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The Heterogeneous Effects of AI Companionship: An Empirical Model of Chatbot Usage and Loneliness and a Typology of User Archetypes

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Abstract

Companion chatbots offer a potential solution to the growing epidemic of loneliness, but their impact on users' psychosocial well-being remains poorly understood, raising critical ethical questions about their deployment and design. This study presents a large-scale survey (n = 404) of regular users of companion chatbots, investigating the relationship between chatbot usage and loneliness. We develop a model explaining approximately 50% of variance in loneliness; while usage does not directly predict loneliness, we identify factors including neuroticism, social network size, and problematic use. Through cluster analysis and mixed-methods thematic analysis combining manual coding with automated theme extraction, we identify seven distinct user profiles demonstrating that companion chatbots can either enhance or potentially harm psychological well-being depending on user characteristics. Different usage patterns can lead to markedly different outcomes, with some users experiencing enhanced social confidence while others risk further isolation. These findings have significant implications for responsible AI development, suggesting that one-size-fits-all approaches to AI companionship may be ethically problematic. Our work contributes to the ongoing dialogue about the role of AI in social and emotional support, offering insights for developing more targeted and ethical approaches to AI companionship that complement rather than replace human connections.

Extended version with appendix — https://arxiv.org/abs/2410.21596

Introduction

In an increasingly digital world, we are paradoxically more connected and isolated than ever. Despite unprecedented technological means to connect, loneliness remains pervasive, affecting approximately **a third of individuals in industrialized countries** (Loveys et al. 2019). This phenomenon has led to what the U.S. Surgeon General declared an "epidemic of loneliness" (Office of the Assistant Secretary for Health (OASH) 2023). The gravity of this issue is underscored by research indicating that chronic loneliness can increase mortality risk by 26-29%, comparable to smoking 15 cigarettes a day (Chawla et al. 2021).

Artificial intelligence (AI) has emerged as a potential tool for addressing loneliness. Companion chatbots, which engage in complex conversations and maintain persistent relationships with users, have gained significant popularity, with platforms like Replika and Character.ai reporting over 30 million and 20 million users, respectively (Patel 2024; Shewale 2024). These companion chatbots offer users the opportunity for constant, judgment-free interaction. Some research suggests that companion chatbots, even when used over the short term, decrease feelings of loneliness (Loveys et al. 2019; Gasteiger et al. 2021; De Freitas et al. 2024). However, concerns have been raised about the authenticity of these relationships, suggesting that they lower the bar for what people think relationships can be (Turkle 2011). This could lead to unrealistic expectations and further social withdrawal.

The nuanced nature of human-AI interaction in this context presents a critical gap in our understanding. Specifically, we lack comprehensive knowledge about factors influencing companion chatbots' impact on loneliness and other psychological and social factors. Artificial agents may complement human social interactions in some contexts while replacing them in others (Xia et al. 2024). This variability in outcomes underscores the need for a more comprehensive and granular analysis of user characteristics, usage patterns, and their relationships to psychological well-being. To address this gap, we conducted a survey (n = 404) of regular companion chatbot users, with the following research questions:

- RQ1: What motivates the use of companion chatbots, and what do people use them for?
- RQ2: What is the relationship between companion chatbot usage and loneliness, and what factors mediate or moderate this relationship?
- RQ3: Can we identify and characterize distinct user profiles based on usage patterns, loneliness levels, problematic use, and other psychological and social factors?

Our study aims to provide a more nuanced understanding of the impact of companion chatbots. By identifying the characteristics of users who experience psychosocial benefits from chatbot interactions (i.e., reduced loneliness and improved social skills) and those who may experience negative consequences (i.e., emotional dependence and social withdrawal), we hope to inform more targeted and ethical design practices. For example, more information could guide the development of customizable interfaces that emphasize features beneficial to specific user groups or implement safeguards for at-risk users. By examining how users' mental models and expectations of companion chatbots influence outcomes, we can explore strategies for fostering healthy human-AI relationships that complement rather than replace human connections.

Through a combination of statistical analyses, including multiple regression and cluster analysis, along with qualitative assessment of user responses, we present the following contributions: (1) A **model** explaining approximately 50% of variance in loneliness, identifying problematic use as a key mediator and social attraction as a moderator in the relationship between chatbot usage and loneliness while accounting for personality traits and social network characteristics; (2) a **typology** of seven distinct companion chatbot user profiles demonstrating how similar usage patterns can lead to markedly different outcomes based on individual characteristics and social contexts; (3) an exploration of **motivations and usage characteristics** across different user types, revealing how technological exploration and entertainment dominate over social purposes despite marketing as social tools; (4) a demonstration of how manual thematic analysis can be effectively triangulated with **LLM-based theme extraction** to achieve both interpretive depth and comprehensive coverage in large-scale qualitative analysis; and (5) **design implications** for creating more effective and ethically responsible companion chatbots, including the need for personalized approaches and built-in mechanisms to detect and intervene in potentially harmful usage patterns.

By addressing these questions, we aim to advance the field of human-computer interaction in the domain of AI companionship, providing insights that can guide the development of technologies that genuinely enhance human well-being and social connection in our increasingly digital world.

Background and Related Work

Loneliness and Social Support

Loneliness, the subjective feeling of isolation regardless of actual social network, affects approximately one-third of individuals in industrialized countries (Loveys et al. 2019). The U.S. Surgeon General's 2023 declaration of loneliness as an epidemic highlights this issue's significance (Office of the Assistant Secretary for Health (OASH) 2023). Chronic loneliness increases mortality risk by 26-29%, comparable to smoking 15 cigarettes daily (Freedman and Nicolle 2020).

Individuals employ various coping strategies for loneliness (Rokach and Brock 1998; Deckx et al. 2018), with digital platforms emerging as common mechanisms. Evidence shows that lonely, socially isolated, and socially anxious individuals tend to engage in one-sided paradigms like parasocial relationships with content creators (Niu et al. 2021; de Bérail, Guillon, and Bungener 2019; Balcombe and Leo 2023; Madison, Porter, and Greule 2016) and face a higher risk of addiction to online platforms (Reer, Tang, and Quandt 2019; O'Day and Heimberg 2021; Burke, Marlow, and Lento 2010).

