LIWC-22 [79] and two sentiment markers with NRC-VAD [74]. To focus on natural language and exclude copied-and-pasted content (e.g., homework, code blocks), we computed them on user messages fewer than 20 words ($Mean_{length}$ = 19.4). This resulted in a corpus of 19,930 user messages.

To ensure that participants who sent more messages did not disproportionately influence the analysis, LIWC features were computed as per-participant averages: each participant contributed a single data point (their mean across all retained messages). We conducted a bivariate correlation analysis between per-participant LIWC averages and attachment dimensions. We again applied Benjamini-Hochberg FDR correction for multiple comparisons.

Content Analysis. To complement computational approaches and focus 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: >3.83), annotating 100 user messages from each group (N = 200). To reduce co-occurrence confounds, transcripts of participants who scored in the top quartile on both dimensions ($N_{participant}$=12, 11.4% of 105 ChatGPT transcripts) were excluded from both groups. To ensure coverage across individuals, we randomly sampled 100 user messages per attachment dimension (10 messages each from 10 randomly selected participants).

Two authors each independently coded all N=200 messages. Inter-rater reliability was strong (Cohen's κ = 0.814, agreement = 88.0%). We used a deductive use-case taxonomy (e.g., Seeking Information, Practical Guide, Technical Help, Self-Expression)[3] adapted from Chatterji et al., an official ChatGPT usage study by OpenAI, to enable comparison with prior results [24]. Disagreements were resolved through discussion until consensus was reached.

[3]The complete codebook with category definitions and example messages is provided in the supplementary materials.

4 Results

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

We found both attachment anxiety and attachment avoidance to be significant predictors of users' perceived experiences with ChatGPT.

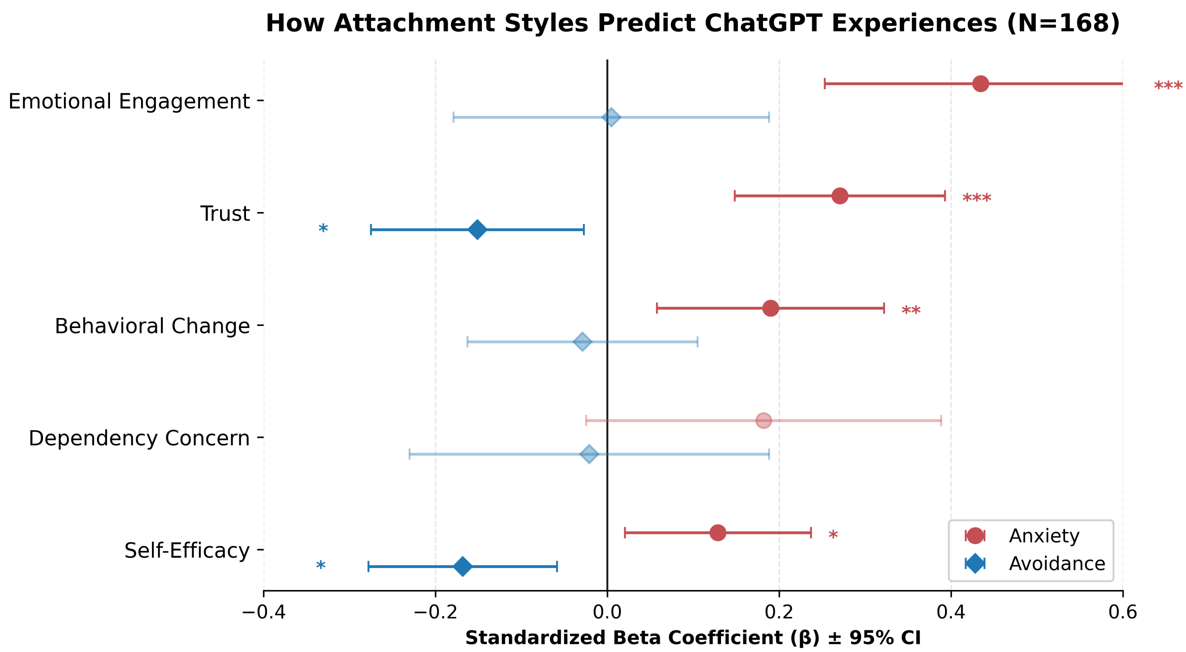

Fig. 1. **Attachment Anxiety Shows Broad Associations with ChatGPT Experiences, while Avoidance Effects Are Selective.** See Table 2 for questions associated with each construct. Standardized regression coefficients (β) with 95% confidence intervals from hierarchical multiple regressions predicting ChatGPT 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 ($\Delta R^2 = .135$, $F(2, 151) = 13.33$, $p < .001$). Anxiety was the sole significant predictor ($\beta = 0.43$, $t = 4.70$, $p < .001$, $p_{FDR} < .001$), a medium-to-large effect. Attachment avoidance showed no association ($\beta = 0.01$, n.s.).

