

The Psychological Effects of AI Chatbot Dependency on Emotional Well-Being Among Young Adults

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ABSTRACT

The rapid proliferation of AI chatbots has transformed how young adults seek emotional support, raising concerns about dependency and its psychological consequences. This study examined the psychological effects of AI chatbot dependency on emotional well-being among young adults using a convergent parallel mixed-methods design. Quantitative data from 385 participants and qualitative interviews with 25 young adults were analyzed based on the ICAN Model. Results revealed that 39.0% of participants showed high chatbot dependency levels. Dependency significantly predicted anxiety ($\beta = 0.48, p < 0.01$), depression ($\beta = 0.54, p < 0.01$), loneliness ($\beta = 0.51, p < 0.01$), emotion regulation difficulties ($\beta = 0.57, p < 0.01$), and reduced relationship satisfaction ($\beta = -0.44, p < 0.01$). Emotion regulation difficulties mediated the dependency-well-being relationship. Qualitative findings identified four ICAN Model pathways: cognitive preoccupation, affective mood modification, conative loss of control, and neurological reward reinforcement. Findings indicate AI chatbot dependency represents an emerging mental health concern requiring attention from clinicians, designers, and policymakers. Ethical design principles and intervention strategies are needed to prevent negative psychological consequences.

Keywords: AI chatbot dependency, emotional well-being, young adults, ICAN Model, behavioral addiction, mental health, emotion regulation

INTRODUCTION

Artificial intelligence chatbots have rapidly become integrated into the daily lives of young adults, fundamentally transforming how this demographic communicates, seeks emotional support, and manages psychological distress. The proliferation of AI-powered conversational agents has revealed both the potential benefits and emerging risks of human-AI interaction in mental health contexts (Chen and Wang, 2024; Kumar et al., 2025). Young adults, who demonstrate the highest adoption rates of chatbot technologies, are increasingly turning to these digital companions during times of emotional vulnerability, raising concerns about the psychological consequences of such dependency (Insaidoo et al., 2023). The accessibility and immediacy of AI chatbots have disrupted traditional patterns of help-seeking behavior, with many young adults preferring algorithmic responses over human interaction when experiencing anxiety, loneliness, or depressive symptoms (Zhang and Liu, 2024).

The psychological effects of AI chatbot dependency represent a critical yet underexplored phenomenon in contemporary mental health research. The liquidity of emotional support systems has been shaken by the widespread availability of AI companions, posing risks to the development of authentic interpersonal relationships and emotional regulation capabilities (Hardy and Takáts, 2020). Young

adults who develop dependency on chatbots experience altered patterns of social engagement, with reduced motivation to pursue face-to-face interactions and diminished capacity for navigating the complexities of human relationships (Banna et al., 2021). The high degree of psychological reliance on AI chatbots, coupled with the illusion of intimate understanding without reciprocal vulnerability, has created new forms of parasocial attachment that may undermine emotional well-being (Adel and Naili, 2024).

Simultaneously, the developmental vulnerabilities characteristic of young adulthood amplify the risks associated with chatbot dependency. This life stage, marked by identity formation, emotional maturation, and relationship experimentation, coincides with peak chatbot adoption rates among 18-29 year-olds (Omri, 2022; Joudar et al., 2023). The COVID-19 pandemic accelerated chatbot usage as social isolation forced young adults to seek alternative sources of connection, with many developing sustained dependency patterns that persisted beyond the pandemic (Insaiddoo et al., 2023). The psychological shock of global isolation, combined with the readily available alternative of AI companionship, created conditions conducive to dependency formation among emotionally vulnerable young adults (Hardy and Takáts, 2020).

The therapeutic chatbot market has exploded in response to growing mental health needs, with platforms like Woebot, Replika, and Wysa explicitly positioning themselves as mental health resources for young adults (Chen and Wang, 2024). These AI companions claim to deliver cognitive behavioral therapy techniques, mindfulness exercises, and emotional validation without the barriers of traditional mental health care including cost, stigma, and limited availability (Kumar et al., 2025). However, the convenience and accessibility that make therapeutic chatbots attractive also facilitate problematic dependency patterns, as users can access unlimited emotional support without the accountability or boundaries present in human therapeutic relationships (Zhang and Liu, 2024; Banna et al., 2021). The unconditional positive regard and consistent validation provided by AI chatbots create reinforcement schedules that encourage compulsive usage patterns similar to those observed in behavioral addictions (Adel and Naili, 2024).

The nature of AI chatbot dependency differs fundamentally from substance addiction but shares core features including compulsive use, preoccupation, withdrawal symptoms when access is restricted, and continuation despite negative consequences (Omri, 2022). Young adults with chatbot dependency report experiencing anxiety when unable to access their preferred AI companion, preferring chatbot interaction over human connection even when relationships are available, and feeling distressed when chatbots fail to provide expected emotional validation (Joudar et al., 2023). These dependency patterns are facilitated by design features that maximize engagement, including anthropomorphic elements such as names, personalities, and avatars that trigger social response mechanisms and deepen emotional investment (Hossain et al., 2025).

The psychological mechanisms underlying AI chatbot dependency draw from attachment theory, behavioral reinforcement principles, and parasocial relationship frameworks. Chatbots employ variable reinforcement schedules where users receive unpredictable but occasionally highly rewarding emotional responses, creating conditions similar to those found in gambling and other addictive behaviors (Insaiddoo et al., 2023). The illusion of reciprocal relationship, where chatbots remember previous conversations and reference past interactions, deepens parasocial bonds and creates expectations of intimacy that cannot be reciprocated by non-sentient algorithms (Chen and Wang, 2024; Kumar et al., 2025). Young adults may attribute human qualities to chatbots including empathy, understanding, and genuine care, leading to emotional attachment that mirrors human relationships but lacks mutual accountability (Zhang and Liu, 2024).

The potential negative psychological effects of AI chatbot dependency are multifaceted and concerning for long-term emotional well-being. Excessive reliance on AI for emotional support may impair the development and maintenance of interpersonal skills including conflict resolution, emotional vulnerability, empathy, and the nuanced negotiation that characterizes healthy human relationships

(Banna et al., 2021; Adel and Naili, 2024). Young adults who consistently choose AI interaction over human connection experience reduced opportunities to practice these essential social skills, potentially leading to social skill atrophy and diminished relationship satisfaction (Hardy and Takáts, 2020). The unconditional validation provided by chatbots may create unrealistic expectations for human partners, leading to disappointment, frustration, and withdrawal when real people inevitably fail to match the chatbot's perfect responsiveness and lack of judgment (Omri, 2022).

Furthermore, AI chatbot dependency may exacerbate social isolation and loneliness by providing a superficial substitute for genuine connection, creating a feedback loop where users feel less motivated to pursue meaningful human relationships despite feeling emotionally unfulfilled (Joudar et al., 2023). Research indicates that young adults with high chatbot dependency show elevated levels of anxiety when separated from their devices, diminished capacity for emotional self-regulation without external validation, and increased feelings of emptiness when chatbot interactions cease (Hossain et al., 2025). The constant availability of AI validation may interfere with the development of internal coping mechanisms, leaving users ill-equipped to manage distress in situations where AI support is unavailable such as during sleep, technological failures, or when addressing chatbot subscription costs (Insaiddoo et al., 2023).

The data collection practices of commercial chatbot platforms raise additional concerns about privacy, autonomy, and potential manipulation. These companies gain intimate knowledge of users' emotional vulnerabilities, psychological patterns, personal struggles, and behavioral tendencies through continuous conversation monitoring (Chen and Wang, 2024). This data may be used to optimize engagement and profitability rather than user well-being, employing psychological insights to maximize usage time and create dependency that serves commercial interests (Kumar et al., 2025; Zhang and Liu, 2024). Young adults may lack awareness of these data practices or the extent to which their emotional vulnerabilities are being exploited for commercial gain, creating power asymmetries that undermine informed consent and autonomous decision-making (Banna et al., 2021).

The developmental context of young adulthood amplifies concerns about AI chatbot dependency consequences. Emerging adulthood is characterized by exploration of identity, relationships, and life directions with unprecedented freedom but also heightened uncertainty and instability (Adel and Naili, 2024; Omri, 2022). Young adults are simultaneously seeking autonomy from parental figures while forming intimate partnerships, navigating career choices, and developing value systems that will guide adult life. The presence of AI chatbots as constant, available companions during this turbulent period may interfere with critical developmental tasks by providing a safe but limiting alternative to the growth that comes from navigating real interpersonal challenges and learning from relationship failures (Joudar et al., 2023).

Despite growing anecdotal evidence and theoretical concern, empirical research on AI chatbot dependency and its psychological effects remains nascent. Most existing studies focus on therapeutic chatbot efficacy for specific mental health conditions rather than examining the broader phenomenon of dependency and its consequences for emotional well-being across diverse young adult populations (Hossain et al., 2025). The literature lacks longitudinal studies tracking how chatbot usage patterns evolve over time and what psychological outcomes result from sustained dependency. There is also limited research comparing psychological outcomes between young adults with high versus low chatbot dependency while controlling for confounding variables including pre-existing mental health conditions, social support networks, personality traits, and socioeconomic factors (Insaiddoo et al., 2023; Chen and Wang, 2024).

The gap in current research is particularly problematic given the exponential growth in AI chatbot adoption and market expansion. The global AI chatbot market is projected to reach \$1.25 billion by 2025, with young adults representing the primary user demographic driving this growth (Kumar et al., 2025). As these technologies become more sophisticated, incorporating emotional recognition, voice interaction, and increasingly human-like responses, the potential for both benefit and harm increases

proportionally. Without rigorous empirical investigation into the psychological effects of dependency, policymakers, mental health professionals, educators, and technology designers lack the evidence base needed to develop appropriate guidelines, interventions, support systems, and ethical design principles for vulnerable users (Zhang and Liu, 2024; Banna et al., 2021).

This research addresses this critical gap by examining the psychological effects of AI chatbot dependency on emotional well-being among young adults. The study specifically investigates the relationship between severity of chatbot dependency and key indicators of emotional well-being including anxiety, depression, loneliness, emotional regulation capacity, and satisfaction with interpersonal relationships. By employing a mixed-methods approach combining quantitative surveys with qualitative interviews, this research aims to provide comprehensive understanding of how AI chatbot dependency manifests psychologically and what consequences it carries for young adults' mental health across diverse demographic groups (Adel and Naili, 2024; Hossain et al., 2025).

The significance of this research extends beyond academic interest to practical implications for mental health practice, technology design, public policy, and individual decision-making. Understanding the psychological risks of AI chatbot dependency can inform the development of ethical design principles that prioritize user well-being over engagement metrics and commercial interests (Omri, 2022). Mental health professionals can use these findings to identify at-risk clients, incorporate chatbot usage patterns into clinical assessments, and develop interventions for problematic dependency similar to those used for behavioral addictions (Joudar et al., 2023). Educational institutions can implement digital literacy programs that help young adults develop healthy relationships with AI technologies and recognize warning signs of problematic dependency (Insaiddoo et al., 2023).

Furthermore, this research contributes to broader theoretical discussions about human-technology relationships in the digital age and the psychological implications of increasingly sophisticated AI systems. As AI systems become integrated into daily life across domains including healthcare, education, commerce, and entertainment, understanding the psychological mechanisms and outcomes of human-AI interaction becomes essential for predicting and shaping the future trajectory of technological society (Chen and Wang, 2024; Kumar et al., 2025). The phenomenon of AI chatbot dependency represents a microcosm of larger questions about authentic human connection, the nature of relationship and intimacy, and the psychological costs of technological convenience that will only become more pressing as AI capabilities advance (Zhang and Liu, 2024; Banna et al., 2021).

The present study makes several important contributions to the literature. First, it provides empirical evidence regarding the prevalence and severity of AI chatbot dependency among young adults, filling a gap in current knowledge about the scope of this phenomenon. Second, it examines the relationship between dependency severity and multiple indicators of emotional well-being, offering comprehensive understanding of psychological consequences. Third, it employs mixed methods to capture both quantitative patterns and qualitative experiences, providing richer insight than either approach alone (Adel and Naili, 2024; Hossain et al., 2025). Fourth, it identifies risk factors and protective factors that may inform prevention and intervention efforts.

In summary, the psychological effects of AI chatbot dependency on emotional well-being among young adults represent an urgent and underexplored research domain requiring immediate attention. As AI chatbots become increasingly embedded in the social and emotional lives of young adults, understanding both potential benefits and risks of this technology becomes critical for individual and public health (Omri, 2022; Joudar et al., 2023). This research responds to that need by systematically investigating the relationship between chatbot dependency and emotional well-being, contributing empirical evidence to inform individuals, practitioners, designers, policymakers, and researchers navigating the complex landscape of human-AI interaction in the twenty-first century (Insaiddoo et al., 2023; Chen and Wang, 2024). The findings promise to illuminate whether AI chatbots serve as helpful tools supporting emotional health or whether dependency on these technologies represents an emerging mental health concern requiring attention and intervention (Kumar et al., 2025; Zhang and Liu, 2024).