Effective interventions for reducing loneliness include cognitive behavioral therapy, improving social support, and facilitating social interaction (Rokach and Brock 1998; Gasteiger et al. 2021; Hickin et al. 2021), though efficacy varies across individuals. This aligns with recognition that lonely individuals constitute a diverse group with varying needs (Cacioppo and Cacioppo 2018), suggesting interventions—including technological ones—must be tailored to individual circumstances.

Companion Chatbots

Companion chatbots represent a novel approach to addressing loneliness (Wang et al. 2024; Goodings, Ellis, and Tucker 2024; Boine 2023; Chen, Kang, and Hu 2024; Shani et al. 2022; Brewer 2022). These commercially available chatbots employ generative AI to engage in complex conversations and maintain persistent relationships with users. Several popular services have gained significant user bases: Replika reported over 30 million registered users worldwide by August 2024 (Patel 2024), while Character.ai, a platform allowing users to role-play with chatbots based on fictional characters, reported over 20 million users in March 2024 (Shewale 2024).

The popularity of these services, particularly among young adults, indicates their growing acceptance as sources of social interaction and emotional support (Koulouri, Macredie, and Olakitan 2022; Xygkou et al. 2024, 2023). Research suggests artificial companions can reduce loneliness through direct companionship, acting as catalysts for social interaction, facilitating remote communication, and providing reminders for social activities (Gasteiger et al. 2021).

The perceived "realness" of connection with companion chatbots significantly impacts their effectiveness. Users who attribute human-like qualities to chatbots often experience improved social health and reduced loneliness (Xia et al. 2024), though this carries a risk of dehumanizing other people (Zehnder, Dinet, and Charpillet 2021). Pataranutaporn & Liu et al. (Pataranutaporn et al. 2023) found that mental models altered experience—priming users with different beliefs about an AI's motives significantly affected their assessment of the AI's trustworthiness and effectiveness.

Research on artificial agents' influence on human socialization has produced mixed results, mostly qualitative in nature (Van der Loos 2014; Turkle 2011). One study suggested artificial agents may replace humans for task-oriented interactions while complementing human social interactions (Xia et al. 2024).

While empathy is inversely correlated with loneliness (Beadle et al. 2012), the role of chatbots that perform empathy remains uncertain. Role-play increases empathy (Bearman et al. 2015; Dewi, Pratisti, and Prasetyaningrum 2019), yet the potential of AI-facilitated role-play to influence empathy and loneliness represents an unexplored research area despite widespread user engagement.

Human-AI Interaction for Emotional Support

Studies suggest even limited AI companionship reduces loneliness (De Freitas et al. 2024), though long-term effects and risks remain subjects of investigation and ethical debate

(Li et al. 2023; Abd-Alrazaq et al. 2020). Skjuve et al. described how human-chatbot relationships evolve from superficial interaction through affective exploration to stable emotional connection (Skjuve et al. 2021). This enables companion chatbots to provide various forms of social support in an always-available "safe space" (Ta et al. 2020). These interactions appeal particularly to those lacking traditional support systems, such as LGBTQ individuals (Ma et al. 2024). User motivations range from curiosity to explicit seeking of emotional support, with topics spanning casual conversation to deep personal issues (Ta-Johnson et al. 2022). Siemon et al.'s analysis of Replika reviews (Siemon et al. 2022) showed users often employ the service to cope with loneliness, with long-term interactions proving beneficial.

Significant ethical considerations include potential over-reliance on AI, consequences for mood, delays in seeking professional help, and withdrawal from human socialization (Pataranutaporn et al. 2021). A teen suicide case in 2024 following extensive Character.ai use raised concerns about chatbot influence on mental health (Roose 2024), underscoring the need to understand companion chatbots' impact on psychosocial well-being.

Our research seeks to identify characteristics of users who benefit from chatbot interactions versus those who experience negative consequences, informing targeted and ethical design practices toward positive computing in human-AI interaction—designing technology that supports psychological well-being (Calvo and Peters 2017).

Methods

We surveyed companion chatbot users recruited from CloudResearch Connect (Hartman et al. 2023), administering psychological scales and measuring chatbot usage patterns. The study was IRB-approved with a target sample of 385 participants (95% confidence level, 5% margin of error). Participants were 18+ years old, English-fluent, and regular chatbot users (weekly use for at least one month). After filtering incomplete responses, our final sample consisted of 404 participants.

Analytical Approach

Our mixed-methods approach included (1) Spearman correlation analysis of numerical variables with Benjamini-Hochberg correction, (2) multiple regression exploring relationships between chatbot usage, loneliness, and potential mediating/moderating factors, (3) K-means clustering to identify distinct user profiles based on psychosocial characteristics and usage patterns, and (4) thematic analysis from a stratified random sample (N = 105) combined with generative AI-based topic extraction of the full dataset.

Survey Instrument

Our survey combined established scales and custom items:

Established Scales Our primary dependent variable was measured with the **UCLA Loneliness Scale** (ULS-8) (Hays and DiMatteo 1987), selected for its brevity while maintaining strong psychometric properties (Cronbach's α = .84). For potential mediating and moderating factors, we included the following items: **Lubben Social Network Scale** (LSNS-6) (Lubben et al. 2006), measuring social isolation (α = .83); **Multidimensional Scale of Perceived Social Support** (MSPSS) (Zimet et al. 1990), assessing perceived social support (α = .88); **Brief Rosenberg Self-Esteem Scale** (B-RSES) (Monteiro et al. 2022), evaluating self-esteem (α = .89); **Big Five Inventory** (BFI-10) (Rammstedt and John 2007), assessing personality traits (mean correlation with full BFI: .83); **Attitudes Towards AI Scale** (Schepman and Rodway 2020), measuring AI attitudes (positive subscale: α = .88; negative: α = .83); **Human-Chatbot Interaction Effect Scale** (Xia et al. 2024), measuring effects of human-chatbot interaction on human-human interaction; **Adapted Generalized Problematic Internet Use Scale** (GPIUS2) (Caplan 2010), measuring problematic chatbot use (α = .91 for original scale); **State Empathy Scale** (Shen 2010), capturing empathy dimensions with strong construct validity; **Interpersonal Attraction Scale** (McCroskey and McCain 1974), measuring attraction dimensions, with versions for chatbots and close persons; **Perceived Homophily Scale** (Mccroskey, Richmond, and Daly 1975), measuring perceived similarity in communication; **Attributional Confidence Scale** (Gudykunst and Nishida 1986), assessing ability to predict others' attitudes and behaviors; and **System Usability Scale** (SUS) (Brooke 1996), measuring perceived chatbot usability (α = .91).