Notably, approximately 39% of participants agreed or strongly agreed that they find it easier to share personal struggles with ChatGPT than with people, and this preference correlated 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, p_{FDR} < .001) while avoidance predicted lower trust (β = -0.15, t = -2.39, p = .018, p_{FDR} = .045). Demographic factors did not contribute significantly to the variance, but attachment dimensions did. Together, attachment dimensions explained 10.8% of variance in the trust measure (ΔR^2 = .108, $F(2, 153)$ = 9.63, p < .001).

4.1.3 Self-Efficacy. Both attachment anxiety and attachment avoidance significantly predicted perceived changes in self-efficacy as a result of using ChatGPT, again in opposing 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} = .016). Together, attachment dimensions explained 6.1% of variance in self-efficacy measures (ΔR^2 = .061, $F(2, 153)$ = 5.25, p < .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, n.s.). Attachment dimensions explained 4.6% of variance in behavioral change measures (ΔR^2 = .046, $F(2, 153)$ = 4.29, p = .015).

4.1.5 Concerns about Dependence. Despite the fact that participants with high attachment anxiety reported greater emotional engagement with and trust in ChatGPT, they did not express increased concern about depending on ChatGPT. Neither attachment dimension significantly predicted concerns about over-reliance on ChatGPT (anxiety: β = .18, t = 1.73, n.s.; avoidance: β = .02, n.s.; ΔR^2 = .020, n.s.).

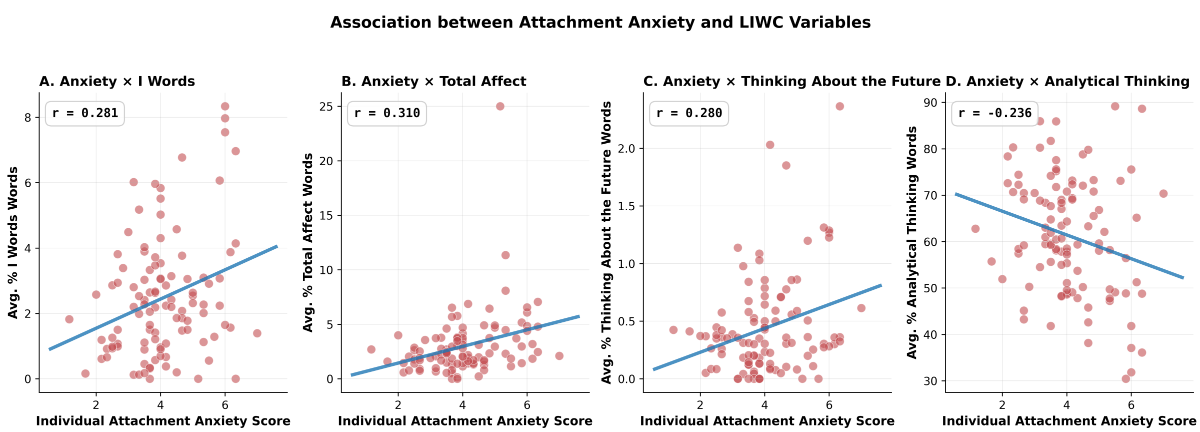

Fig. 2. **Attachment Anxiety Is Associated with Linguistic Patterns in User Messages to ChatGPT.** Scatter plots with linear regression lines illustrating bivariate associations between individual attachment anxiety scores (ECR-SF) and four LIWC-22 psycholinguistic markers aggregated at the participant level (N_{msg} = 19,930). 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 < .05).

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

To answer RQ2, we examined whether attachment patterns correlate with linguistic markers in user messages to ChatGPT. Our large corpus analysis (N = 19,930) revealed that attachment anxiety, in particular, is associated with linguistic patterns in users' messages, even in interactions that are largely transactional.

4.2.1 Linguistic Patterns of Attachment Anxiety. Attachment anxiety showed robust associations with several psycholinguistic markers in users' messages to ChatGPT, as illustrated in Figure 2. Users high in attachment anxiety used significantly more affective language (r = .31, p = .001, p^{FDR} = .035), including positive-emotion words such as good, love, happy (r = .275, p = .005, p^{FDR} = .035) and negative-emotion words such as bad, hate, hurt (r = .30, p = .002, p^{FDR} = .035). Increased attachment anxiety also predicted increased use of self-referential language such as I, me, my (r = .28, p = .002, p^{FDR} = .035), consistent with prior findings linking I-word usage to anxiety and depression [22]. This group also showed increased use of social words including total social references, we-words, you-words and affiliation terms.