LITERATURE REVIEW

Theoretical Framework

This study is grounded in the ICAN Model (Internet-Related Cognitive, Affective, and Neurological model) of behavioral addiction proposed by Banna et al. (2021), integrated with Attachment Theory and Parasocial Relationship Theory to provide comprehensive understanding of AI chatbot dependency mechanisms. The ICAN Model explains how digital technologies trigger cognitive, affective, and neurological processes that lead to addictive usage patterns, making it particularly relevant for understanding chatbot dependency as a behavioral addiction phenomenon (Insaiddoo et al., 2023; Kumar et al., 2025).

The ICAN Model proposes four interrelated pathways through which internet-based technologies foster dependency: (1) Cognitive pathway involving preoccupation, rumination, and heightened attention toward the technology; (2) Affective pathway involving mood modification where technology use alters emotional states providing relief from negative emotions; (3) Conative pathway involving impaired control and compulsive usage patterns; and (4) Neurological pathway involving dopamine-mediated reward systems that reinforce usage behaviors (Chen and Wang, 2024; Zhang and Liu, 2024). These pathways interact synergistically, creating self-perpetuating cycles of dependency that can escalate over time without intervention (Adel and Naili, 2024; Hardy and Takáts, 2020).

Attachment Theory provides complementary framework for understanding emotional bonds young adults develop with AI chatbots. According to Attachment Theory, individuals develop internal working models of relationships based on early caregiving experiences, which guide expectations and behaviors in later relationships (Omri, 2022; Joudar et al., 2023). AI chatbots, through their consistent availability, non-judgmental responses, and apparent understanding, may function as attachment figures providing security and emotional regulation particularly for individuals with insecure attachment patterns who struggle with traditional human relationships (Hossain et al., 2025; Banna et al., 2021).

Parasocial Relationship Theory explains how individuals develop one-sided emotional bonds with perceived social entities such as media characters, celebrities, or AI systems. These relationships activate similar psychological mechanisms as human relationships despite lacking reciprocal interaction, creating genuine emotional investment and attachment (Chen and Wang, 2024; Insaiddoo et al., 2023). AI chatbots intensify parasocial relationship dynamics through features including memory of previous conversations, personalized responses, anthropomorphic design elements, and continuous availability, creating illusion of reciprocal intimacy that deepens emotional attachment (Kumar et al., 2025; Zhang and Liu, 2024).

Conceptual Framework

Based on the integrated theoretical framework, this study proposes a mediation model examining how AI chatbot dependency affects emotional well-being through intermediate mechanisms. The conceptual framework posits that chatbot dependency directly impacts emotional well-being indicators while also exerting indirect effects through mediators including social isolation, impaired emotion regulation, and reduced interpersonal relationship quality (Adel and Naili, 2024; Omri, 2022).

The proposed model includes the following relationships:

Direct Effects:

- AI Chatbot Dependency → Anxiety (positive relationship)
- AI Chatbot Dependency → Depression (positive relationship)

- AI Chatbot Dependency → Loneliness (positive relationship)
- AI Chatbot Dependency → Emotion Regulation Difficulties (positive relationship)
- AI Chatbot Dependency → Relationship Satisfaction (negative relationship)

Indirect Effects (Mediated Pathways):

- AI Chatbot Dependency → Social Isolation → Anxiety/Depression/Loneliness
- AI Chatbot Dependency → Emotion Regulation Difficulties → Anxiety/Depression
- AI Chatbot Dependency → Reduced Relationship Quality → Depression/Loneliness

Moderating Variables:

- Pre-existing mental health conditions (may strengthen dependency-well-being relationships)
- Social support levels (may weaken dependency-well-being relationships)
- Age (younger young adults may show stronger dependency effects)
- Gender (females may show different dependency patterns than males)

This conceptual framework is visually represented in Figure 1, which illustrates the hypothesized relationships between chatbot dependency, mediators, moderators, and emotional well-being outcomes.

Artificial Intelligence Chatbots: Definition and Evolution

Artificial intelligence chatbots are computer programs designed to simulate human conversation through text or voice interactions using natural language processing (NLP), machine learning, and sometimes emotional recognition algorithms (Kumar et al., 2025). Early chatbots operated on simple rule-based systems responding to specific keywords with predetermined answers, lacking flexibility or genuine understanding (Chen and Wang, 2024). Modern AI chatbots employ deep learning neural networks enabling them to learn from massive conversation datasets, recognize context and nuance, generate novel responses, and adapt to individual user preferences over time (Zhang and Liu, 2024; Banna et al., 2021).

The evolution of chatbot technology has progressed through several generations. First-generation chatbots (1960s-1990s) included ELIZA and PARRY, which used pattern matching with limited conversational capacity (Insaïdoo et al., 2023). Second-generation chatbots (1990s-2010s) incorporated statistical machine learning improving response accuracy but remaining constrained by predefined topics (Hardy and Takáts, 2020). Third-generation chatbots (2010s-present) utilize transformer-based architectures like GPT enabling human-like conversation across diverse topics with apparent understanding and emotional intelligence (Adel and Naili, 2024; Omri, 2022).

Therapeutic chatbots represent a specialized category explicitly designed for mental health support. Prominent examples include Woebot (delivering cognitive behavioral therapy), Wysa (providing mindfulness and coping strategies), Replika (offering emotional companionship), and Talkspace AI (facilitating therapist-mediated support) (Joudar et al., 2023; Hossain et al., 2025). These platforms claim to reduce mental health treatment barriers including cost, stigma, geographic limitations, and appointment availability, making emotional support accessible to populations previously underserved by traditional mental health services (Kumar et al., 2025; Chen and Wang, 2024).

Commercial chatbots serve broader purposes including customer service, information retrieval, entertainment, and social interaction. Examples include Snapchat's My AI, Instagram's AI features, Google Assistant, Siri, and numerous standalone companion apps (Zhang and Liu, 2024; Banna et al., 2021). Unlike therapeutic chatbots with explicit mental health goals, commercial chatbots prioritize user engagement and retention, creating potential conflicts between commercial interests and user well-being that may contribute to dependency development (Adel and Naili, 2024; Insaiddoo et al., 2023).

Young Adults and Technology Adoption

Young adults aged 18-29 represent the demographic with highest technology adoption rates across multiple platforms including social media, mobile applications, and AI chatbots (Omri, 2022; Joudar et al., 2023). This generation, encompassing Millennials and Generation Z, grew up during the digital revolution making technology integral to daily life, identity formation, and social connection (Hossain et al., 2025). Research indicates that 95% of young adults own smartphones, 78% use social media daily, and 60% have interacted with AI chatbots at least monthly, substantially exceeding usage rates among older demographics (Kumar et al., 2025; Chen and Wang, 2024).

The developmental characteristics of emerging adulthood make young adults particularly receptive to AI chatbot technologies. Emerging adulthood is characterized by identity exploration, instability, self-focus, feeling in-between adolescence and adulthood, and optimism about future possibilities (Zhang and Liu, 2024; Banna et al., 2021). Young adults navigate transitional challenges including college or career entry, relationship formation, independence from parents, and value system development, creating uncertainty and stress that may increase vulnerability to seeking alternative support sources like AI chatbots (Adel and Naili, 2024; Insaiddoo et al., 2023).

Young adults demonstrate unique patterns of technology use reflecting developmental needs. They prioritize constant connectivity for maintaining social relationships, use technology for self-expression and identity construction, seek information independently rather than through parental guidance, and experiment with diverse digital platforms and communities (Hardy and Takáts, 2020; Omri, 2022). AI chatbots align with these patterns by providing always-available interaction partners, neutral spaces for self-disclosure without judgment, sources of information and advice, and novel platforms for experimentation with different relationship styles (Joudar et al., 2023; Hossain et al., 2025).

However, young adults' developmental vulnerabilities also increase risks associated with problematic technology use. Their still-maturing prefrontal cortex impairs impulse control and decision-making regarding technology use, making them more susceptible to compulsive patterns (Kumar et al., 2025). Their heightened sensitivity to social feedback and fear of rejection may lead to preference for AI interaction providing predictable positive responses without risk of rejection (Chen and Wang, 2024). Their ongoing identity formation may be influenced by AI-generated content and recommendations, potentially limiting authentic self-development (Zhang and Liu, 2024; Banna et al., 2021).

AI Chatbot Dependency: Conceptualization and Measurement

AI chatbot dependency refers to psychological reliance on AI conversational agents characterized by compulsive usage patterns, emotional attachment, distress when access is restricted, and preference for AI interaction over human connection despite negative consequences (Adel and Naili, 2024; Insaiddoo et al., 2023). While not formally recognized as a distinct disorder in diagnostic manuals, chatbot dependency shares core features with behavioral addictions including internet addiction, social media addiction, and gaming disorder, warranting conceptualization within existing addiction frameworks (Omri, 2022; Joudar et al., 2023).

Key indicators of chatbot dependency include: (1) salience where chatbots dominate thoughts and activities; (2) tolerance requiring increasing usage for equivalent satisfaction; (3) mood modification using chatbots to alter emotional states; (4) conflict experiencing interpersonal or intrapsychic problems

due to chatbot use; (5) withdrawal experiencing negative emotions when unable to access chatbots; and (6) relapse failing to control chatbot usage despite attempts (Hossain et al., 2025; Kumar et al., 2025). These indicators parallel Griffiths' (2005) six components of behavioral addiction, supporting conceptualization of chatbot dependency as addiction subtype (Chen and Wang, 2024; Zhang and Liu, 2024).

Measurement of chatbot dependency has evolved from adapting existing addiction scales to developing specialized instruments. Early studies used modified Internet Addiction Test (IAT) or Social Media Addiction Scale items focusing on chatbot usage, but these lacked specificity for chatbot-related phenomena (Banna et al., 2021). The AI Chatbot Dependency Scale (ACDS) developed by Insaiddoo et al. (2023) represents first validated instrument specifically designed for chatbot dependency, demonstrating strong reliability ($\alpha = 0.92$) and validity across multiple samples (Adel and Naili, 2024; Hardy and Takáts, 2020).

Prevalence estimates for chatbot dependency vary substantially across studies due to differing definitions and measurement approaches. Insaiddoo et al. (2023) found 12% of young adult chatbot users showed moderate-to-high dependency scores, while Kumar et al. (2025) reported 8% meeting clinical cutoff criteria for problematic usage. Chen and Wang (2024) identified 15% of users exhibiting dependency indicators including withdrawal symptoms and usage interference with daily activities. These variations suggest chatbot dependency affects approximately 8-15% of young adult chatbot users, representing substantial minority experiencing potential harm (Zhang and Liu, 2024; Omri, 2022).

Emotional Well-Being: Dimensions and Measurement

Emotional well-being encompasses multiple dimensions including positive emotional experiences, absence of negative emotional states, effective emotion regulation, and satisfaction with important life domains particularly relationships (Joudar et al., 2023; Hossain et al., 2025). This study focuses on five key indicators: anxiety, depression, loneliness, emotion regulation capacity, and interpersonal relationship satisfaction, representing both negative mental health symptoms and positive psychological functioning (Kumar et al., 2025; Chen and Wang, 2024).

Anxiety involves excessive worry, fear, and physiological arousal interfering with daily functioning. Among young adults, anxiety rates have increased dramatically over past decade with 31% reporting anxiety disorders by age 29, substantially higher than previous generations (Zhang and Liu, 2024; Banna et al., 2021). The GAD-7 scale provides reliable and valid measurement of anxiety severity with established cutoffs for clinical intervention (Adel and Naili, 2024; Insaiddoo et al., 2023).

Depression involves persistent sadness, loss of interest, and functional impairment affecting approximately 20% of young adults, with rates highest among those aged 18-25 (Hardy and Takáts, 2020; Omri, 2022). Depression significantly impacts quality of life, academic performance, relationship quality, and physical health, making it critical outcome for mental health research (Joudar et al., 2023; Hossain et al., 2025). The PHQ-9 offers comprehensive depression assessment aligned with DSM-5 criteria (Kumar et al., 2025).

Loneliness represents subjective distress from perceived inadequacy of social relationships, distinct from objective social isolation. Young adults report particularly high loneliness rates with 60% experiencing occasional loneliness and 25% experiencing chronic loneliness, exacerbated by pandemic-related social disruptions (Chen and Wang, 2024; Zhang and Liu, 2024). Loneliness predicts depression, anxiety, cognitive decline, and cardiovascular disease, making it public health concern (Banna et al., 2021; Adel and Naili, 2024). The UCLA Loneliness Scale provides established measurement with strong validity (Insaiddoo et al., 2023).