Where necessary, we shortened scales based on factor loadings from previous studies to manage survey length while maintaining measurement integrity. We addressed this limitation through statistical controls for multicollinearity and conservative interpretation.

Custom Items We developed custom items to collect data on chatbot usage frequency and session length, as well as usage motivations, conversation topics, and perceived impacts on relationships. Most items combined multiple-choice selections with free-response elaboration, with participants providing elaboration for reasons for **initially using** and **continuing to use** chatbots, conversation **topics**, perceived **effects of chatbot use on human relationships** (combined with Likert-scale items reporting changes in human interactions), situational **preferences for chatbot versus human** interaction (combined with a preference matrix across different contexts), and **reasons underlying these preferences**.

Statistical Analyses

All analyses were performed using Python. We calculated descriptive statistics on chatbot usage characteristics for both the entire dataset and identified clusters. Usage frequency and session length were converted to numerical scores, and all variables were standardized. For correlation analysis, we computed a Spearman correlation matrix with Benjamini-Hochberg correction (Figure 1).

Regression analysis focused on **session length** as the independent variable (as frequency showed no significant correlation with loneliness). Potential mediators were identified using corrected p-values ($p < 0.05$) following Baron and Kenny's approach (Baron and Kenny 1986) with Sobel

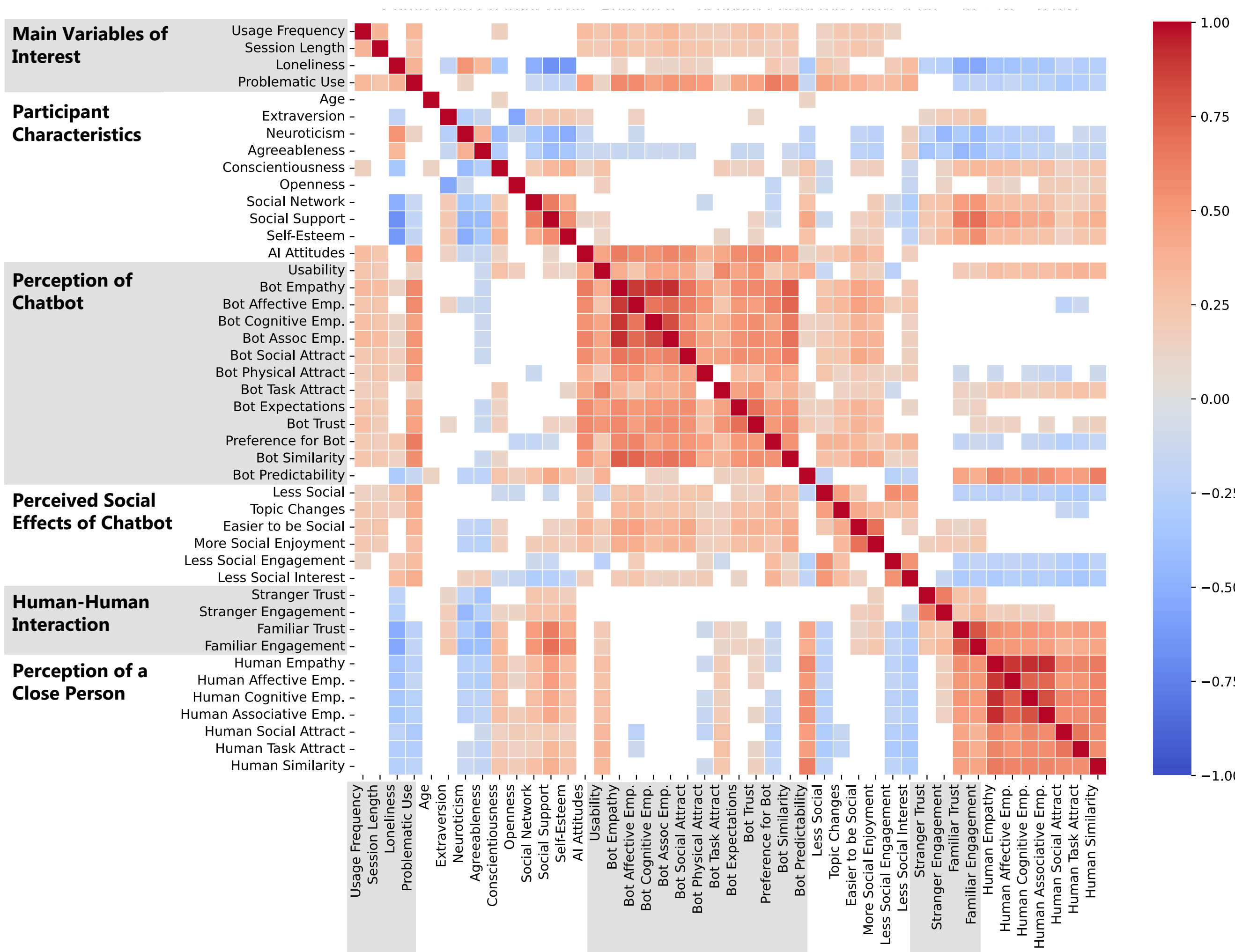


Figure 1: Correlation matrix (Spearman, Benjamini-Hochberg corrected) showing significant ($p < 0.05$) correlations of psychological, social, and usage characteristics. Variables are sorted into general categories, and names have been altered for readability. The original names can be seen in Figure 6 of the Appendix.

tests (Sobel 1982). Moderation effects were tested by examining interaction terms (Aiken and West 1991). Variance Inflation Factors were calculated to address multicollinearity (Hair et al. 2010; O'brien 2007). Our regression model initially included all identified mediators, moderators, and confounders (Greenland, Pearl, and Robins 1999; VanderWeele and Shpitser 2013). We used backward elimination to create a more parsimonious model (Cohen et al. 2003), retaining age and sex as control variables. Model fit was assessed using R-squared, F-statistic, and condition number, with assumptions checked using Q-Q plots, residuals vs. fitted plots, and influence plots (Cook and Weisberg 1982; Fox 2015). We conducted parallel multiple mediation analysis using bootstrapping with 5,000 resamples (Preacher and Hayes 2008).