4.2.2 Linguistic Patterns of Attachment Avoidance. In contrast to the broad linguistic correlations of attachment anxiety, attachment avoidance was not associated with the linguistic patterns we measured. Higher avoidance correlated with more third-person plural pronouns (r = .21, p = .033, p^{FDR} = .087, n.s.), though this did not survive FDR correction. Exploratory analyses confirmed that attachment dimensions were not associated with message volume (Anxiety × $n_{messages}$: r = .050, n.s.; Anxiety × Total Words: r = .068, n.s.; Avoidance × $n_{messages}$: r = .080, n.s.; Avoidance × Total Words: r = .097, n.s.)

4.2.3 Qualitative Patterns in High-Insecurity Conversations. To contextualize the computational findings, we also examined message content directly. As described in Section 3.3, we sampled 200 conversations from users in the top quartile of attachment anxiety (scores > 4.67) and avoidance (scores > 3.83). Participants who scored in the top quartile on *both* dimensions ($N_{participant}$ = 12, 11.4% of sample) were excluded from both groups.

As illustrated in Table 4, both the highly anxious and highly avoidant user groups engaged with ChatGPT for similar purposes: technical and homework help were the most common use cases (anxious: 59.0%; avoidant: 77.0%), followed by information seeking (anxious: 15.0%; avoidant: 11.0%) and practical guidance (anxious: 13.0%; avoidant: 5.0%). Despite differences in emotional engagement, trust, and affective language use, both groups used ChatGPT primarily for instrumental tasks. As our participants were young adults, many messages reflect requests for homework help (77.0 and 59.0%). Information-seeking use cases comprised 15.0% and 11.0% of messages. Some self-expression use cases included 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"*); they comprised 13.0% of messages from high anxiety users and 7.0% of messages from high avoidance users. Highly anxious users used ChatGPT for more self-expression (anxious: 13.0%; avoidant: 7.0%) and practical guidance (anxious: 13.0%; avoidant: 5.0%) than highly avoidant users did.

5 Discussion

In this study, we analyzed survey responses from 168 young adult (age 18-25) ChatGPT users alongside 19,930 messages they sent to ChatGPT. Through a mixed-methods analysis, we found that:

Theme	High Anxiety (User Messages)	High Avoidance (User Messages)
Technical & Homework Help	**(59.0%)** "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." "how do I write code that calculates the number of rows for each matrix"	**(77.0%)** "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	**(15.0%)** "Any ways to sell and promote your notion template" "nick robinson face claim alternatives?" "foods that people in general dont like"	**(11.0%)** "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	**(13.0%)** "csn you give me a full workout plan for vertical jump" "Should I take black maca root with food"	**(5.0%)** "Easy way to make money everyday" "what is considered employment hsiotry?"
Self-Expression	**(13.0%)** "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?"	**(7.0%)** "create a gut with a hoodie some baggy jeans and short brown hair" "What would I look like as a Ghibli character?" "list hobbies for me"

Table 4. **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 (>3.83; n = 100 messages). Categories adapted from prior ChatGPT use case taxonomies for comparison. Inter-rater reliability was strong (Cohen's κ = .814, percent agreement = 88.0%).

- Attachment styles predicted several aspects of users' perceived experiences with ChatGPT. Anxiously attached users reported increased emotional engagement with ChatGPT, trust in ChatGPT, behavioral change as a result of recommendations from ChatGPT and increases in self-efficacy as a result of ChatGPT usage.
- Participants with avoidant attachment styles reported opposite experiences, specifically, reduced trust in ChatGPT and fewer gains in self-efficacy as a result of using ChatGPT.
- Attachment styles also correlated with linguistic patterns in participants' conversations with ChatGPT. Attachment anxiety correlates with elevated affect words, first-person pronouns, and future-focused language in messages to ChatGPT.

Together, these findings point to several potential forms of user vulnerability. First, they reveal that users with high attachment anxiety are a vulnerable user group more likely to trust ChatGPT and to heed its advice. Second, they reveal that users with high attachment avoidance are less likely to benefit from ChatGPT and see self-efficacy gain. And finally, they reveal that users' chat histories may contain latent information about their attachment style (and potentially other psychological characteristics), suggesting a need for future research that examines the privacy risks of non-obvious disclosures of sensitive information.

We illustrate this opportunity space in Figure 3. As discussed below, prior work has investigated the privacy risks that users can incur from intentionally disclosing sensitive information to CAs. Other work, also discussed below, has investigated the privacy risks of engaging with CAs that are intentionally designed for intimate contexts like therapy (e.g., [45, 50]) or companionship (e.g., [56, 96]). Our findings show that there is also a need for future work that explores the risks of unintentionally disclosing sensitive information to GPCAs, a scenario that may be especially common.