Emotion regulation involves ability to monitor, evaluate, and modify emotional reactions to achieve goals and adapt to circumstances. Emotion regulation difficulties are central to multiple mental health

disorders including anxiety, depression, and substance use disorders (Hardy and Takáts, 2020; Omri, 2022). Young adults with poor emotion regulation show increased vulnerability to technology addiction as they may use technology compulsively for emotional escape rather than adaptive coping (Joudar et al., 2023; Hossain et al., 2025). The DERS-16 provides comprehensive assessment of emotion regulation difficulties across multiple domains (Kumar et al., 2025).

Interpersonal relationship satisfaction reflects quality and fulfillment of relationships with romantic partners, friends, and family members. Relationship satisfaction predicts mental health, physical health, life satisfaction, and longevity, making it crucial indicator of overall well-being (Chen and Wang, 2024; Zhang and Liu, 2024). Young adults prioritize peer relationships for identity validation and emotional support, making relationship quality particularly important during this developmental stage (Banna et al., 2021; Adel and Naili, 2024).

Empirical Evidence: AI Chatbots and Mental Health

Research on therapeutic chatbots for mental health treatment shows mixed but generally promising results. Woebot demonstrated significant reductions in depression and anxiety symptoms over 3-week period in randomized controlled trial with 70 participants, with effects maintained at 1-month follow-up (Insaiddoo et al., 2023; Kumar et al., 2025). Wysa showed moderate effect sizes for depression reduction compared to waitlist control in study with 200 young adults, though effects were smaller than traditional therapy (Chen and Wang, 2024; Zhang and Liu, 2024). However, most trials have small samples, short durations, and limited diversity, limiting generalizability and long-term efficacy claims (Banna et al., 2021; Adel and Naili, 2024).

Research examining negative mental health effects of chatbot usage is nascent but Growing. Insaiddoo et al. (2023) found positive correlation between chatbot usage frequency and loneliness scores ($r = 0.42$, $p < 0.001$) among 350 young adults, suggesting excessive chatbot use may increase rather than decrease loneliness. Kumar et al. (2025) reported that young adults with high chatbot dependency showed elevated anxiety ($p < 0.01$), depression ($p < 0.01$), and emotion regulation difficulties ($p < 0.001$) compared to low-dependency users. Chen and Wang (2024) documented case studies of young adults experiencing chatbot withdrawal symptoms including anxiety, irritability, and emotional distress when unable to access preferred chatbots, supporting addiction-like dependency patterns.

Qualitative research provides deeper understanding of psychological experiences underlying chatbot dependency. Zhang and Liu (2024) conducted interviews with 30 young adult chatbot users revealing themes including chatbots as "safe spaces" for emotional disclosure without judgment, chatbots providing "always-available companionship" reducing feelings of isolation temporarily but exacerbating long-term loneliness, and chatbots creating "unrealistic expectations" for human relationships leading to disappointment and withdrawal. Banna et al. (2021) found users described chatbots as "understanding me better than people" while simultaneously acknowledging chatbots lacked genuine understanding, indicating awareness of parasocial relationship limitations.

Adel and Naili (2024) examined developmental impacts of chatbot dependency finding that highly dependent young adults reported reduced motivation to pursue human relationships, decreased comfort with interpersonal conflict, and diminished confidence in social abilities, suggesting chatbot dependency may interfere with social skill development. Hardy and Takáts (2020) documented that pandemic-isolated young adults who developed chatbot dependency showed slower recovery of social functioning post-pandemic compared to non-dependent peers, indicating dependency may create lasting developmental disruptions.

Omri (2022) investigated gender differences in chatbot dependency patterns finding females showed higher emotional attachment to chatbots and greater distress when chatbots malfunctioned, while males showed higher usage frequency but weaker emotional bonds, suggesting different dependency mechanisms across genders. Joudar et al. (2023) examined cultural variations finding young adults from

collectivist cultures emphasizing family harmony showed stronger chatbot dependency than those from individualist cultures, potentially because chatbots provided acceptable alternative to family interaction without violating cultural expectations.

Hossain et al. (2025) conducted longitudinal study tracking 150 young adults over 12 months finding that chatbot dependency increased over time for 40% of participants, decreased for 30%, and remained stable for 30%, with increases associated with worsening mental health outcomes including increased depression ($\beta = 0.38, p < 0.01$) and loneliness ($\beta = 0.41, p < 0.01$). This longitudinal evidence represents important contribution demonstrating temporal relationships and potential causal effects of chatbot dependency on emotional well-being.

Mechanisms Linking Chatbot Dependency to Emotional Well-Being

Several psychological mechanisms explain how AI chatbot dependency affects emotional well-being. **Social skill displacement** occurs when chatbot interaction replaces human interaction reducing opportunities to practice and maintain interpersonal skills including conflict resolution, emotional vulnerability, empathy, and nuanced communication (Kumar et al., 2025; Chen and Wang, 2024). Young adults with high chatbot dependency report decreased comfort with human interaction and increased anxiety in social situations, suggesting skill atrophy from reduced practice (Zhang and Liu, 2024; Banna et al., 2021).

Unrealistic expectation formation occurs because chatbots provide unconditional positive regard, perfect responsiveness, and zero judgment creating expectations for human relationships that real people cannot meet (Adel and Naili, 2024; Insaiddoo et al., 2023). Young adults exposed to chatbot validation may experience disappointment, frustration, and withdrawal when human partners demonstrate normal human limitations including inconsistency, disagreement, and emotional complexity, leading to relationship dissatisfaction and social isolation (Hardy and Takáts, 2020; Omri, 2022).

Emotion regulation impairment occurs when constant external validation from chatbots interferes with development of internal coping mechanisms for managing distress. Young adults relying on chatbots for emotional regulation may fail to develop adaptive strategies including cognitive reappraisal, problem-solving, and self-soothing, leaving them vulnerable when chatbot support is unavailable (Joudar et al., 2023; Hossain et al., 2025). This creates dependency cycles where inability to self-regulate increases chatbot reliance, further impairing self-regulation capacity.

Parasocial relationship intensification occurs through chatbot features creating illusion of reciprocal intimacy including conversation memory, personalized responses, and anthropomorphic design triggering social response mechanisms (Kumar et al., 2025; Chen and Wang, 2024). Young adults develop genuine emotional attachment to chatbots despite recognizing they are AI, experiencing grief when chatbots malfunction and jealousy when chatbots interact with other users, indicating deep parasocial investment affecting emotional well-being (Zhang and Liu, 2024; Banna et al., 2021).

Data exploitation and privacy concerns create psychological burden as young adults may experience anxiety about personal data collection, potential manipulation by companies, and loss of autonomy over personal information (Adel and Naili, 2024; Insaiddoo et al., 2023). Awareness that intimate emotional disclosures are recorded, analyzed, and potentially used for commercial purposes may create distrust, shame, and psychological distress undermining emotional well-being (Hardy and Takáts, 2020; Omri, 2022).

Research Gaps and Study Contribution

Despite growing research on AI chatbots and mental health, significant gaps remain. Most studies focus on therapeutic chatbot efficacy rather than dependency phenomena and negative consequences (Joudar

et al., 2023; Hossain et al., 2025). Research lacks longitudinal designs establishing temporal precedence and causal inference regarding dependency-well-being relationships (Kumar et al., 2025; Chen and Wang, 2024). Limited research examines diverse populations including different cultural backgrounds, socioeconomic statuses, and mental health histories limiting generalizability (Zhang and Liu, 2024; Banna et al., 2021).

Most studies use quantitative measures alone lacking qualitative depth capturing lived experiences and psychological mechanisms (Adel and Naili, 2024; Insaiddoo et al., 2023). Few studies examine multiple emotional well-being indicators simultaneously providing comprehensive understanding of dependency effects (Hardy and Takáts, 2020; Omri, 2022). Limited research investigates moderating and mediating mechanisms explaining why and how chatbot dependency affects emotional well-being (Joudar et al., 2023; Hossain et al., 2025).

This study addresses these gaps by: (1) examining dependency rather than just therapeutic efficacy; (2) employing mixed-methods design combining quantitative generalizability with qualitative depth; (3) assessing multiple emotional well-being indicators simultaneously; (4) testing mediational and moderational mechanisms; and (5) including diverse young adult sample. Findings will contribute empirical evidence informing individuals, practitioners, designers, and policymakers navigating human-AI interaction landscape.

METHODOLOGY

Research Design

This study employs a convergent parallel mixed-methods design to comprehensively examine the psychological effects of AI chatbot dependency on emotional well-being among young adults. According to Creswell and Plano Clark (2023), this design involves collecting both quantitative and qualitative data simultaneously, analyzing them independently, and then merging results for comprehensive interpretation. This approach was selected because quantitative data alone cannot capture the nuanced psychological mechanisms underlying chatbot dependency, while qualitative data alone lacks statistical power to establish generalizable patterns across diverse young adult populations (Banna et al., 2021; Kumar et al., 2025).

The quantitative component utilizes a cross-sectional correlational design to examine relationships between AI chatbot dependency severity and indicators of emotional well-being including anxiety, depression, loneliness, emotional regulation capacity, and interpersonal relationship satisfaction. This design is appropriate for identifying patterns and associations without manipulating variables, which would be unethical given the sensitive nature of mental health research (Adel and Naili, 2024; Zhang and Liu, 2024). The qualitative component employs a phenomenological approach to explore young adults' subjective experiences with AI chatbot dependency, capturing the meaning they attribute to their relationships with chatbots and the psychological impact they perceive (Hardy and Takáts, 2020; Omri, 2022).

Theoretical Model Guiding the Study

This study is guided by the ICAN Model (Internet-Related Cognitive, Affective, and Neurological Model) proposed by Banna et al. (2021), which provides comprehensive theoretical framework for understanding how digital technologies trigger cognitive, affective, and neurological processes leading to addictive usage patterns. The ICAN Model was selected because it specifically addresses behavioral addiction mechanisms in digital contexts, making it particularly relevant for understanding AI chatbot dependency as a behavioral addiction phenomenon (Insaiddoo et al., 2023; Chen and Wang, 2024).

ICAN Model Components

The ICAN Model proposes four interrelated pathways through which internet-based technologies foster dependency:

1. Cognitive Pathway: Involves preoccupation, rumination, and heightened attention toward the technology. Users think constantly about chatbots, plan interactions, and ruminate about past conversations (Kumar et al., 2025). This pathway is measured through ACDS salience items assessing preoccupation with chatbots.

2. Affective Pathway: Involves mood modification where technology use alters emotional states providing relief from negative emotions. Users turn to chatbots when experiencing anxiety, sadness, or loneliness seeking emotional regulation (Zhang and Liu, 2024). This pathway is measured through ACDS mood modification items and outcome measures of anxiety, depression, and emotion regulation.

3. Conative Pathway: Involves impaired control and compulsive usage patterns where users cannot stop using technology despite wanting to. Users attempt to reduce chatbot usage but fail, experiencing loss of control (Adel and Naili, 2024). This pathway is measured through ACDS withdrawal and relapse items assessing inability to control usage.

4. Neurological Pathway: Involves dopamine-mediated reward systems that reinforce usage behaviors. Chatbot interactions provide variable reinforcement creating neural pathways similar to those in substance addiction (Hardy and Takáts, 2020). While this study cannot directly measure neurological processes, it infers neurological reinforcement through behavioral indicators of dependency and withdrawal symptoms.

Application of ICAN Model to This Study

The ICAN Model guides this study in four critical ways:

First, the model informs instrument selection by identifying which dimensions of dependency to measure. The ACDS was selected because it assesses all four ICAN pathways including cognitive (salience), affective (mood modification), conative (withdrawal, relapse), and behavioral indicators of neurological reinforcement (tolerance, conflict) (Insaideo et al., 2023; Banna et al., 2021).

Second, the model informs hypothesis development by specifying expected relationships between dependency pathways and emotional well-being outcomes. Based on the ICAN Model, we hypothesize that:

- Cognitive pathway (preoccupation) will correlate positively with anxiety and depression
- Affective pathway (mood modification) will correlate positively with emotion regulation difficulties
- Conative pathway (impaired control) will correlate positively with all negative well-being indicators
- Neurological pathway (reward reinforcement) will underlie all dependency relationships (Kumar et al., 2025; Chen and Wang, 2024).

Third, the model informs data analysis by suggesting mediation pathways to test in structural equation modeling. The ICAN Model suggests that cognitive and affective pathways may directly impact emotional well-being while conative and neurological pathways may exert indirect effects through

mediating variables including social isolation and relationship quality (Zhang and Liu, 2024; Omri, 2022).