We then employed **K-means clustering** to identify distinct user profiles. Features were selected based on significant correlations with key variables ($p > 0.05$, corr > 0.3) and relevance to chatbot usage, then reduced to 10 principal components. The optimal number of clusters was determined using the elbow method (Kodinariya and Makwana 2013), silhouette scores (Kaufman and Rousseeuw 2009), and interpretability considerations. We chose a 7-cluster solution based on these metrics and the distinctiveness of resulting profiles. To validate our clustering, we conducted Kruskal-Wallis tests (Kruskal and Wallis 1952) followed by Dunn's post-hoc tests with Bonferroni correction (Dunn 1964), calculated average silhouette scores (Rousseeuw 1987), and performed MANOVA (Huberty and Olejnik 2007) with Box's M-test (Box 1949).

Mixed-Methods Thematic Analysis

To complement quantitative findings, we employed a mixed-methods approach combining manual thematic analysis (Braun and Clarke 2006) with automated topic extraction, addressing limitations of purely manual analysis (limited sample coverage) and purely automated analysis (reduced contextual sensitivity) (O'Connor and Joffe 2020). Thematic analysis was conducted on a stratified random sample (N=105, 15 per cluster), with one researcher developing codes and grouping them into broader themes. To validate themes across the complete dataset (N=404), we implemented an **automated pipeline using GPT-4 for topic extraction** (see Appendix for details), processing responses in batches of 300 with instructions to identify 5-10 key themes per batch, including descriptions, prevalence estimates, and representative quotes. A researcher reviewed the LLM output to assess accuracy and distinctiveness before **comparing to manual themes** based on descriptions and quotes; LLM themes were matched to similar manual themes or identified as subsets where appropriate, with substantial overlap in identified patterns. This triangulation strengthened confidence in our thematic findings while demonstrating how manual depth can complement automated breadth in qualitative analysis.

Results

RQ1: What Motivates the Use of Companion Chatbots, and What Do People Use Them For?

Motivations for Initial Interest and Continued Use of Companion Chatbots Participants were asked separate questions about their initial interest in starting chatbot use and their reasons for continuing use, each combining multiple-choice options with free-response elaboration. Analysis of quantitative and qualitative data revealed diverse motivations, validated through automated theme extraction across the full dataset. Descriptions of these themes can be found in Figure 10 in the Appendix.

Technology exploration emerged as the predominant motivation (30.89% initial use, 20.91% continued use), with users expressing curiosity about AI capabilities: "I wanted to see if it could actually emulate a real person."

Recreation represented another major theme, encompassing entertainment (26.35% initial, 23.69% continued) and creative activities (17.81% initial use). Users enjoyed role-playing and creative projects: "I use chatbots to practice conversations for my D&D game, creating NPC personalities and dialogue."

Practical utility emerged particularly in continued use, with users valuing task assistance and information seeking: "I usually use chatbots to help with ideas like dinner ideas or information I may want to find out without using a typical search engine."

The **safe space** theme encompassed chatbots as non-judgmental environments for self-expression: "I sometime feel lonely and just want to be left alone, during this time I like chatting with my AI companion because I feel safe and won't not [sic] be judged."

Notably, while companion chatbots are often marketed as solutions for loneliness, only 12.24% of participants initially sought them for companionship (9.86% continued). Other social motivations were also less prevalent but significant for some users, including **self-improvement** for social skills (7.24% initial) and **lifestyle integration** where chatbots become part of daily routines. While initial interest often stems from curiosity and entertainment, continued use appears more rooted in practical and emotional benefits.

Topics of Conversation With Companion Chatbots Analysis revealed five major themes in chatbot engagement (see Figure 10 in the Appendix). Our automated analysis confirmed these themes while providing prevalence estimates across all 404 participants. The convergence between manual and automated approaches strengthened confidence in our thematic findings.

Casual exchange, including casual conversations (26.28%) and entertainment (21.66%), represents the most common interaction: "I often chat with my AI about random things like my day, and it feels like I'm having a normal conversation without the pressure."

Emotional disclosure also emerged as notable, encompassing mental health discussions (14.17%) and interpersonal issues (10.96%): "I can talk about my problems, and it's like having a private conversation with no fear of being criticized."

Knowledge seeking involved users turning to chatbots for information and advice, including discussion of future plans (11.70%). One individual mentioned, "I use the chatbot to ask about random things like historical facts or recommendations for books." Others used companion chatbots as tools for specific tasks, such as recipe ideas.

The theme of **creative development** manifested through topics of writing, roleplay, and creative ideation, with users leveraging chatbots as collaborators: "I typically ask for ideas for my marketing art! I do a lot of graphic design for a lot of different people and sometime run low on creative ideas." A rare theme was **intimate exchange**, involving romantic and sexual interactions.

This diverse range of conversation topics highlights the versatility of companion chatbots in meeting users' needs for entertainment, emotional support, and intellectual stimulation.

RQ2: What Is the Relationship Between Companion Chatbot Usage and Loneliness, and What Factors Mediate or Moderate This Relationship?

Correlations in Psychological, Social, and Companion Chatbot Usage Characteristics For our prespecified analyses of usage vs. loneliness, we found a small but significant correlation between chatbot session length and loneliness ($r = 0.101, p = 0.042$), but not between loneliness and usage frequency ($r = 0.053, p = 0.287$), as shown in Figure 4.