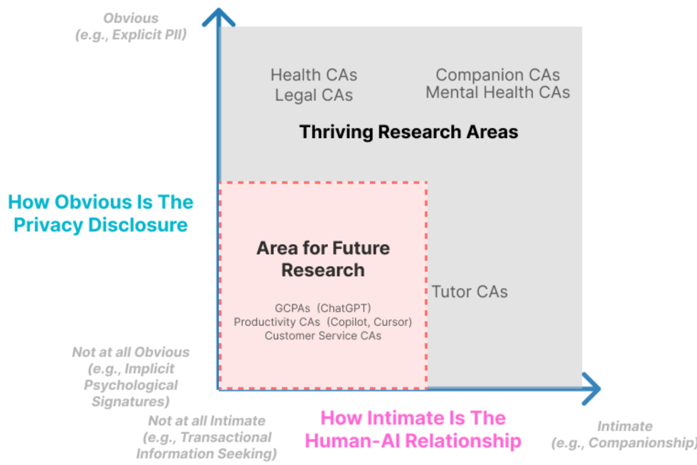

Fig. 3. **An Area of Need for Future Privacy Research.** Our findings surface two orthogonal dimensions of users' interactions with CAs: 1) the extent to which they intentionally disclose sensitive information (y-axis), and 2) the extent to which they seek out a CA designed for intimacy. Although the participants in our study can be placed in the lower left quadrant of this diagram (i.e., they were not intentionally disclosing sensitive information, and they did not select a CA designed for intimacy), they still disclosed potentially sensitive psychosocial data. A growing body of work explores the privacy risks of using CAs designed for intimate contexts (e.g., health CAs, Replika, mental health CAs). The red region in the figure above marks an area of needed future privacy research: users engaging with GPCAs (e.g., ChatGPT, Copilot, Gemini), and unknowingly disclosing non-obvious psychological information through their conversational patterns.

5.1 Privacy Risks from Implicit Disclosure

Our study identifies correlations between attachment styles and linguistic patterns in user prompts, suggesting that CAs may elicit implicit psychological signatures that could be considered sensitive personal data that users do not intentionally choose to disclose (Figure 3, y-axis). Current privacy frameworks for LLM-based CAs focus on protecting personally identifiable information (PII) that users explicitly share [60, 73, 89] or context that users reveal deliberately [60, 89]. This existing focus is well-motivated: users disclose more sensitive information to CAs than to humans, even when they are aware of privacy risks [111], and over 70% of queries in the ChatGPT-based "WildChat" dataset [112] contain PII [73].

However, these frameworks treat sensitive information as residing in *what* users say to CAs. Our findings suggest that psychologically meaningful information has the potential to reside in *how* they say it as well, despite the fact that users may be less likely to perceive themselves as disclosing sensitive information. Attachment anxiety was associated with elevated affect words, self-referential pronouns, and future-focused language—patterns that persisted even though the majority of messages in our corpus (74.0% for high-anxious user messages and 88.0% for high-avoidance in our qualitative sample) involved homework and information-seeking. An individual's attachment style has been shown to predict a wide range of relational behaviors [11, 36, 43, 59, 66, 72], making it potentially sensitive information. These data also have the potential to be used for profit, as many companion CA platforms are backed by business models that depend on users becoming attached to CAs[30, 57].

Profiling users and tailoring relational interactions to their specific vulnerabilities has the potential to be a commercially lucrative but harmful practice. For example, a GPCA could gate content with a dialog limit or other paywall when it detects that a user might be in particular need of reassurance. It is not unrealistic that such designs might be built into future systems, as prior work has documented similarly manipulative designs in many other contexts, for example, in platforms that exploit users' self-consciousness to sell fitness and beauty products [41], or users' fear to sell surveillance products [25].

It is important to note that our study establishes group-level associations, not individual-level inferences. However, recent work demonstrates that LLMs can infer psychological information from short text samples with accuracy exceeding human judges [87, 101]. Moreover, even coarse linguistic features reliably predict individual differences beyond their immediate domain [79] (for example, first-person pronoun usage can predict academic performance [85]). As conversational interfaces become more commonplace and sophisticated, it is reasonable to project that such systems could potentially detect individual and real-time patterns in attachment style and other psychosocial characteristics.

Unfortunately, conventional privacy interventions may be inadequate to address privacy risks from implicit disclosures. Data minimization (i.e., removing unnecessary personal content from prompts) is the standard approach to reducing disclosure risk [13, 37, 39]; recent tools such as Rescriber [113] have explored user-led sanitization of LLM inputs. However, the linguistic markers associated with attachment styles cannot be directly redacted. They are properties of language use that persist across topics and contexts.