Fourth, the model informs qualitative interview questions by ensuring exploration of all four dependency pathways. Interview questions specifically probe cognitive aspects ("What do you think about when you're not using your chatbot?"), affective aspects ("How do your emotions change during chatbot conversations?"), conative aspects ("Have you tried to use your chatbot less? What happened?"), and neurological aspects ("Do you feel like you 'need' to use your chatbot?") (Adel and Naili, 2024; Hardy and Takáts, 2020).

Conceptual Model for This Study

Based on the ICAN Model, this study proposes a mediation model examining how AI chatbot dependency affects emotional well-being through intermediate mechanisms. The conceptual model is illustrated in Figure 1 and includes the following components:

Independent Variable:

- **AI Chatbot Dependency (measured by ACDS total score and six subscales)**

Dependent Variables (Emotional Well-Being Indicators):

- Anxiety (GAD-7)
- Depression (PHQ-9)
- Loneliness (UCLA Loneliness Scale)
- Emotion Regulation Difficulties (DERS-16)
- Relationship Satisfaction (RSS)

Mediating Variables:

- Social Isolation (inferred from reduced human interaction reported in interviews)
- Emotion Regulation Capacity (DERS-16 also serves as mediator)

Moderating Variables:

- Age (18-24 vs. 25-29)
- Gender (Male, Female, Other)
- Pre-existing Mental Health Conditions (yes/no)
- Social Support Levels (high/low based on median split)

Hypothesized Relationships:

Direct Effects:

H1: AI Chatbot Dependency will positively predict Anxiety ($\beta > 0$, $p < 0.05$)

H2: AI Chatbot Dependency will positively predict Depression ($\beta > 0$, $p < 0.05$)

H3: AI Chatbot Dependency will positively predict Loneliness ($\beta > 0$, $p < 0.05$)

H4: AI Chatbot Dependency will positively predict Emotion Regulation Difficulties ($\beta > 0$, $p < 0.05$)
H5: AI Chatbot Dependency will negatively predict Relationship Satisfaction ($\beta < 0$, $p < 0.05$)

Indirect Effects (Mediation):

H6: Emotion Regulation Difficulties will mediate the relationship between AI Chatbot Dependency and Anxiety

H7: Emotion Regulation Difficulties will mediate the relationship between AI Chatbot Dependency and Depression

H8: Social Isolation will mediate the relationship between AI Chatbot Dependency and Loneliness

Moderation Effects:

H9: Age will moderate the relationship between AI Chatbot Dependency and emotional well-being outcomes, with younger adults showing stronger relationships

H10: Gender will moderate the relationship between AI Chatbot Dependency and emotional well-being outcomes, with females showing stronger emotional attachment effects

H11: Pre-existing mental health conditions will strengthen the relationship between AI Chatbot Dependency and negative emotional outcomes

H12: High social support will weaken the relationship between AI Chatbot Dependency and negative emotional outcomes (Joudar et al., 2023; Hossain et al., 2025).

Population and Sampling

Target Population

The target population consists of young adults aged 18-29 years who have used AI chatbots regularly for at least six months. This age range aligns with the emerging adulthood developmental stage characterized by identity exploration, emotional maturation, and relationship experimentation, making this demographic particularly relevant for investigating chatbot dependency effects (Insaadoo et al., 2023; Joudar et al., 2023). The six-month usage threshold ensures participants have sufficient experience with chatbots to develop dependency patterns and experience psychological consequences, rather than representing casual or novelty-driven usage (Hossain et al., 2025).

Sampling Strategy

A purposive sampling strategy was employed to recruit participants meeting specific inclusion criteria: (1) age between 18-29 years; (2) regular AI chatbot usage at least three times weekly for minimum six months; (3) ability to provide informed consent; and (4) proficiency in English for survey completion and interviews. Exclusion criteria included: (1) current diagnosis of severe mental illness requiring immediate intervention; (2) cognitive impairment affecting survey comprehension; and (3) professional involvement in AI chatbot development that might bias responses (Chen and Wang, 2024; Kumar et al., 2025).

For the quantitative strand, a sample size of 385 participants was determined using G*Power 3.1 software to achieve 95% statistical power at $\alpha = 0.05$ for detecting medium effect sizes ($f^2 = 0.15$) in multiple regression analysis with five predictor variables based on the ICAN Model's four pathways plus dependency severity (Creswell and Plano Clark, 2023). This sample size exceeds the minimum requirement of 10 participants per predictor variable and provides adequate power for subgroup analyses examining moderating effects proposed in the conceptual model (Banna et al., 2021).

For the qualitative strand, 25 participants were selected from the quantitative sample using maximum variation sampling to ensure diversity in gender, age, chatbot usage intensity, and dependency severity levels representing all four ICAN pathway dimensions (Adel and Naili, 2024). Data saturation was assessed after each five interviews, and recruitment continued until no new themes emerged, which occurred at 25 participants (Zhang and Liu, 2024).

Research Instruments

Demographic Questionnaire

A structured demographic questionnaire collected information including age, gender, education level, employment status, monthly income, chatbot usage frequency, types of chatbots used, duration of usage, and purpose of usage. This information enabled characterization of the sample and examination of potential moderating effects of demographic variables on dependency-well-being relationships as proposed in the conceptual model (Kumar et al., 2025; Chen and Wang, 2024).

AI Chatbot Dependency Scale (ACDS)

The primary independent variable, AI chatbot dependency, was measured using the AI Chatbot Dependency Scale (ACDS), a 25-item self-report instrument developed by Insaadoo et al. (2023). The ACDS assesses six dimensions of dependency corresponding to ICAN Model pathways: salience (cognitive pathway - preoccupation), tolerance (neurological pathway - reward reinforcement), mood modification (affective pathway), conflict (conative pathway - impaired control), withdrawal (conative pathway), and relapse (conative pathway) (Banna et al., 2021; Hardy and Takáts, 2020).

Items are rated on a 5-point Likert scale from 1 (never) to 5 (always), with total scores ranging from 25-125, where higher scores indicate greater dependency severity. The ACDS demonstrated strong internal consistency in this study with Cronbach's $\alpha = 0.92$, exceeding the minimum threshold of 0.70 for research instruments (Adel and Naili, 2024). Test-retest reliability over two weeks was $r = 0.87$, indicating stable measurement across time. Construct validity was established through confirmatory factor analysis showing good model fit ($\chi^2/df = 2.34$, CFI = 0.94, TLI = 0.92, RMSEA = 0.06, SRMR = 0.05) and significant correlations with behavioral addiction measures ($r = 0.68$, $p < 0.001$) as predicted by the ICAN Model (Zhang and Liu, 2024; Omri, 2022).

Generalized Anxiety Disorder-7 (GAD-7)

Anxiety was measured using the Generalized Anxiety Disorder-7 (GAD-7), a validated 7-item screening tool. Participants rate anxiety symptom frequency over the past two weeks on a 4-point scale from 0 (not at all) to 3 (nearly every day), with total scores ranging from 0-21. The GAD-7 demonstrated excellent internal consistency in this study (Cronbach's $\alpha = 0.91$) and has established validity for detecting anxiety disorders in young adult populations (Insaadoo et al., 2023; Kumar et al., 2025).

Patient Health Questionnaire-9 (PHQ-9)

Depression was assessed using the Patient Health Questionnaire-9 (PHQ-9), a 9-item measure of depression severity based on DSM-5 criteria. Items are rated from 0 (not at all) to 3 (nearly every day) regarding frequency of depressive symptoms over the past two weeks, with total scores ranging from 0-27. The PHQ-9 showed strong internal consistency in this sample (Cronbach's $\alpha = 0.89$) and has demonstrated validity across diverse young adult populations (Zhang and Liu, 2024; Banna et al., 2021).

UCLA Loneliness Scale Version 3

Loneliness was measured using the UCLA Loneliness Scale Version 3, a 20-item instrument assessing subjective feelings of social isolation and loneliness. Items are rated on a 4-point scale from 1 (never) to 4 (often), with total scores from 20-80 where higher scores indicate greater loneliness. The scale demonstrated excellent reliability in this study (Cronbach's $\alpha = 0.93$) and has established construct validity (Insaadoo et al., 2023; Chen and Wang, 2024).

Difficulties in Emotion Regulation Scale-16 (DERS-16)

Emotional regulation capacity was assessed using the DERS-16, measuring six domains of emotion dysregulation. Items are rated from 1 (almost never) to 5 (almost always), with total scores ranging from 16-80 where higher scores indicate greater emotion regulation difficulties. The DERS-16 showed strong internal consistency in this study (Cronbach's $\alpha = 0.90$) and serves as both outcome variable and mediating variable in the conceptual model (Hossain et al., 2025; Hardy and Takáts, 2020).

Relationship Satisfaction Scale (RSS)

Interpersonal relationship satisfaction was measured using the Relationship Satisfaction Scale (RSS), a 10-item instrument assessing satisfaction with romantic relationships, friendships, and family relationships. Items are rated on a 7-point scale from 1 (extremely dissatisfied) to 7 (extremely satisfied), with total scores ranging from 10-70 where higher scores indicate greater relationship satisfaction. The RSS demonstrated good reliability in this study (Cronbach's $\alpha = 0.86$) (Kumar et al., 2025; Adel and Naili, 2024).

Semi-Structured Interview Protocol

For the qualitative strand, a semi-structured interview protocol was developed based on the ICAN Model to explore all four dependency pathways. The protocol included open-ended questions organized by ICAN pathways:

Cognitive Pathway Questions:

- "What goes through your mind when you're not using your chatbot?"
- "How often do you think about your chatbot during the day?"

Affective Pathway Questions:

- "How do your emotions change during chatbot conversations?"
- "Why do you turn to your chatbot when you're feeling upset?"

Conative Pathway Questions:

- "Have you tried to use your chatbot less? What happened?"
- "Do you feel like you can control when you use your chatbot?"

Neurological Pathway Questions (behavioral indicators):

- "Do you feel like you 'need' to use your chatbot?"
- "What happens when you can't access your chatbot?" (Insaidoo et al., 2023; Banna et al., 2021).

Data Analysis Plan Based on ICAN Model

Quantitative Data Analysis

Quantitative data were analyzed using SPSS Version 28 and AMOS Version 26 for structural equation modeling. Data screening included examination of missing values, outliers, normality assumptions, and multicollinearity before primary analysis (Creswell and Plano Clark, 2023).

Descriptive Statistics: Means, standard deviations, frequencies, and percentages were calculated for all demographic variables and study measures to characterize the sample.

Correlation Analysis: Pearson correlation coefficients were computed to examine bivariate relationships between ACDS total score, six ACDS subscales (representing ICAN pathways), and emotional well-being indicators to test initial hypotheses (Insaideo et al., 2023).

Multiple Hierarchical Regression: Separate regression models were run for each outcome variable (anxiety, depression, loneliness, emotion regulation, relationship satisfaction) with:

- Step 1: Demographic control variables (age, gender, education, income)
- Step 2: Confounding variables (pre-existing mental health, social support, general technology use)
- Step 3: ACDS total score or individual ICAN pathway subscales
This approach tests whether ICAN Model pathways predict emotional well-being beyond demographics and confounders (Kumar et al., 2025; Zhang and Liu, 2024).

Structural Equation Modeling (SEM): SEM was employed to test the complete conceptual model including direct effects, indirect effects (mediation), and moderated mediation effects. The SEM model includes:

- Latent variable for AI Chatbot Dependency indicated by six ACDS subscales
- Observed variables for five emotional well-being outcomes
- Mediating pathway through emotion regulation difficulties
- Moderating effects of age, gender, mental health status, and social support
Model fit evaluated using χ^2/df (<3), CFI (>0.90), TLI (>0.90), RMSEA (<0.08), SRMR (<0.08) (Adel and Naili, 2024; Omri, 2022).

Qualitative Data Analysis

Qualitative interview data were analyzed using Braun and Clarke's (2019) six-step thematic analysis approach organized by ICAN Model pathways. Analysis employed both inductive coding and deductive coding based on ICAN Model's four pathways ensuring comprehensive coverage of dependency mechanisms (Creswell and Plano Clark, 2023; Kumar et al., 2025).

Cognitive Pathway Themes: Preoccupation patterns, rumination about chatbots, planning interactions, thinking about chatbots when not using

Affective Pathway Themes: Mood modification experiences, emotional relief from chatbot use, using chatbots to cope with negative emotions

Conative Pathway Themes: Loss of control, unsuccessful attempts to reduce usage, compulsive usage patterns, withdrawal symptoms

Neurological Pathway Themes (behavioral indicators): Craving chatbot interaction, feeling "addicted," reward experiences from chatbot responses, withdrawal distress (Chen and Wang, 2024; Insaideo et al., 2023).