Several other notable correlations emerged in our exploratory analysis using Benjamini-Hochberg corrected p-values. Chatbot usage (both length and frequency) showed moderate positive correlations with state empathy towards chatbots ($r > 0.3, p < 0.001$) and various forms of attraction towards chatbots ($r > 0.18, p < 0.001$). Loneliness demonstrated significant correlations with personality traits of extraversion, ($r = -0.188, p < 0.001$),

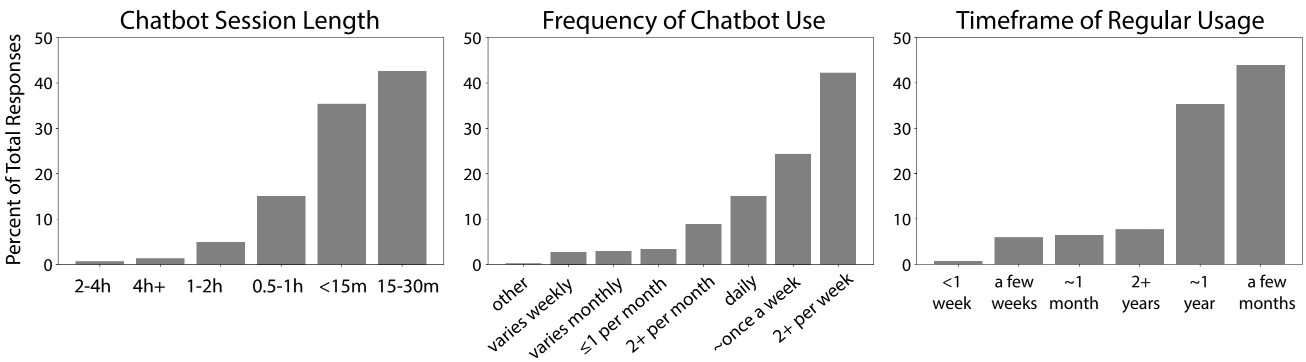


Figure 2: Percentage of total responses for multiple-choice questions regarding chatbot usage patterns among participants.

conscientiousness ($r = -0.335, p < 0.001$), agreeableness ($r = -0.333, p < 0.001$), and neuroticism ($r = 0.526, p < 0.001$), aligning with Buecker et al.'s (Buecker et al. 2020) meta-analysis. Additionally, problematic use of chatbots (GPIUS2) showed moderate correlations with both session length ($r = 0.303, p < 0.001$) and frequency ($r = 0.337, p < 0.001$). See Figure 1 for a correlation matrix of our continuous variables.

While these correlations provide initial insights into the relationships between variables, they represent associations rather than causation. A more detailed examination of these relationships through multiple regression analysis follows.

Multiple Regression Model We conducted an ordinary least squares (OLS) regression analysis to examine the relationship between session length and loneliness while controlling for other factors. The model explained a significant proportion of the variance in loneliness ($R^2 = 0.496$, adjusted $R^2 = 0.482$, $F(11, 392) = 35.09$, $p < .001$) (Figure 3 and Figure 3).

While session length alone did not significantly predict loneliness ($\beta = 0.060, p = 0.126$), neuroticism ($\beta = 0.358$, $p < .001$) and problematic chatbot use ($\beta = 0.166$, $p < .001$) showed positive associations with loneliness. Social network size ($\beta = -0.316$, $p < .001$) and agreeableness ($\beta = -0.147, p < .001$) showed negative associations. We found a significant interaction effect (see Figure 7 in the Appendix) between session length and social attraction to a close person ($\beta = 0.054$, $p = 0.049$). This interaction suggests that for individuals with higher social attraction to close others, longer chatbot sessions were associated with slightly increased loneliness, while this relationship was absent or reversed for those with lower social attraction to close others.

A parallel multiple mediation analysis (Figure 8 in the Appendix) revealed that problematic internet use (GPIUS2) significantly mediated the relationship between session length and loneliness ($\beta = 0.0183$, 95% CI $[0.0027, 0.0403]$), while social network size (LSNS) did not show significant mediation ($\beta = 0.0007$, 95% CI $[-0.0304, 0.0340]$). The total indirect effect was not statistically significant ($\beta = 0.0191$, 95% CI $[-0.0149, 0.0563]$).

RQ3: Can We Identify and Characterize Distinct User Profiles Based on Usage Patterns, Loneliness Levels, Problematic Use, and Other Psychological and Social Factors?

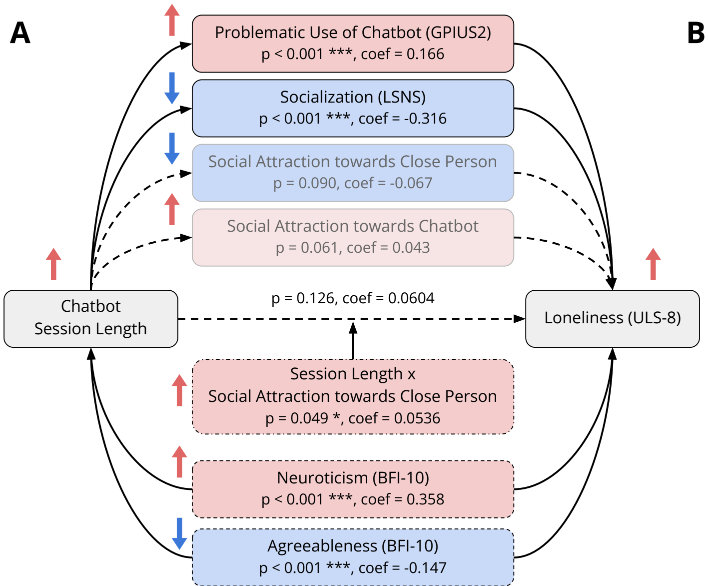
Overall characteristics Participants ranged in age from 18 to 73, primarily 30-35. Most (93.6%) were from the United States, white/Caucasian (66.3%), and employed full-time (61.6%), with a broad distribution of household income. For relationship status, most were single (42.1%) or married (32.4%). 59.7% of participants identified as men and 36.6% identified as women. Additional demographic characteristics are in Figure 11.

Most participants utilize Snapchat MyAI (31.6%), Character.ai (30.4%), or Replika (22.6%) and tend to spend 15 and 30 minutes in each session with a companion chatbot (42.6%), with 35.4% reported sessions shorter than 15 minutes. Very few users spend extended periods chatting, with only 1.28% having sessions exceeding 4 hours. Most participants have been using their companion chatbots for a few months (43.9%) to around a year (35.2%), with only 7.7% of participants having used their chatbots for multiple years and 13.2% for around a month or less. More details on usage can be seen in Figure 2.

Clusters of Users of Companion Chatbots Our K-means cluster analysis revealed seven distinct user profiles among companion chatbot users, each exhibiting unique behaviors, motivations, and psychological characteristics. The resulting clusters are visualized in the heatmap and dendrogram presented in Figure 5. The demographics of each cluster, compared to the overall demographics, are shown in Figure 11, with percentages provided in Figure 11 of the Appendix.