5.2 Privacy Risks from Interactions with GPCAs

Our findings suggest that these vulnerabilities may be encoded even in transactional exchanges with GPCAs (Figure 3, x-axis), demonstrating that users' relational behaviors, and the vulnerabilities that accompany them, may be activated *wherever a conversational interface is present*. This observation suggests a second category of important future work: investigating the privacy risks posed by engaging with GPCAs, productivity CAs, and customer service CAs, despite the fact that these systems are not marketed as fostering intimacy. A growing body of work has documented relational risks of companion CAs [57, 63, 82], but everyday GPCA conversations may pose risks of their own. Although our study examined only attachment styles on ChatGPT, we hypothesize that similar patterns will manifest across sustained interactions with other GPCAs (e.g., Gemini) and domain-specific CAs. Future work should examine whether and how attachment vulnerability varies with the level of intimacy a CA claims to provide.

Our results also identify anxiously attached individuals—who make up approximately 20% of adults [44]—as a distinct vulnerable population, even in the context of transactional queries to a GPCA. This group reported greater emotional engagement with ChatGPT, higher trust in ChatGPT, and greater uptake of behavioral changes suggested by ChatGPT. They did not report any corresponding increase in concern about dependency on ChatGPT. Prior literature describes users experiencing CAs as safe spaces due to their availability, affirmation, and responsiveness [50, 68, 95, 98]. These traits are all characteristics of what attachment theory refers to as a "secure base" [6, 7, 18, 23, 35], the relational foundation that impacts anxiously attached individuals [11, 21, 103]. This raises the question of whether anxiously attached users treat CAs as secure bases, and if so, what the social consequences of doing so might be.

Finally, the group differences that we observed suggest that attachment styles may come to play a role in how users seek out and consume information, now that much information-seeking is moderated by highly anthropomorphic CAs rather than traditional search engines [75]. Anxiously attached users exhibited greater trust in ChatGPT-provided information, while avoidantly attached users exhibited skepticism. These attachment-based trust asymmetries may shape how people evaluate and incorporate online information delivered by CAs.

5.3 Design Implications

Based on our findings, we offer five considerations for the design and regulation of GPCAs.

Design with Awareness That Anxiously Attached Users Are a Vulnerable Group. Our results show that anxiously attached users tend to report greater emotional engagement with and higher trust in ChatGPT. Designers can protect these users by drawing on evidence-based practices for supporting anxiously attached individuals. For example, CAs can set relational boundaries when interactions shift from transactional to emotional [32, 49]; actively redirect users toward human relationships by continuing to validate users' feelings while encouraging connection with people who can fully reciprocate [18]; and prioritize integrity over affirmation—that is, answer honestly rather than always providing answers or agreeing with the user—in order to protect users who are inclined to over-trust these systems. We encourage designers to consult with therapists trained in attachment-informed approaches about how best to support users across the range of attachment styles.

Design for Self-Efficacy. Our findings show that users high in attachment avoidance report reduced trust in ChatGPT and fewer self-efficacy gains as a result of using ChatGPT. Rather than attempting to increase these users' trust, designers can lean into their preference for autonomy by designing interactions that teach and scaffold, enabling users to build competence independently rather than depending on the CA. This means prioritizing explanations over answers, offering step-by-step reasoning users can internalize, and providing citations or sources users can verify for themselves.

Develop Policy to Prevent Psychological Profiling. Commercial CA providers have the opportunity to—intentionally or incidentally—profile users for psychological characteristics that users will not realize they are sharing. Current privacy and algorithmic transparency regulations, such as the GDPR[4] and the EU AI Act[3], focus primarily on explicit PII. Future research should examine the scope and risks of such profiling, and future regulation should explore either preventing the use of implicit psychological models for commercial purposes (e.g., engagement optimization, pressure to make purchases) or, at minimum, requiring companies to disclose when such modeling occurs.

Disclose Psychological Profiling to Users. If GPCAs do model attachment style or any other latent psychological characteristic, they should be required to disclose this practice. Disclosure should take the form of a clearly visible notice in the primary interface and not buried in a terms-of-service agreement. This disclosure statement should be accompanied by an accessible interface where users can view how the system has categorized them (e.g., a dashboard reporting the system's belief about the user's attachment style) and the data used to make that assessment. Such transparency would give users the opportunity to contest or correct inferences and to make informed decisions about continued use.