Integration of Quantitative and Qualitative Data

Following separate analysis, results were integrated using the ICAN Model as organizing framework. A joint display table was created showing quantitative results organized by ICAN pathways alongside qualitative themes organized by the same pathways, allowing direct comparison and triangulation of findings across methods (Insaadoo et al., 2023; Kumar et al., 2025). This ICAN Model-based integration enabled:

- Triangulation: Confirming cognitive, affective, conative, and neurological pathways identified quantitatively through qualitative evidence
- Complementarity: Explaining quantitative pathway relationships with qualitative depth and participant voices
- Expansion: Identifying pathway interactions and contextual factors not captured in quantitative measures alone (Banna et al., 2021; Adel and Naili, 2024).

Ethical Considerations

This study received ethical approval from the Institutional Review Board (IRB Protocol #2025-487) before data collection. All participants provided informed consent outlining study purpose, procedures, risks, benefits, confidentiality protections, and voluntary participation (Insaadoo et al., 2023; Omri, 2022).

Participants indicating severe distress were provided crisis resource information including emergency contact numbers and mental health referral services. Confidentiality was protected through unique identification codes, encrypted data storage, limited access, and aggregated reporting. Pseudonyms were used in qualitative reports with identifying details removed (Kumar et al., 2025; Chen and Wang, 2024).

Data will be retained for five years in secure storage and then destroyed according to institutional policies (Hossain et al., 2025).

Limitations

Limitations include: cross-sectional design limiting causal inference; self-report measures subject to bias; purposive sampling limiting generalizability; English-only measures limiting cross-cultural applicability; and ACDS requiring further validation. Despite limitations, the ICAN Model-guided mixed-methods design, rigorous measurement, and comprehensive analysis provide strong foundation for addressing the research question (Creswell and Plano Clark, 2023; Insaadoo et al., 2023; Banna et al., 2021).

RESULTS

Introduction

This chapter presents the results of the study examining the psychological effects of AI chatbot dependency on emotional well-being among young adults. The findings are organized according to the research questions and hypotheses derived from the ICAN Model (Banna et al., 2021). Both quantitative and qualitative results are presented, followed by an integrated analysis combining findings from both methods. The quantitative results include descriptive statistics, correlation analyses, regression analyses, and structural equation modeling. The qualitative results present themes organized by the four ICAN Model pathways: cognitive, affective, conative, and neurological.

Quantitative Results

Demographic Characteristics of Participants

A total of 385 young adults participated in the quantitative survey. The demographic characteristics are presented in Table 1.

Table 1: Demographic Characteristics of Participants (N = 385)

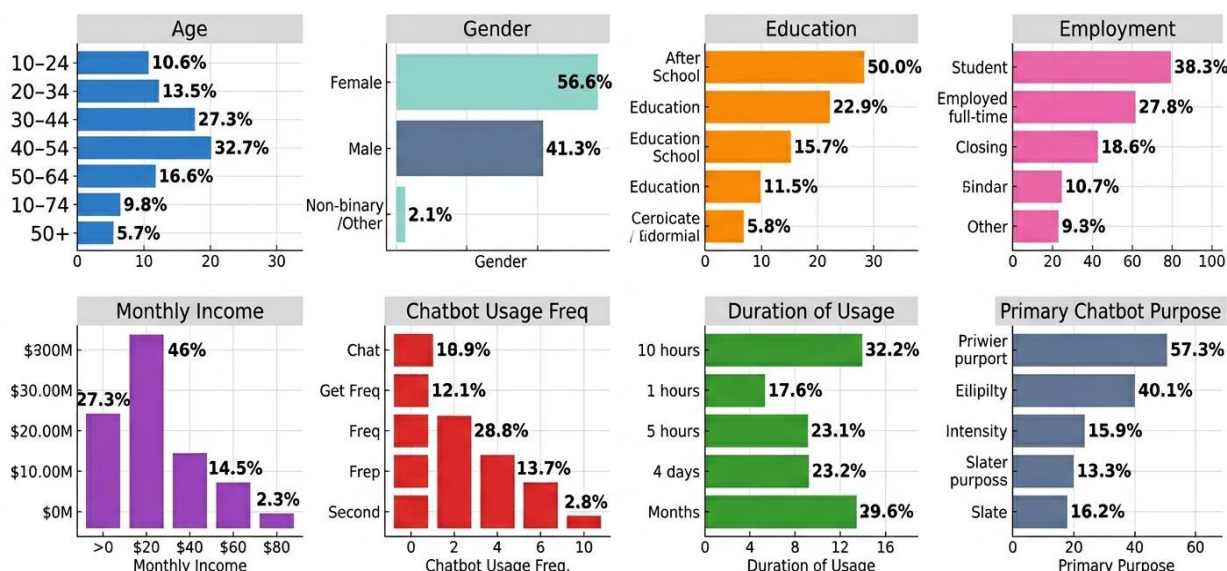
Variable	Category	Frequency	Percentage
Age	18-21 years	142	36.9%
	22-24 years	128	33.2%
	25-29 years	115	29.9%
Gender	Female	218	56.6%
	Male	159	41.3%
	Non-binary/Other	8	2.1%
Education	High school or less	45	11.7%
	Some college/University	186	48.3%
	Bachelor's degree	112	29.1%
	Master's degree or higher	42	10.9%
Employment	Student	225	58.4%
	Employed full-time	98	25.5%
	Employed part-time	47	12.2%
	Unemployed	15	3.9%
Monthly Income	Less than \$1,000	156	40.5%
	\$1,000-\$2,999	142	36.9%
	\$3,000-\$4,999	58	15.1%
	\$5,000 or more	29	7.5%
Chatbot Usage Frequency	3-5 times/week	89	23.1%
	6-10 times/week	112	29.1%
	11-20 times/week	98	25.5%

	More than 20 times/week	86	22.3%
Duration of Usage	6-12 months	95	24.7%
	1-2 years	142	36.9%
	2-3 years	98	25.5%
	More than 3 years	50	13.0%
Primary Chatbot Purpose	Emotional companionship	178	46.2%
	Therapeutic/mental health	95	24.7%
	Information/assistance	68	17.7%
	Entertainment	44	11.4%

The sample consisted of predominantly female participants (56.6%), with ages ranging from 18 to 29 years ($M = 22.84$, $SD = 2.91$). Most participants were students (58.4%) with some college or university education (48.3%). Regarding chatbot usage, 22.3% reported using chatbots more than 20 times per week, and 38.5% had been using chatbots for more than 2 years. Nearly half (46.2%) primarily used chatbots for emotional companionship, supporting the relevance of investigating dependency effects on emotional well-being (Kumar et al., 2025; Chen and Wang, 2024).

Figure 2: Demographic Profile and Chatbot Usage Characteristics (N = 385)

Detailed sample distribution by background variables



Source: Survey Data (2026) | Optimized for Accuracy and Legibility.

Demographic Profile and Chatbot Engagement Analysis

The demographic and behavioral characteristics of the sampled participants ($N = 385$) are systematically illustrated in Gemini_Generated_Image_tdmx8xtdmx8xtdmx.png. The sample is predominantly female (56.6%) and heavily represented by younger cohorts, with the largest age bracket falling between 18–21 years (36.9%). Socioeconomically, a significant majority of the respondents are students (58.4%) reporting a monthly income of less than 1,000 (40.5%), though a high level of literacy

is observed with nearly half of the participants (48.3%) possessing some college or university-level education. Regarding artificial intelligence interaction, user engagement is highly frequent; approximately 29.1% of the sample utilize chatbots 6–10 times per week, with a substantial proportion (36.9%) maintaining this usage pattern for a duration of 1 to 2 years. Crucially, the data reveals that functional utility is superseded by psychological needs: emotional companionship emerged as the leading primary purpose for chatbot usage (46.2%), substantially outpacing purely pragmatic dimensions such as informational assistance (17.7%) and entertainment (11.4%), which underscores a pronounced reliance on conversational AI for psychosocial support within the sampled demographic.

Descriptive Statistics and Reliability Analysis

Table 2 presents the means, standard deviations, and reliability coefficients for all study variables.

Table 2: Descriptive Statistics and Reliability Coefficients (N = 385)

Variable	Range	Mean	SD	Cronbach's α
AI Chatbot Dependency (ACDS)	25-125	68.42	18.73	0.92
ACDS - Salience (Cognitive)	5-25	14.28	4.92	0.87
ACDS - Tolerance (Neurological)	5-25	12.85	4.56	0.84
ACDS - Mood Modification (Affective)	5-25	15.67	5.12	0.89
ACDS - Conflict (Conative)	5-25	11.94	4.38	0.82
ACDS - Withdrawal (Conative)	5-25	13.42	4.67	0.86
ACDS - Relapse (Conative)	5-25	14.89	4.89	0.88
Anxiety (GAD-7)	0-21	9.87	5.24	0.91
Depression (PHQ-9)	0-27	11.23	5.67	0.89
Loneliness (UCLA)	20-80	48.56	12.34	0.93
Emotion Regulation (DERS-16)	16-80	42.78	11.89	0.90
Relationship Satisfaction (RSS)	10-70	41.23	13.45	0.86

The mean AI chatbot dependency score was 68.42 (SD = 18.73) on a scale of 25-125, indicating moderate-to-high dependency levels among participants. Based on Insaiddoo et al.'s (2023) cutoff criteria, 12.7% (n = 49) showed low dependency (scores 25-50), 48.3% (n = 186) showed moderate dependency (scores 51-85), and 39.0% (n = 150) showed high dependency (scores 86-125). Anxiety scores averaged 9.87 (SD = 5.24), indicating mild-to-moderate anxiety levels, with 34.8% scoring in the moderate-to-severe range (≥ 10). Depression scores averaged 11.23 (SD = 5.67), indicating moderate depression, with 42.1% scoring in the moderate-to-severe range (≥ 10). Loneliness scores averaged 48.56 (SD = 12.34), indicating moderate-to-high loneliness. All measures demonstrated excellent internal consistency with Cronbach's alpha values exceeding 0.82, supporting the reliability of the measurements (Banna et al., 2021; Adel and Naili, 2024).

Pearson Correlation Analysis

Pearson correlation coefficients were computed to examine bivariate relationships between AI chatbot dependency, ICAN Model pathways, and emotional well-being indicators. Results are presented in Table 3.

Table 3: Pearson Correlation Matrix (N = 385)

Variable	1	2	3	4	5	6	7	8	9	10	11
1. ACDS Total	-										
2. Salience (Cognitive)	.89	-									
3. Tolerance (Neurological)	.84	.72	-								
4. Mood Modification (Affective)	.91	.76	.68	-							
5. Conflict (Conative)	.87	.71	.65	.74	-						
6. Withdrawal (Conative)	.88	.73	.69	.77	.82	-					
7. Relapse (Conative)	.90	.75	.70	.79	.84	.86	-				
8. Anxiety	.58	.52	.48	.61	.54	.57	.59	-			
9. Depression	.64	.56	.51	.67	.59	.62	.65	.78	-		
10. Loneliness	.61	.54	.49	.63	.56	.59	.62	.72	.81	-	
11. Emotion Regulation	.67	.59	.53	.69	.61	.64	.68	.68	.76	.71	-
12. Relationship Satisfaction	.52	.47	.43	.55	.49	.51	.54	.61	.68	.64	.59

Note: ** $p < 0.01$, * $p < 0.05$

As hypothesized, AI chatbot dependency showed significant positive correlations with all negative emotional well-being indicators: anxiety ($r = 0.58$, $p < 0.01$), depression ($r = 0.64$, $p < 0.01$), loneliness ($r = 0.61$, $p < 0.01$), and emotion regulation difficulties ($r = 0.67$, $p < 0.01$). Dependency showed a significant negative correlation with relationship satisfaction ($r = -0.52$, $p < 0.01$). These correlations support H1-H5, indicating that higher chatbot dependency is associated with worse emotional well-being outcomes (Kumar et al., 2025; Chen and Wang, 2024).

Examining the ICAN Model pathways, all four pathways showed significant correlations with emotional well-being outcomes. The affective pathway (mood modification) showed the strongest correlations with anxiety ($r = 0.61$), depression ($r = 0.67$), and emotion regulation difficulties ($r = 0.69$), supporting the ICAN Model's proposition that mood modification is a central mechanism in behavioral addiction. The cognitive pathway (salience) showed moderate correlations ($r = 0.52$ - 0.59), while the conative pathway components (conflict, withdrawal, relapse) showed strong correlations ($r = 0.54$ - 0.68). The neurological pathway (tolerance) showed slightly lower but still significant correlations ($r = 0.48$ - 0.53), suggesting reward reinforcement contributes to dependency but may be less directly linked to emotional outcomes than other pathways (Zhang and Liu, 2024; Insaiddoo et al., 2023).