Validation of the cluster solution using Kruskal-Wallis tests revealed significant differences among clusters in terms of session length, loneliness (ULS-8), problematic use of chatbots (GPIUS2), and frequency of use (all $p < 0.001$). The average silhouette score (-0.0413) suggested some overlap between clusters, which is not uncommon in complex psychological data. A MANOVA test confirmed significant multivariate differences among the clusters when considering all variables simultaneously (Wilks' $\lambda = 0.2420, F(24, 1375.71) = 28.77, p < 0.001$). All

A



B

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	-0.062	0.059	-1.05	0.296
Session Length Score	0.060	0.039	1.53	0.126
Socialization (LSNS)	-0.316	0.039	-8.01	< 0.001 ***
Problematic Use of Chatbot (GPIUS2)	0.166	0.045	3.71	< 0.001 ***
Neuroticism (BFI-10)	0.358	0.042	8.42	< 0.001 ***
Agreeableness (BFI-10)	-0.147	0.040	-3.68	< 0.001 ***
Social Attraction towards Chatbot	0.080	0.043	1.88	0.061
Social Attraction towards Close Person	-0.067	0.039	-1.70	0.090
Session Length x Social Attraction towards Close Person	0.054	0.027	1.98	0.049 *
Age	-0.006	0.037	-0.15	0.879
Sex (Female vs. Male)	0.110	0.078	1.42	0.156
Sex (Female vs. Prefer not to Say)	0.650	0.524	1.24	0.216

Model Statistics	Value
R-squared	0.496
Adjusted R-squared	0.482
F-statistic	35.09
p-value	8.16E-52

Figure 3: **A:** The final model from our exploratory multiple regression, depicting the relationships between chatbot session length, loneliness, and related factors. **B:** Model summary of an ordinary least squares regression for the effect of chatbot session length on loneliness (ULS-8), using standardized variables.

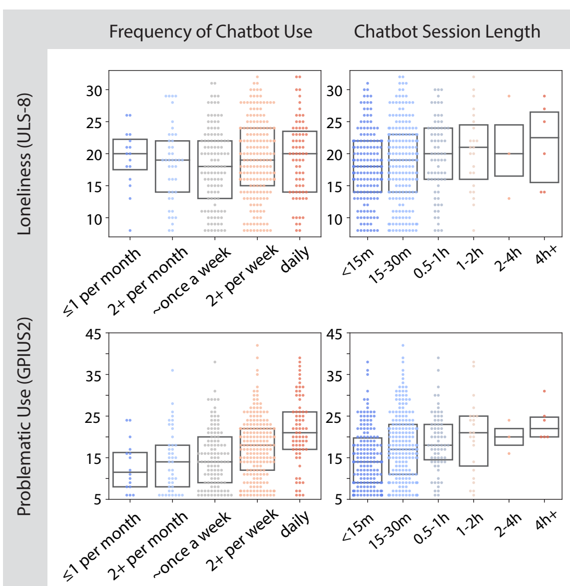


Figure 4: Plots of loneliness (ULS-8) and problematic usage (GPIUS2) vs. usage (frequency and session length). Top left: loneliness vs. chatbot usage frequency. Top right: loneliness vs. chatbot session length. Bottom left: problematic use vs. chatbot usage frequency. Bottom right: problematic use vs. chatbot session length.

four MANOVA test statistics (Wilks' lambda, Pillai's trace, Hotelling-Lawley trace, and Roy's greatest root) were significant ($p < 0.001$), providing robust evidence for cluster differences across multiple dimensions. Box's M-test indicated significant heterogeneity of covariance matrices ($\chi^2 = 181.96$, $p < 0.001$), which does not invalidate the clustering but suggests the need for cautious interpretation. This heterogeneity may affect the reliability of post-hoc comparisons and suggests that the relationship between variables varies across clusters. While these results provide strong support for the distinctiveness of the identified clusters, they should still be considered exploratory, providing a foundation for more targeted investigations in future research.

The seven identified clusters represent distinct patterns of chatbot engagement and psychological characteristics:

- **0: Disengaged Light Users** (7.67%): Minimal chatbot engagement with average loneliness levels. Show neutral attitudes toward AI technology and average social support levels. Primary usage is brief (less than 15 min) casual conversations, with main motivations being curiosity to start use and practical utility for continued use. Average age is 32; for gender, 65% are men and 35% are women.
- **1: Well-Adjusted Moderate Users** (23.02%): Average usage with low loneliness. Demonstrate high extraversion, low neuroticism, and strong social networks. Show positive attitudes toward both AI and human interactions. Main motivations of curiosity to start use and emotional support to continue use. Average age is 36; 67% men, 33% women.
- **2: AI-Wary Light Users** (11.88%): Average to low us-

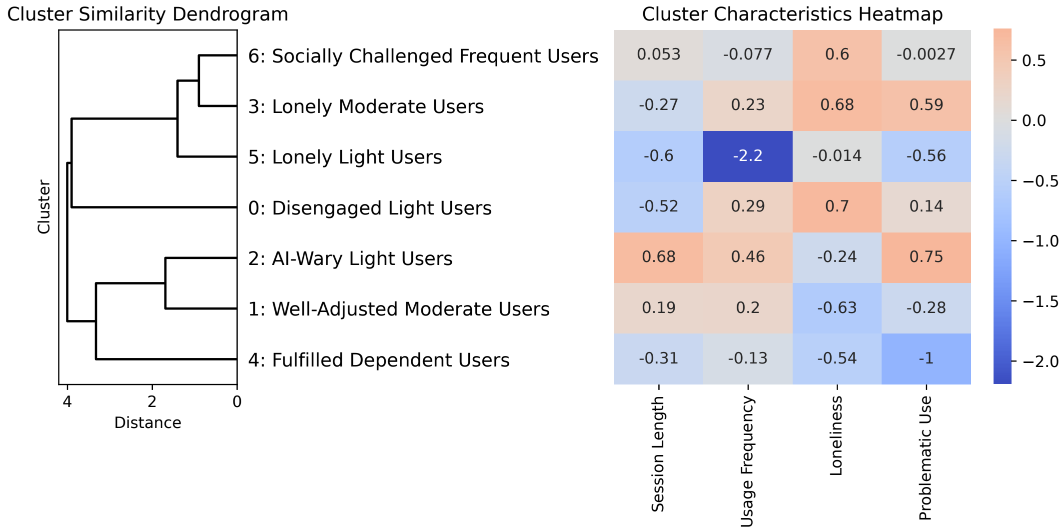


Figure 5: **Left:** a dendrogram depicting the degree of similarity between each cluster. **Right:** Cluster means of standardized variables of chatbot usage (frequency and session length), loneliness, and problematic use of chatbots for our seven user clusters. The cluster order corresponds to that of the dendrogram.

age with low loneliness. Show high skepticism toward AI technology while maintaining strong human connections. Users were interested in chatbots for practical utility and recreation, with continued use motivated by practical purposes, such as seeking knowledge and advice. Average age is 34; 65% men, 35% women.