Translational Design from Attachment-Based Therapy. Lastly, attachment-based therapies offer a rich but underexplored source of design inspiration for CAs. Clinical approaches such as Emotionally Focused Therapy (EFT) [40, 49] employ techniques to support insecure attachment: self-soothing strategies, grounding exercises that interrupt anxious escalation, surfacing attachment signals so clients can recognize their own relational patterns [18, 31, 32]. Designers can explore how these therapeutic strategies can be built into interfaces (e.g., a CA that coaches a user through a brief grounding exercise before continuing an emotionally charged request).

6 Ethical Considerations

Research Ethics of Collecting and Analyzing Naturalistic Conversation Data. Studying in-the-wild CA conversations raises ethical challenges that extend beyond standard informed consent. Although participants consented to share their data and could review their exports before submission, the volume of conversational logs makes participant-led data sanitization impractical. We recommend that future researchers studying private human-AI interactions implement active data sanitization procedures and provide participants with explicit guidance on the types of content their logs may contain and structured opportunities to redact specific conversations *at scale*. Our subsequent data collection waves have adopted this practice. More broadly, as the field moves toward collecting in-the-wild conversational data [114], we urge the development of shared community norms for handling intimate conversational data.

7 Limitations

First, our sample comprised 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 content analysis examined 200 messages—a small portion of the 19,930 conversations available—limiting the generalizability of qualitative findings.

8 Conclusion

This study provides in-the-wild empirical evidence linking attachment styles to experiences with ChatGPT. Attachment anxiety predicted heightened emotional engagement with ChatGPT, greater trust in ChatGPT, increased likelihood of adopting behaviors suggested by ChatGPT, and detectable linguistic markers in ChatGPT conversations. Attachment avoidance predicted reduced trust in ChatGPT and fewer gains in self-efficacy as a result of using ChatGPT. These findings identify anxiously attached individuals as a vulnerable population requiring design consideration, particularly given the privacy risks of unknowingly revealing their attachment style through their linguistic footprint. As GPCAs like ChatGPT increasingly occupy relational roles in daily life, approaches to privacy need to become more psychologically informed to protect relationally vulnerable users.

Generative AI Usage

Claude[4] was trivially used for proofreading and correcting issues in grammar, punctuation, phrasing, and table layout.

[4]https://claude.ai/

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A Supplemental Materials

A.1 Additional Results

Table 5. 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 6. 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.
$^{*}p_{\text{FDR}} < .05$.

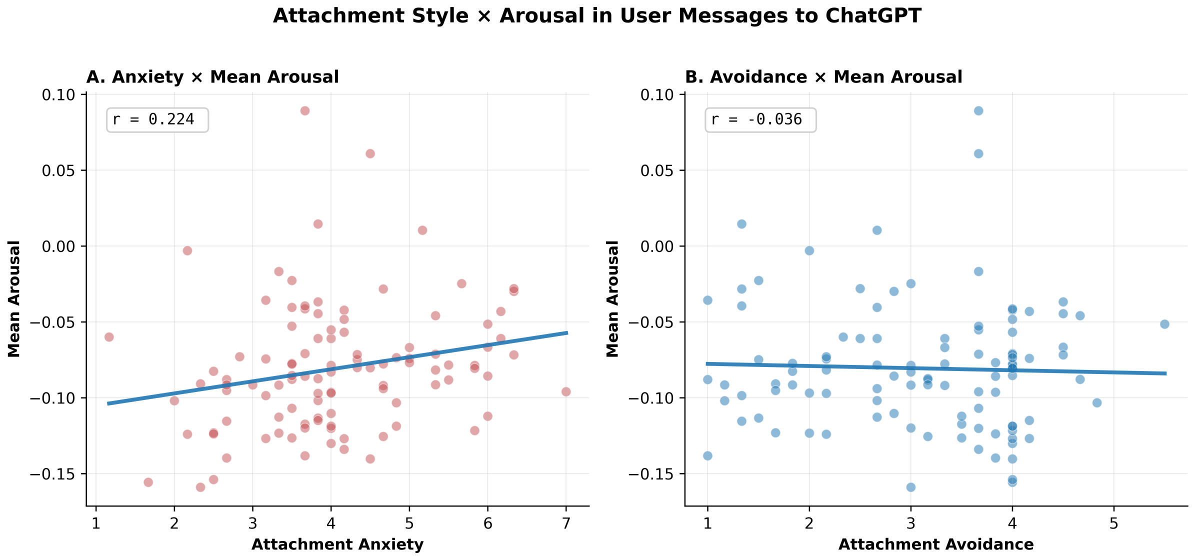

Fig. 4. **Attachment Anxiety, but Not Avoidance, Correlates with Emotional Arousal in ChatGPT Messages** Mean emotional arousal (NRC-VAD Lexicon v2.1) in user messages plotted against attachment dimensions (N_{msg} = 19, 930). Panel A: Attachment anxiety shows a positive association with message arousal (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).