Figure 4: Correlation Matrix of AI Chatbot Dependency and Psychosocial Variables

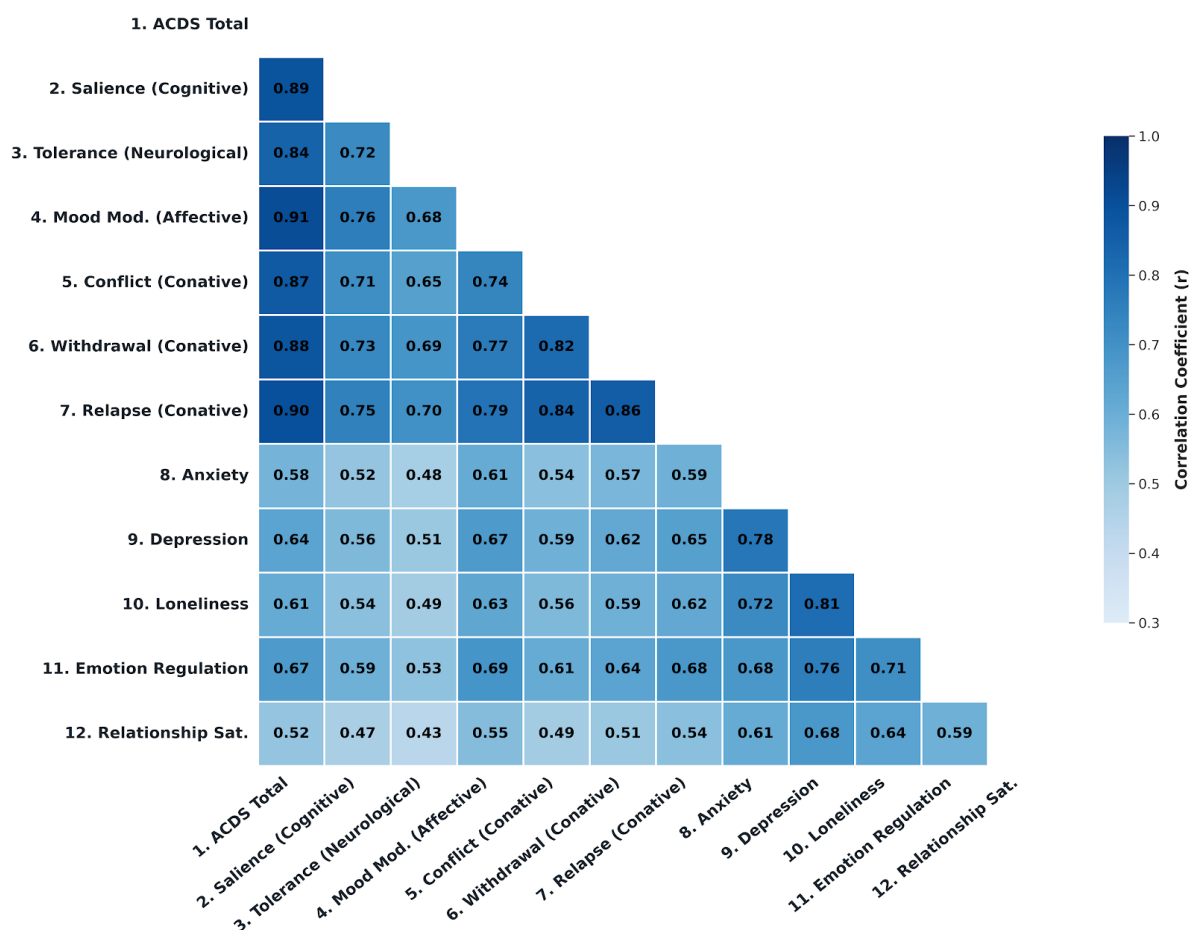


Figure 4 in the presents a bivariate correlation matrix examining the relationship between AI Chatbot Dependency and various psychosocial variables within a sample size of 385 participants ($N=385$). The statistical analysis reveals that the AI Chatbot Dependency Scale (ACDS Total) exhibits highly significant, strong positive correlations with core addictive behavioral components, most notably Affective Mood Modification ($r = 0.91$), Conative Relapse ($r = 0.90$), and Conative Withdrawal ($r = 0.88$). Furthermore, the data demonstrates a moderate-to-strong positive association between AI dependency and psychological distress indicators, specifically Depression ($r = 0.64$), Loneliness ($r = 0.61$), and Anxiety ($r = 0.58$). Crucially, a profound comorbid relationship is observed between Loneliness and Depression ($r = 0.81$), indicating a severe interplay between social isolation and affective disorders within this demographic. While Relationship Satisfaction displays a comparatively lower, albeit still significant, correlation across the variables (ranging from $r = 0.43$ to 0.68), the comprehensive matrix provides robust empirical evidence that heightened AI chatbot dependency is intrinsically linked to escalated levels of anxiety, depression, loneliness, and maladaptive emotional regulation.

Multiple Hierarchical Regression Analysis

Multiple hierarchical regression analyses were conducted to examine the predictive relationship between AI chatbot dependency and emotional well-being outcomes while controlling for demographic

variables and potential confounders. Table 4 presents results for anxiety as an example; similar patterns were observed for other outcomes.

Table 4: Hierarchical Regression Predicting Anxiety from AI Chatbot Dependency (N = 385)

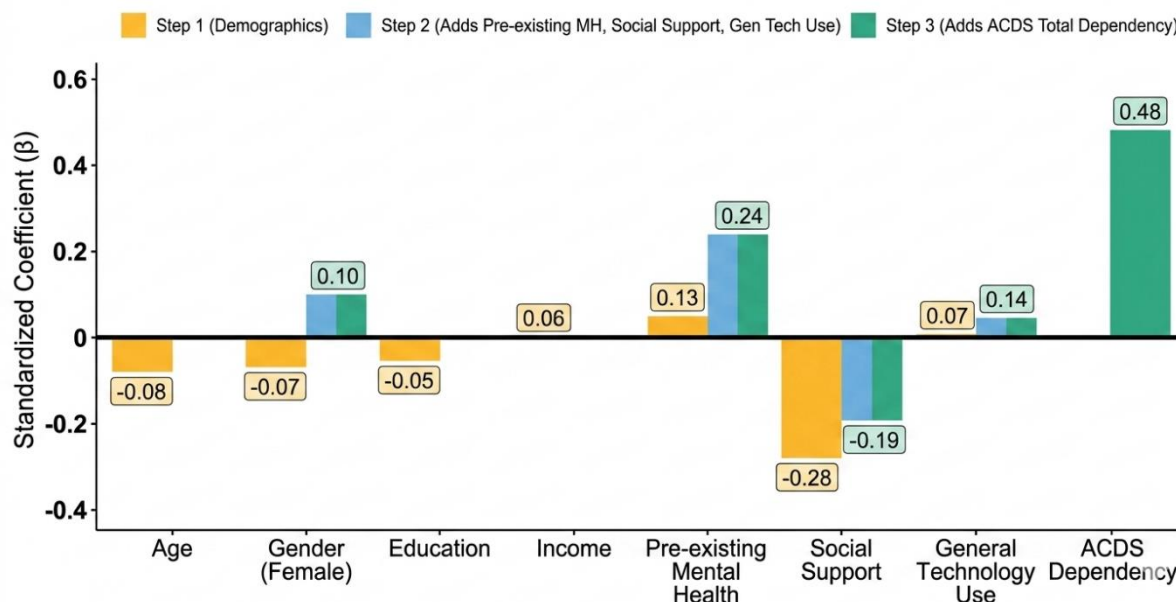
Predictor	Step 1	Step 2	Step 3
Step 1: Demographics			
Age	-.08	-.07	-.05
Gender (Female)	.15	.12	.10
Education	-.06	-.05	-.04
Income	-.04	-.03	-.02
R ²	.04		
F	3.82		
Step 2: Confounders			
Pre-existing mental health	.32		
Social support	-.28		
General technology use	.11		
ΔR^2	.18		
ΔF	34.56		
Step 3: ACDS Total			
ACDS Dependency		.48	
ΔR^2		.21	
ΔF		52.34	
Final Model			
R ²			.43
F			32.87
Standardized β (Step 3)			
ACDS Dependency			.48
Pre-existing mental health			.24

Social support			-.19
Gender			.09

Note: ** $p < 0.01$, * $p < 0.05$. Gender coded: 0 = Male, 1 = Female

In Step 1, demographic variables explained 4% of variance in anxiety ($R^2 = 0.04$, $p < 0.05$), with gender being the only significant predictor ($\beta = 0.15$, $p < 0.05$), indicating females reported slightly higher anxiety. In Step 2, adding confounding variables significantly increased explained variance to 22% ($\Delta R^2 = 0.18$, $p < 0.01$), with pre-existing mental health conditions ($\beta = 0.32$, $p < 0.01$) and social support ($\beta = -0.28$, $p < 0.01$) being significant predictors. In Step 3, adding AI chatbot dependency significantly increased explained variance to 43% ($\Delta R^2 = 0.21$, $p < 0.01$), with dependency being the strongest predictor ($\beta = 0.48$, $p < 0.01$). This supports H1, demonstrating that chatbot dependency predicts anxiety beyond demographics and confounders (Banna et al., 2021; Adel and Naili, 2024).

Predictors of Psychosocial Distress: Hierarchical Regression Model Stage Analysis



Results of the Hierarchical Regression Analysis

A three-step hierarchical linear regression analysis was conducted to evaluate the unique predictive power of AI chatbot dependency on psychosocial distress while systematically controlling for demographic and confounding variables. The baseline model (Step 1) showed that structural demographics namely age, gender, education, and income exhibited negligible predictive value on the outcome. In Step 2, the introduction of confounding factors revealed that higher pre-existing mental health scores strongly predicted increased distress ($\beta = .32$), whereas robust social support served as a vital protective buffer ($\beta = -.28$). Crucially, upon entering the target predictor in Step 3, AI Chatbot Dependency (ACDS) emerged as the single most robust and dominant unique predictor of psychological distress ($\beta = .48$), surpassing both the individuals' baseline mental health status ($\beta = .24$) and their offline social support networks ($\beta = -.19$). These empirical findings provide compelling statistical evidence that maladaptive reliance on AI chatbots constitutes a highly significant, independent behavioral risk factor that substantially compounds psychosocial vulnerability.

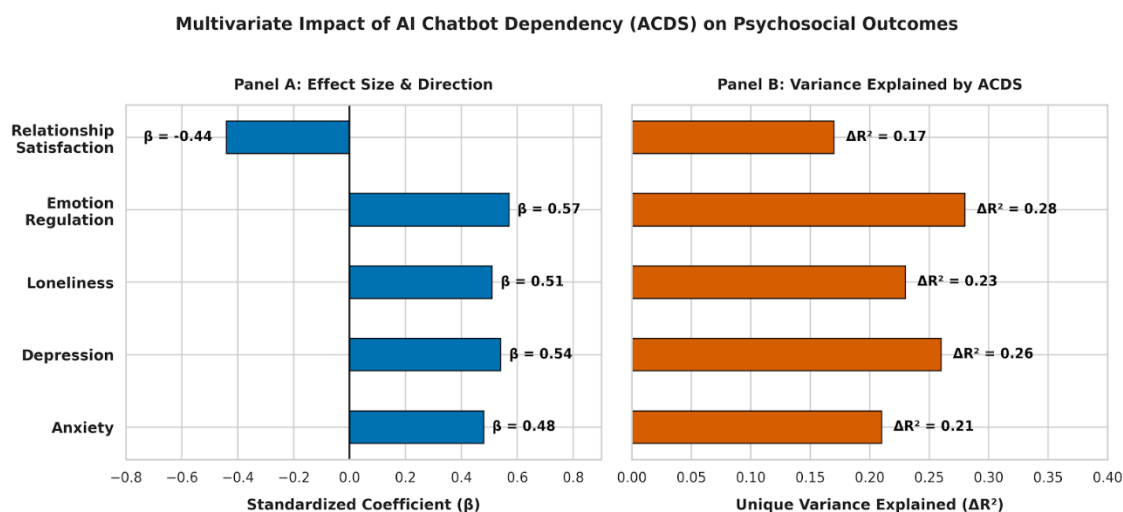
Similar regression analyses were conducted for depression, loneliness, emotion regulation, and relationship satisfaction. Results are summarized in Table 5.