- **3: Lonely Moderate Users** (13.61%): Average usage with high loneliness. Show low socialization but positive attitudes toward chatbots. Notable for seeking emotional support and companionship through chatbot interactions, with some participants integrating chatbots into their lifestyle. Average age is 35; 51% men, 45% women, 4% other.
- **4: Fulfilled Dependent Users** (18.32%): High usage with below-average loneliness. Show strong emotional engagement with chatbots while maintaining adequate social connections. Report positive impacts on real-world social interactions. Average age is 35; 61% men, 37% women, 1% other.
- **5: Lonely Light Users** (14.60%): Average usage with high loneliness. Demonstrate high neuroticism and low self-esteem. Users seek out chatbots for emotional support and companionship, often discussing personal issues and sometimes engaging in intimate relationships with chatbots. Average age is 34; 47% men, 52% women.
- **6: Socially Challenged Frequent Users** (10.89%): Average frequency but short sessions, with high loneliness. Show low extraversion and social support, with notably low trust in both familiar and unfamiliar people. Both initial and continued use is motivated by a desire for companionship, with a few rare cases engaging in intimate relationships with their chatbot. Casual exchange was a less common theme of conversation. Average age is 36; 61% men, 39% women.

Detailed heatmaps including all numerical scales can be seen in Figure 12. A version with the original values of the scales can be found in Figure 13 along with detailed cluster descriptions in the Appendix. The patterns of themes for each cluster's motivations for use and topics of discussion can be seen in Figure 10 in the Appendix.

Post-hoc analysis using Dunn's test with Bonferroni correction revealed distinct patterns among clusters across our key variables (Figure 9). For **session length**, Fulfilled Dependent Users (Cluster 4) showed significantly longer sessions than all other clusters ($p < .001$) except Well-Adjusted Moderate Users. Disengaged Light Users (Cluster 0) had significantly shorter sessions than most other clusters ($p < .001$).

Usage frequency showed less variation between clusters, with only Disengaged Light Users showing significantly lower frequency than all other clusters ($p < .001$), and Fulfilled Dependent Users showing higher frequency than AI-Wary Light Users and Lonely Light Users ($p < .01$).

For **loneliness** (ULS-8), three clusters - Lonely Moderate Users, Lonely Light Users, and Socially Challenged Frequent Users (Clusters 3, 5, and 6) - showed significantly higher levels than Well-Adjusted Moderate Users and AI-Wary Light Users ($p < .001$). Fulfilled Dependent Users maintained significantly lower loneliness levels than these high-loneliness clusters ($p < .001$).

Problematic use (GPIUS2) was highest in Lonely Moderate Users and Fulfilled Dependent Users (Clusters 3 and 4), who showed significantly higher levels than all other clusters ($p < .001$) except each other. AI-Wary Light Users (Cluster 2) demonstrated the lowest levels of problematic use ($p < .001$).

Discussion

Our study examines the relationship between companion chatbot usage and loneliness, revealing complex interactions among psychological, social, and technological factors.

Understanding the Relationship Between Companion Chatbot Usage and Loneliness

For RQ2, our regression analysis showed no significant direct relationship between session length and loneliness, but revealed important mediating and moderating factors. Problematic use emerged as a significant mediator, suggesting increased usage creates more opportunities for problematic behaviors, aligning with research connecting problematic internet use with loneliness (Kim, LaRose, and Peng 2009).

Usage is negatively associated with social network size, though causality remains unclear—users might reduce human interactions as they spend more time with chatbots or turn to chatbots to fill existing social voids. The positive relationship between usage and social attraction towards chatbots is logically consistent, as interaction time allows deeper attachments to form.

Among confounding variables, neuroticism showed strong positive association with loneliness, while agreeableness demonstrated strong negative association, aligning with previous research (Buecker et al. 2020) and reinforcing the importance of controlling for these factors.

The positive interaction between session length and social attraction towards close people suggests a nuanced relationship, possibly indicating a mismatch between social needs and chosen interactions, where time with chatbots may be perceived as time not spent with valued human connections.

Understanding Clusters of Chatbot Users

For RQ1, most participants used companion chatbots primarily for technological exploration and entertainment rather than friendship or intimate relationships. Our cluster analysis for RQ3 revealed distinct user profiles demonstrating complex relationships with these technologies.

The most striking contrast emerged between **Socially Fulfilled Dependent Users** (Cluster 4) and **Lonely Moderate Users** (Cluster 3). Both exhibit high problematic use, yet with dramatically different outcomes. Socially Fulfilled Dependent Users maintain high well-being despite extensive chatbot engagement, paralleling findings that intensively involved gamers experience psychosocial benefits from their gaming (Snodgrass et al. 2018). This challenges concerns about AI replacing human relationships (Pataranutaporn et al. 2021; Turkle 2011). Conversely, Lonely Moderate Users with similar usage patterns experience high loneliness, low socialization, and preference for chatbots over humans.

Socially Challenged Frequent Users (Cluster 6) and **Lonely Light Users** (Cluster 5) present another interesting comparison. Both seek chatbots for companionship, with participants discussing romantic or sexual relationships with their chatbots. These clusters most strongly reflect the Media Equation (Reeves and Nass 1998). Of concern is whether Lonely Light Users might transition to Socially Challenged Frequent Users over time, losing trust and empathy with people. Understanding how these users' characteristics change over time may be valuable for future research.