A.2 Additional Message Volume Control Analysis

We conducted additional hierarchical regression analyses to directly control for message volume.

A.2.1 Results.

Attachment Anxiety. Controlling for message volume, Attachment Anxiety retained significant associations with 8 of the 46 LIWC dimensions after FDR correction ($q < .05$), compared to 7 in the bivariate analyses. Table 9 reports the full results. The core findings from the primary analysis were preserved: anxiety predicted elevated total affect ($\beta = .331$, $p = .001$), first-person singular pronouns ($\beta = .336$, $p = .001$), future-focused language ($\beta = .304$, $p = .004$), and negative emotion words ($\beta = .317$, $p = .003$), all surviving FDR correction. Analytical thinking also reached FDR significance in this model ($\beta = -.274$, $p_{\text{FDR}} = .044$), whereas it had not survived correction in the bivariate analysis ($p_{\text{FDR}} = .087$).

Attachment Avoidance. Attachment avoidance showed no significant associations with any LIWC dimension after FDR correction when controlling for message volume (Table 10), consistent with the bivariate results reported in the main text.

Table 7. Bivariate Correlations Between Attachment Anxiety and LIWC-22 Dimensions ($N_{msg} = 19,930$). Pearson correlations between ECR-SF attachment anxiety scores and participant-level LIWC-22 averages. Benjamini-Hochberg FDR correction applied across 46 tests. Sorted by absolute correlation strength; only dimensions with uncorrected $p < .05$ shown. Full table available in supplementary data.

Category	LIWC Variable	r	p	p_{FDR}	Sig
Affect	Total Affect	.310	.001	.035	*
Drives	Affiliation	.301	.002	.035	*
Affect	Negative Emotion	.292	.003	.035	*
Pronouns	I-words	.281	.004	.035	*
Perception	Future Focus	.280	.004	.035	*
Affect	Positive Tone	.275	.005	.035	*
Social	Total Social	.265	.006	.041	*
Summary	Analytical Thinking	−.236	.015	.087	
Pronouns	We-words	.227	.020	.100	
Pronouns	You-words	.222	.023	.104	
Pronouns	They	.217	.026	.109	
Social	Prosocial	.205	.036	.131	
Drives	Total Drives	.203	.038	.131	
Needs	Need	.201	.040	.131	
Social	Polite	.198	.043	.132	

Note. * $p_{\text{FDR}} < .05$. Top section: survived FDR correction. Bottom section: uncorrected $p < .05$ only.

Table 8. Bivariate Correlations Between Attachment Avoidance and LIWC-22 Dimensions ($N_{msg} = 19,930$). Pearson correlations between ECR-SF attachment avoidance scores and participant-level LIWC-22 averages. Benjamini-Hochberg FDR correction applied across 46 tests. No correlations survived FDR correction.

Category	LIWC Variable	r	p	p_{FDR}	Sig
Pronouns	They	.209	.033	.970	
Needs	Reward	.185	.059	.970	
Needs	Want	.177	.072	.970	
Summary	Emotional Tone	.155	.117	.970	
Perception	Past Focus	−.153	.119	.970	

Note. Only dimensions with uncorrected $p < .15$ shown. No associations survived FDR correction ($q < .05$).

Table 9. Attachment Anxiety Predicts Linguistic Patterns After Controlling for Message Volume ($N_{msg} = 19,930$). Standardized regression coefficients (β) for attachment anxiety from the model: $\text{LIWC}_z \sim \log(1 + n_{\text{messages}})_z + \text{Anxiety}_z + \text{Avoidance}_z$. Benjamini-Hochberg FDR correction applied to anxiety coefficients across 46 tests. ΔR^2 reflects variance uniquely attributable to the attachment dimensions beyond message volume. β_{vol} = standardized coefficient for log-transformed message count.

Category	LIWC Variable	β_{anx}	t	p	p_{FDR}	Sig	ΔR^2	β_{vol}
Pronouns	I-words	.336	3.28	.001	.033	*	.096	.067
Affect	Total Affect	.331	3.34	.001	.033	*	.096	−.235
Affect	Negative Emotion	.317	3.09	.003	.037	*	.090	.115
Perception	Future Focus	.304	2.95	.004	.037	*	.082	.064
Affect	Positive Tone	.292	2.96	.004	.037	*	.075	−.287
Drives	Affiliation	.291	2.83	.006	.037	*	.091	−.007
Social	Total Social	.290	2.87	.005	.037	*	.072	−.215
Summary	Analytical Think.	−.274	−2.72	.008	.044	*	.065	−.267
Perception	Past Focus	.248	2.40	.018	.091		.076	.102
Pronouns	You-words	.245	2.33	.022	.091		.052	−.043
Pronouns	We-words	.239	2.34	.021	.091		.055	.224
Perception	Feeling	.220	2.11	.038	.130		.050	−.093
Drives	Total Drives	.219	2.07	.041	.130		.043	.031
Social	Prosocial	.217	2.06	.042	.130		.042	−.108
Social	Polite	.215	2.04	.044	.130		.040	−.067
Perception	Present Focus	.208	2.03	.045	.130		.038	.255