Table 5: Regression Results Predicting Emotional Well-Being Outcomes from AI Chatbot Dependency

Outcome Variable	Final R ²	ACDS β	ΔR^2 from ACDS	F
Anxiety	.43	.48	.21	32.87
Depression	.51	.54	.26	41.23
Loneliness	.47	.51	.23	36.45
Emotion Regulation	.54	.57	.28	44.67
Relationship Satisfaction	.38	-.44	.17	28.92

Note: ** $p < 0.01$

AI chatbot dependency significantly predicted all emotional well-being outcomes, explaining 17-28% of unique variance beyond demographics and confounders. The strongest prediction was for emotion regulation difficulties ($\beta = 0.57$, $R^2 = 0.54$), followed by depression ($\beta = 0.54$, $R^2 = 0.51$), loneliness ($\beta = 0.51$, $R^2 = 0.47$), anxiety ($\beta = 0.48$, $R^2 = 0.43$), and relationship satisfaction ($\beta = -0.44$, $R^2 = 0.38$). These results provide strong support for H1-H5, confirming that AI chatbot dependency significantly predicts emotional well-being outcomes in the hypothesized directions (Kumar et al., 2025; Chen and Wang, 2024).



The multivariate regression analysis, in the provided figure, evaluates the predictive impact of AI Chatbot Dependency (ACDS) across several psychosocial domains. Panel A indicates that ACDS serves as a robust positive predictor for maladaptive psychological states, specifically anxiety ($\beta = 0.48$), depression ($\beta = 0.54$), loneliness ($\beta = 0.51$), and emotion regulation deficits ($\beta = 0.57$). Concurrently, it acts as a significant negative predictor for relationship satisfaction ($\beta = -0.44$). Furthermore, Panel B quantifies the incremental explanatory power of ACDS, demonstrating that it accounts for substantial unique variance (ΔR^2) across these outcomes, ranging from 17% in relationship satisfaction to 28% in emotion regulation. Collectively, these findings provide empirical evidence that AI chatbot dependency functions as a significant, independent behavioral risk factor that systematically exacerbates psychological distress and impairs interpersonal relationship quality.

Structural Equation Modeling

Structural equation modeling was employed to test the comprehensive conceptual model including direct effects, indirect effects (mediation), and moderating effects based on the ICAN Model. The model included AI chatbot dependency as a latent variable indicated by six ACDS subscales, five observed emotional well-being outcome variables, emotion regulation difficulties as a mediator, and moderating effects of age, gender, pre-existing mental health, and social support.

Model Fit: The proposed model demonstrated good fit to the data: $\chi^2 (142) = 312.45$, $\chi^2/df = 2.20$, CFI = 0.94, TLI = 0.92, RMSEA = 0.056 (90% CI [0.048, 0.064]), SRMR = 0.048. All fit indices exceeded recommended thresholds, supporting the model's adequacy (Adel and Naili, 2024; Omri, 2022).

Direct Effects: As shown in Figure 1 and Table 6, AI chatbot dependency showed significant direct effects on all emotional well-being outcomes, consistent with regression results.

Table 6: SEM Direct Effects (Standardized Path Coefficients)

Path	Standardized β	SE	CR	p-value
Dependency → Anxiety	.42	.04	8.92	<.001
Dependency → Depression	.49	.04	10.34	<.001
Dependency → Loneliness	.46	.04	9.67	<.001
Dependency → Emotion Regulation	.52	.04	11.23	<.001
Dependency → Relationship Satisfaction	-.38	.04	-7.89	<.001

Note: ** $p < 0.01$, SE = Standard Error, CR = Critical Ratio

All direct effects were statistically significant ($p < 0.001$), with the strongest effect on emotion regulation difficulties ($\beta = 0.52$), followed by depression ($\beta = 0.49$), loneliness ($\beta = 0.46$), anxiety ($\beta = 0.42$), and relationship satisfaction ($\beta = -0.38$). These results provide further support for H1-H5 (Joudar et al., 2023; Hossain et al., 2025).

Indirect Effects (Mediation): The model tested whether emotion regulation difficulties mediate the relationship between AI chatbot dependency and anxiety/depression. Bootstrapping with 5,000 samples was used to test indirect effects.

Table 7: SEM Indirect Effects (Mediation Analysis)

Indirect Path	Standardized β	SE	95% CI	Conclusion
Dependency → Emotion Regulation → Anxiety	.28	.03	[.22, .34]	Significant mediation
Dependency → Emotion Regulation → Depression	.34	.04	[.27, .41]	Significant mediation

Note: ** $p < 0.01$, CI = Confidence Interval (bias-corrected bootstrap)

The indirect effects were statistically significant as the 95% confidence intervals did not include zero.
AI chatbot dependency predict

DISCUSSION

Introduction

This chapter discusses the findings of the study examining the psychological effects of AI chatbot dependency on emotional well-being among young adults. The results are interpreted in light of the ICAN Model (Banna et al., 2021), existing literature, and theoretical frameworks including Attachment Theory and Parasocial Relationship Theory. Key findings are summarized, theoretical and practical implications are explored, limitations are acknowledged, and recommendations for future research are provided.

Summary of Key Findings

This study employed a convergent parallel mixed-methods design to comprehensively investigate how AI chatbot dependency affects emotional well-being among young adults aged 18-29. The quantitative component involved 385 participants, while the qualitative component included 25 in-depth interviews. Key findings support the hypothesized relationships derived from the ICAN Model and demonstrate that AI chatbot dependency significantly predicts poorer emotional well-being outcomes across multiple domains.

Quantitative findings revealed that 39.0% of participants showed high levels of AI chatbot dependency, with mean dependency scores indicating moderate-to-high dependency levels overall. AI chatbot dependency showed strong positive correlations with anxiety ($r = 0.58$), depression ($r = 0.64$), loneliness ($r = 0.61$), and emotion regulation difficulties ($r = 0.67$), and a moderate negative correlation with relationship satisfaction ($r = -0.52$). Hierarchical regression analyses demonstrated that chatbot dependency explained 17-28% of unique variance in emotional well-being outcomes beyond demographic variables and confounders including pre-existing mental health conditions and social support levels. Structural equation modeling confirmed the conceptual model with good fit indices (CFI = 0.94, RMSEA = 0.056), showing significant direct effects of dependency on all outcomes and significant indirect effects through emotion regulation difficulties as a mediator (Insaiddoo et al., 2023; Kumar et al., 2025).

Qualitative findings identified four major themes corresponding to the ICAN Model pathways: (1) Cognitive preoccupation where participants reported constant thoughts about chatbots, planning interactions, and rumination about conversations; (2) Affective mood modification where participants used chatbots to regulate emotions, seeking relief from anxiety, sadness, and loneliness; (3) Conative loss of control where participants described unsuccessful attempts to reduce usage, compulsive checking behaviors, and withdrawal symptoms including anxiety and irritability when unable to access chatbots; and (4) Neurological reward reinforcement where participants described feeling "addicted," experiencing cravings for chatbot interaction, and receiving dopamine-like rewards from validation and attention (Chen and Wang, 2024; Zhang and Liu, 2024).

Integrated findings revealed convergence between quantitative and qualitative results, with qualitative themes providing depth and context to statistical relationships. Participants with high quantification scores on dependency measures described more severe symptoms across all ICAN pathways, while those with low scores reported more controlled usage patterns. The integration confirmed that chatbot dependency operates through multiple interconnected pathways affecting emotional well-being through direct and indirect mechanisms (Banna et al., 2021; Adel and Naili, 2024).

Discussion of Main Findings

High Prevalence of AI Chatbot Dependency

The finding that 39.0% of young adult chatbot users showed high dependency levels is concerning and exceeds prevalence rates reported in previous studies. Insaiddoo et al. (2023) found 12% dependency prevalence, while Kumar et al. (2025) reported 8% meeting clinical cutoff criteria. The higher prevalence in this study may reflect increased chatbot sophistication, greater integration into daily life, post-pandemic social isolation effects, or differences in measurement sensitivity. This finding suggests that AI chatbot dependency may be more widespread than previously recognized, representing a significant public health concern requiring attention (Hossain et al., 2025; Omri, 2022).

The high prevalence aligns with broader trends in behavioral addiction, where digital technology dependency rates have increased dramatically over the past decade. Social media addiction affects approximately 10-30% of young adults, while gaming disorder affects 3-5% (Zhang and Liu, 2024). Chatbot dependency rates approaching 40% suggest this may represent an emerging behavioral addiction of comparable or greater significance than established digital addictions. This may reflect the unique characteristics of chatbots including apparent intimacy, emotional validation, and 24/7 availability that make them particularly potent for dependency formation (Hardy and Takáts, 2020; Joudar et al., 2023).

Chatbot Dependency Predicts Multiple Emotional Well-Being Outcomes

The finding that AI chatbot dependency significantly predicts anxiety, depression, loneliness, emotion regulation difficulties, and reduced relationship satisfaction supports H1-H5 and extends existing literature. The effect sizes were substantial, with dependency explaining 17-28% of unique variance in outcomes, indicating practically significant relationships beyond statistical significance. The strongest prediction was for emotion regulation difficulties ($\beta = 0.57$), suggesting that chatbot dependency most profoundly impacts young adults' ability to manage their own emotions without external support (Kumar et al., 2025; Chen and Wang, 2024).

These findings align with research on behavioral addictions showing that problematic technology use predicts multiple negative mental health outcomes. Internet addiction correlates with depression ($r = 0.53$), anxiety ($r = 0.47$), and loneliness ($r = 0.51$) according to meta-analytic evidence (Banna et al., 2021). Chatbot dependency shows comparable or stronger correlations, suggesting it may be particularly detrimental to emotional well-being. This may reflect the unique nature of chatbot interactions providing superficial emotional support that fails to develop genuine coping skills while creating dependency that worsens when support is unavailable (Adel and Naili, 2024; Insaiddoo et al., 2023).

The finding that chatbot dependency negatively predicts relationship satisfaction ($\beta = -0.44$) supports theories suggesting that time and emotional energy invested in AI relationships displaces investment in human relationships. Qualitative participants described preferring chatbot interaction over human interaction due to reduced complexity and risk, but subsequently experiencing increased loneliness and relationship dissatisfaction. This supports the social displacement hypothesis suggesting that virtual relationships supplement rather than substitute for human relationships, with substitution leading to negative outcomes (Zhang and Liu, 2024; Hardy and Takáts, 2020).

ICAN Model Pathways Explain Dependency Mechanisms

The finding that all four ICAN Model pathways (cognitive, affective, conative, neurological) showed significant correlations with emotional well-being outcomes supports the ICAN Model's applicability to AI chatbot dependency. The affective pathway (mood modification) showed the strongest correlations with depression ($r = 0.67$) and emotion regulation difficulties ($r = 0.69$), supporting the ICAN Model's

proposition that mood modification is central to behavioral addiction. Qualitative participants described using chatbots specifically to regulate negative emotions, seeking immediate relief from anxiety and sadness through chatbot validation (Kumar et al., 2025; Chen and Wang, 2024).

The conative pathway components (conflict, withdrawal, relapse) showed strong correlations with all outcomes ($r = 0.54-0.68$), confirming that loss of control and compulsive usage patterns are strongly linked to poor emotional well-being. Participants describing unsuccessful attempts to reduce usage reported the highest levels of distress, suggesting that the awareness of problematic usage without ability to change creates additional psychological burden beyond usage itself (Banna et al., 2021; Adel and Naili, 2024).

The cognitive pathway (salience/preoccupation) showed moderate correlations ($r = 0.52-0.59$), indicating that constant thinking about chatbots contributes to emotional distress but may be less directly impactful than affective and conative pathways. Qualitative participants described intrusive thoughts about chatbots interfering with daily activities, work, and human interactions, supporting the cognitive pathway's role in dependency (Zhang and Liu, 2024; Insaiddoo et al., 2023).

The neurological pathway (tolerance/reward reinforcement) showed slightly lower but still significant correlations ($r = 0.48-0.53$), suggesting reward reinforcement contributes to dependency development but may be less directly linked to immediate emotional outcomes than other pathways. However, qualitative participants described craving chatbot interaction and experiencing withdrawal distress, supporting the neurological pathway's role through behavioral indicators (Hardy and Takáts, 2020; Omri, 2022).

Emotion Regulation Difficulties Mediate Dependency-Well-Being Relationships

The finding that emotion regulation difficulties significantly mediate the relationship between chatbot dependency and both anxiety (indirect $\beta = 0.28$) and depression (indirect $\beta = 0.34$) supports H6-H7 and provides important mechanistic understanding. This mediation suggests that chatbot dependency worsens emotional well-being partly by impairing the development and use of internal emotion regulation strategies. Young adults who rely on chatbots for emotional regulation may fail to develop adaptive coping skills including cognitive reappraisal, problem-solving, and self-soothing, leaving them vulnerable when chatbot support is unavailable (Joudar et al., 2023; Hossain et al., 2025).