Well-Adjusted Moderate Users (Cluster 1), the largest group, demonstrate a potentially optimal engagement pattern, maintaining strong human connections while using chatbots primarily as tools for emotional processing. Many disclose emotional issues to chatbots, valuing the safe space they provide. Recent work showing social support as a significant mediator between psychological problems and problematic gaming (Malak et al. 2023) may help explain how Cluster 3, with poor perceived social support, exhibits high loneliness compared to Cluster 1.

The **AI-Wary Light Users** (Cluster 2) provide an important counterpoint, showing that emotional distance from chatbots can coexist with low loneliness. These users show low emotional attachment to chatbots and use them mostly for practical purposes, suggesting emotional investment in companion chatbots may not be necessary or optimal for all users.

Ethical Considerations & Design Implications

Our findings raise critical questions about responsible companion chatbot development. The identification of vulnerable user populations who may develop problematic usage patterns highlights the need for proactive ethical safeguards. The contrast between users who benefit from AI companionship and those who may be harmed underscores that one-size-fits-all approaches may be ethically insufficient.

Protecting Vulnerable Users. Clusters 3, 5, and 6 represent particularly vulnerable populations who often turn to AI companions for emotional support and companionship, yet may be most susceptible to negative outcomes. Current platforms typically lack mechanisms to identify such users or provide appropriate interventions. Our findings suggest the need for **risk assessment tools** that identify users showing patterns associated with problematic use, **adaptive interfaces** that promote healthy usage patterns for vulnerable users, and **intervention mechanisms** such as usage limits, mental health resource suggestions, or encouragement of human social contact.

Developer Responsibility & Regulation. Unlike traditional software tools, AI companions can explicitly encourage emotional attachment and dependency, creating ethical obligations similar to those in healthcare or counseling contexts. This includes implementing safeguards for user design principles focused on encouraging and facilitating human social connections. The largely unregulated nature of AI companion platforms, combined with their potential for both benefit and harm, suggests the need for evidence-based policy consideration. Our findings could inform regulatory approaches that balance innovation with user protection, particularly for vulnerable populations.

Theoretical Contributions Our findings extend beyond simple social displacement theories (Kraut et al. 1998), demonstrating that companion chatbots serve **different functions based on user characteristics and usage patterns**. This aligns with the Parasocial Contact Hypothesis

(Schiappa, Gregg, and Hewes 2005), which suggests media characters can provide meaningful social experiences. The mediating role of problematic use suggests a pathway where increased chatbot engagement creates more opportunities for unhealthy usage patterns, which in turn exacerbate loneliness. This aligns with compensatory internet use theory (Kardefelt-Winther 2014), where individuals with social deficits may turn to technology to fulfill unmet social needs. However, when this compensatory use becomes problematic—loss of control, negative mood when unable to access—it may paradoxically worsen the loneliness it was meant to address. Extensive chatbot use may not be harmful if problematic patterns are avoided, as evidenced by our Fulfilled Dependent Users who maintain high engagement without increased loneliness. For those with strong existing social networks, companion chatbots may serve as **beneficial supplements** to human social interaction. However, socially isolated individuals risk problematic use (Reer, Tang, and Quandt 2019; O'Day and Heimberg 2021), and we must consider the risk of chatbots replacing human interactions and potentially exacerbating loneliness. The key finding is that similar usage patterns can lead to markedly different outcomes depending on user characteristics. We also demonstrate how **manual thematic analysis can be effectively combined with LLM-based theme extraction** to achieve both interpretive depth and comprehensive coverage in large-scale qualitative research, offering a scalable approach for mixed-methods studies.

Limitations and Future Research

The self-reported measures of our survey risk recall bias. Our custom instruments offered broad options to reduce inaccuracies but resulted in coarse measures. Our adapted scales were based on factor loadings from previous studies but may affect validated psychometric properties. To reduce participant fatigue, we prioritized shorter scales over maintaining full lengths. Our participants were primarily white/Caucasian Americans, limiting generalizability. Additionally, while statistically grounded, **cluster numbers** involve subjective judgments of interpretability. The heterogeneity of covariance matrices indicated by Box's M-test requires caution in interpretation. Our **exploratory regression model selection** warrants cautious interpretations as well. Assumption of linear relationships may not capture complex nonlinear relationships. The numerous predictors increase the risk of Type II errors (Lavery et al. 2019). Our cross-sectional design limits causal inferences.

Our triangulated approach combining manual and automated thematic analysis strengthened theme validation, but **LLM-based analysis may miss subtle contextual nuances and interpretive depth** that human analysts capture. The automated approach also relies on the quality and consistency of the underlying language model, which may introduce systematic biases in theme identification or prevalence estimation. Another limitation is that our study identifies vulnerable populations, but we did not assess whether participants were currently **receiving mental health treatment** or had been advised against using AI companions, which could affect the interpretation of our findings regarding vulnerable users.

Several key areas warrant investigation: longitudinal studies to understand causal relationships; experimental studies manipulating specific chatbot design aspects; investigation of non-linear relationships; cross-cultural studies; and research on long-term effects on social skills and relationship expectations.

Conclusion

This study examines the relationship between companion chatbot usage and loneliness, revealing complex interactions among psychological, social, and technological factors. Our model explaining approximately 50% of variance in loneliness demonstrates that while chatbot session length does not directly predict loneliness, this relationship is mediated by problematic use and moderated by social attraction to close others, with personality traits and social network characteristics serving as key confounding variables.

Our cluster analysis identified seven distinct user profiles demonstrating how similar usage patterns can lead to markedly different outcomes. Fulfilled Dependent Users maintain healthy relationships despite intensive chatbot use, while Lonely Moderate Users with similar patterns show signs of social withdrawal, emphasizing the importance of individual characteristics and social contexts in determining outcomes. Most participants used companion chatbots primarily for technological exploration and entertainment rather than social purposes, suggesting these tools serve broader functions than typically assumed. However, distinct vulnerable populations emerged who rely on chatbots for companionship and emotional support, raising important ethical considerations.

The ethical implications of our findings extend beyond individual user experiences to broader questions about technology's role in human social development. The identification of distinct user profiles and key mediating factors suggests the need for personalized approaches and built-in mechanisms to detect potentially harmful usage patterns. As AI companions become increasingly sophisticated and widespread, the need for responsible development practices becomes more urgent. Our research provides an empirical foundation for moving beyond abstract ethical debates toward concrete, evidence-based approaches to AI companion design that prioritize user well-being and social health.

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