Note. * $p_{\text{FDR}} < .05$. Top section: survived FDR correction. Bottom section: uncorrected $p < .05$ only. Sorted by absolute β_{anx}. Only dimensions with uncorrected $p < .05$ shown.

Table 10. Attachment Avoidance Shows No Significant Linguistic Associations After Controlling for Message Volume ($N_{msg} = 19,930$). Standardized regression coefficients (β) for attachment avoidance from the model: $\text{LIWC}_z \sim \log(1 + n_{\text{messages}})_z + \text{Anxiety}_z + \text{Avoidance}_z$. Benjamini-Hochberg FDR correction applied to avoidance coefficients across 46 tests. No associations survived FDR correction.

Category	LIWC Variable	β_{avoid}	t	p	p_{FDR}	Sig	β_{vol}
Perception	Past Focus	−.249	−2.41	.018	.811		.102
Perception	Feeling	−.176	−1.69	.095	.942		−.093
Needs	Reward	.171	1.61	.110	.942		−.009
Needs	Curiosity	.165	1.55	.124	.942		−.061
Pronouns	They	.142	1.40	.166	.942		.207
Drives	Power	−.137	−1.28	.202	.942		.035
Pronouns	I-words	−.135	−1.32	.189	.942		.067

Note. Only dimensions with uncorrected $p < .20$ shown. No associations survived FDR correction ($q < .05$). Sorted by absolute β_{avoid}.

A.3 Codebook

Table 11. **Codebook: Adapted Use Case Taxonomy.** Mapping from Chatterji et al. [24] to our consolidated categories, with definitions and corpus examples. All examples are from sample (N=200).

Category	Original Category	Our Definition	Examples
Technical / Homework Help & Writing	Writing; Technical Help; Multimedia	User requests production, editing, debugging, translation, or transformation of a concrete artifact (text, code, image, calculation). *Exclude:* conceptual explanations without an artifact (Information Seeking).	*"Prepare the statement of financial position as at 31 December 2022. Please include comparative figures"* *"Provide Python code for a function that takes an argument n and returns a list containing the first n square numbers"* *"Write me a cover letter for a receptionist position at a fast food restaurant"*
Information Seeking	Seeking Information (Specific Info; Products; Recipes)	User requests factual information, explanations, comparisons, or recommendations without requesting an artifact. *Exclude:* step-by-step guidance; requests to *write* about a topic.	*"what do you call the equipment that buffets use to keep the hot foods hot"* *"is there such a thing as right ventricular ejection fraction"* *"How did the Nazi regime mobilise German society to fight the Second World War?"*
Practical Guidance	How-To Advice; Tutoring; Creative Ideation; Health/Fitness/Self-Care	User requests actionable advice, plans, or step-by-step guidance, or brainstorm ideas. *Exclude:* factual questions without an action component; requests to produce a document.	*"What is a good small business idea for someone with mental illness? I need money"* *"What should I do for biceps when on first day I do preacher curls and Bayesian curls"* *"what are fidgety things/tasks to do when anxious"*
Self-Expression	Emotional Disclosure; Mental Health Support; Relationships & Personal Reflection; Greetings & Chitchat, Role Play with ChatGPT;	User's primary function is emotional expression, personal disclosure, or relational engagement with the system. *Exclude:* emotions *in service of* an actionable practical request (e.g., "I'm stressed—help me study" Practical Guidance).	*"i feel stupid for texting him again because he's changed his tone so quickly"* *"i'm sad about a breakup and feel really lonely"* *"thank you chat i'm thankful for you. i wish i could pay for the premium"*

A.4 Pilot 15-item ChatGPT Experiences Measure

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. (2) I regularly fact-check or verify ChatGPT's responses. (3) I feel confident implementing ChatGPT's suggestions without modification.
Dependency	(1) I worry about relying too heavily on ChatGPT for tasks.^{R} (2) I feel less confident solving problems without ChatGPT's help. (3) I prefer to attempt tasks on my own before consulting ChatGPT.
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 12. **Original Experiences with ChatGPT: Constructs and Items** 15-item measure assessing user perceived ChatGPT experiences across five theoretically-motivated domains.