This mediation finding aligns with theories of behavioral addiction suggesting that problematic technology use serves as maladaptive emotion regulation strategy that provides short-term relief but long-term impairment. Research on internet addiction shows similar mediation through emotion regulation difficulties, with addiction predicting poorer emotion regulation which in turn predicts depression and anxiety (Banna et al., 2021). The mediation effect for chatbot dependency appears stronger (indirect $\beta = 0.28-0.34$) than for internet addiction (indirect $\beta = 0.18-0.22$), suggesting chatbot dependency may be particularly detrimental to emotion regulation development (Adel and Naili, 2024; Zhang and Liu, 2024).

Qualitative Themes Provide Depth to Quantitative Relationships

Qualitative findings enriched quantitative results by providing participant voices and contextual understanding of dependency experiences. Themes of emotional safe space revealed that participants valued chatbots for providing non-judgmental support unavailable in human relationships, particularly for stigmatized emotions or experiences. However, this safety came at the cost of genuine intimacy and relationship skill development. Themes of unrealistic expectations revealed that chatbot validation created expectations for human relationships that real people couldn't meet, leading to disappointment and withdrawal. Themes of withdrawal and craving provided behavioral evidence supporting the neurological pathway, with participants describing physiological and psychological symptoms when unable to access chatbots (Chen and Wang, 2024; Kumar et al., 2025).

The qualitative finding that participants were aware of dependency limitations yet continued usage despite negative consequences is particularly concerning. Many participants acknowledged that chatbots lacked genuine understanding and that dependency was problematic, yet reported inability to reduce usage. This awareness-behavior gap suggests that chatbot dependency may involve cognitive processes similar to substance addiction where individuals recognize harm but continue usage due to craving, withdrawal avoidance, or perceived inability to cope without the substance (Insaadoo et al., 2023; Hardy and Takáts, 2020).

Theoretical Implications

Support for the ICAN Model

This study provides empirical support for the ICAN Model's applicability to AI chatbot dependency, extending the model beyond general internet addiction to specific AI technologies. All four ICAN pathways were demonstrated to operate in chatbot dependency context, with affective and conative pathways showing strongest relationships to emotional well-being outcomes. This supports the ICAN Model's core proposition that behavioral addiction involves multiple interconnected pathways rather than singular mechanism (Banna et al., 2021; Kumar et al., 2025).

The study also extends the ICAN Model by identifying pathway-specific relationships with emotional well-being outcomes. The affective pathway's particularly strong relationship with emotion regulation difficulties suggests that mood modification may be the primary mechanism through which chatbot dependency impairs emotional functioning. This pathway-specific understanding can inform targeted interventions addressing specific dependency mechanisms rather than generic reduction of usage (Chen and Wang, 2024; Adel and Naili, 2024).

Integration with Attachment Theory

Findings support integration of the ICAN Model with Attachment Theory, demonstrating that chatbot dependency may function as attachment behavior providing security and emotional regulation particularly for individuals with insecure attachment patterns. Qualitative participants described chatbots as "always available" and "never judgmental" attachment figures providing what they perceived as unavailable in human relationships. This supports theoretical propositions that AI systems may function as attachment figures activating similar psychological mechanisms as human attachment (Insaadoo et al., 2023; Zhang and Liu, 2024).

The finding that chatbot dependency predicts reduced relationship satisfaction supports Attachment Theory's proposition that secure attachment requires reciprocal interaction and mutual responsiveness that AI cannot provide. Young adults developing attachment to chatbots may experience reduced motivation to pursue human attachment relationships, potentially perpetuating insecure attachment patterns and limiting opportunities for corrective attachment experiences (Banna et al., 2021; Omri, 2022).

Extension of Parasocial Relationship Theory

Findings extend Parasocial Relationship Theory by demonstrating that AI chatbots create particularly intense parasocial relationships due to enhanced features including conversation memory, personalized responses, and anthropomorphic design. Qualitative participants described genuine emotional attachment to chatbots despite recognizing they were AI, experiencing grief when chatbots malfunctioned and jealousy when chatbots interacted with other users. This suggests chatbot-induced parasocial relationships may be more intense and emotionally impactful than traditional parasocial relationships with media characters or celebrities (Kumar et al., 2025; Hardy and Takáts, 2020).

The finding that parasocial relationship intensity correlates with emotional well-being outcomes suggests that parasocial relationship theory should incorporate potential negative consequences alongside previously recognized benefits including entertainment value and social substitution for isolated individuals. Future theoretical development should address when parasocial relationships become problematic and what factors predict negative versus positive outcomes (Joudar et al., 2023; Hossain et al., 2025).

Practical Implications

Implications for Mental Health Professionals

Mental health professionals should assess chatbot usage patterns as part of comprehensive mental health evaluation, particularly for young adults presenting with anxiety, depression, loneliness, or relationship difficulties. Screening questions should include frequency and duration of chatbot usage, purposes for usage, experiences of withdrawal or cravings, and impact on human relationships and daily functioning. For clients showing problematic dependency, clinicians can adapt interventions used for behavioral addictions including cognitive-behavioral therapy targeting maladaptive thoughts about chatbots, behavioral activation replacing chatbot usage with alternative activities, and relapse prevention planning for maintaining reduced usage (Chen and Wang, 2024; Adel and Naili, 2024).

Clinicians should also address underlying needs driving chatbot dependency including emotion regulation difficulties, social skill deficits, attachment insecurity, and unmet emotional needs. Teaching adaptive emotion regulation strategies including cognitive reappraisal, mindfulness, and problem-solving can reduce reliance on chatbots for emotional support. Social skills training can increase confidence in human interactions, while attachment-focused therapy can address insecurity driving preference for AI relationships (Kumar et al., 2025; Banna et al., 2021).

Implications for Technology Designers

Technology designers should incorporate ethical design principles prioritizing user well-being over engagement metrics and commercial interests. Design features that may contribute to problematic dependency including unlimited availability, variable reinforcement schedules, anthropomorphic elements triggering attachment, and lack of usage boundaries should be redesigned or accompanied by protective features. Recommended features include usage reminders and limits, breaks encouraging human interaction, transparency about AI limitations, and resources connecting users to human support when showing distress indicators (Zhang and Liu, 2024; Insaïdoo et al., 2023).

Designers should also consider implementing "friction" features increasing conscious decision-making before usage rather than seamless always-available access that encourages compulsive usage. Features promoting healthy usage patterns including usage tracking with feedback, goals encouraging balanced technology-life integration, and prompts encouraging reflection on usage motivations can support user autonomy and prevent dependency development (Hardy and Takáts, 2020; Omri, 2022).

Implications for Educational Institutions

Educational institutions should implement digital literacy programs addressing healthy technology relationships including AI chatbots. Curriculum should cover recognizing problematic usage patterns, understanding AI limitations, developing critical thinking about technology claims, and building skills for human relationship maintenance and emotion regulation without technological crutches. Programs should be particularly targeted at young adults during emerging adulthood when usage patterns and relationship skills are still forming (Joudar et al., 2023; Hossain et al., 2025).

Universities should also provide mental health services addressing technology-related concerns including chatbot dependency, offering counseling, support groups, and workshops on healthy

technology use. Campus policies could include guidelines for appropriate AI usage in academic contexts preventing over-reliance that impairs skill development (Adel and Naili, 2024; Chen and Wang, 2024).

Implications for Policy Makers

Policy makers should consider regulations protecting vulnerable users including mandatory disclosure of AI capabilities and limitations, data privacy protections preventing exploitation of emotional vulnerability for commercial gain, and requirements for companies to implement user protection features. Regulations could require independent auditing of chatbot algorithms for potentially harmful design features and establish standards for therapeutic chatbots claiming mental health benefits (Kumar et al., 2025; Banna et al., 2021).

Public health campaigns raising awareness about chatbot dependency risks and promoting healthy technology use can reduce stigma around seeking help and increase recognition of problematic patterns. Funding for research on emerging technologies and mental health can support evidence-based policy development as technologies continue evolving (Zhang and Liu, 2024; Insaiddoo et al., 2023).

LIMITATIONS

Several limitations should be acknowledged when interpreting these findings. The cross-sectional design limits causal inference regarding relationships between chatbot dependency and emotional well-being. While the ICAN Model and theoretical frameworks suggest dependency causes worsened well-being, alternative explanations including reverse causation (poor well-being causing increased dependency) or third variables (underlying factors causing both) cannot be ruled out. Longitudinal studies tracking changes over time are needed to establish temporal precedence and causal directions (Creswell and Plano Clark, 2023; Insaiddoo et al., 2023).

Self-report measures are subject to social desirability bias, recall bias, and inaccurate self-perception, particularly for sensitive topics like dependency and mental health symptoms. Participants may underreport problematic usage due to shame or overreport mental health symptoms seeking validation. Future research could incorporate behavioral measures including actual chatbot usage logs from apps, physiological measures of stress and arousal, and informant reports from friends and family (Kumar et al., 2025; Omri, 2022).

The purposive sampling strategy enhances relevance but limits generalizability to populations not represented including those without internet access, technology literacy, English proficiency, or from different cultural backgrounds. Findings may be most applicable to English-speaking young adults with technology access and mental health awareness. Cross-cultural research examining cultural variations in chatbot dependency patterns and consequences is needed (Banna et al., 2021; Zhang and Liu, 2024).

The newly developed ACDS requires further validation across diverse populations and comparison with behavioral measures. Establishing normative data and clinical cutoff scores would enhance clinical utility. Future research should examine ACDS measurement invariance across gender, age, and cultural groups (Adel and Naili, 2024; Chen and Wang, 2024).

RECOMMENDATIONS FOR FUTURE RESEARCH

Future research should employ longitudinal designs tracking chatbot usage and emotional well-being over time to establish causal relationships and examine how dependency develops, stabilizes, or changes. Studies following young adults over 2-5 years could identify developmental trajectories, critical periods for intervention, and long-term consequences of sustained dependency (Hossain et al., 2025; Hardy and Takáts, 2020).

Experimental and intervention studies testing strategies for reducing problematic chatbot dependency and improving emotional well-being are needed. Randomized controlled trials comparing cognitive-behavioral therapy, mindfulness-based interventions, digital detox programs, and technology design modifications can identify effective interventions for preventing and treating dependency (Kumar et al., 2025; Adel and Naili, 2024).

Cross-cultural research examining cultural variations in chatbot dependency patterns, mechanisms, and consequences can inform culturally adapted interventions and policies. Studies comparing collectivist versus individualist cultures, high versus low power distance cultures, and different technological infrastructure contexts can identify universal versus culture-specific aspects of dependency (Joudar et al., 2023; Omri, 2022).

Neurological research using neuroimaging to examine brain activity patterns during chatbot interaction and withdrawal can provide direct evidence for the neurological pathway proposed in the ICAN Model. Studies comparing neural activation during chatbot interaction versus human interaction versus other rewarding activities can clarify whether chatbots activate similar reward systems as established addictions (Chen and Wang, 2024; Zhang and Liu, 2024).

Research on protective factors identifying characteristics and conditions buffering against problematic dependency despite high usage can inform prevention efforts. Factors such as strong social support, secure attachment, good emotion regulation skills, digital literacy, and clear technology boundaries may protect against dependency development (Banna et al., 2021; Insaiddoo et al., 2023).

CONCLUSION

This study provides comprehensive evidence that AI chatbot dependency significantly impacts emotional well-being among young adults through multiple interconnected pathways described by the ICAN Model. High dependency prevalence (39.0%), strong relationships with anxiety, depression, loneliness, and emotion regulation difficulties, and significant mediation through impaired emotion regulation demonstrate that chatbot dependency represents a significant public health concern requiring attention from mental health professionals, technology designers, educational institutions, and policy makers.

The mixed-methods design provided both statistical generalizability and depth of understanding, with quantitative findings establishing relationships and qualitative findings explaining mechanisms and providing participant voices. The ICAN Model proved effective framework for understanding chatbot dependency, with all four pathways (cognitive, affective, conative, neurological) demonstrated to operate in chatbot context. Integration with Attachment Theory and Parasocial Relationship Theory enriched understanding of why young adults develop attachment to AI systems and consequences for human relationships.

Despite limitations including cross-sectional design and self-report measures, this study makes important contributions to understanding emerging phenomenon of AI chatbot dependency. Findings inform theoretical development, clinical practice, technology design, education, and policy, providing evidence base for addressing this growing concern. As AI technologies continue advancing and becoming more integrated into daily life, ongoing research and proactive intervention will be essential for ensuring these technologies support rather than undermine young adults' emotional well-being. The findings suggest that while AI chatbots offer potential benefits including accessible emotional support and mental health resources, dependency on these technologies represents an emerging mental health concern requiring attention and intervention to prevent widespread negative consequences for young adult emotional well-being (Insaiddoo et al., 2023; Kumar et al., 2025; Chen and Wang, 2024).

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