From Psychological Need Satisfaction to AI Dependency: The Divergent Roles of Basic and AI-Specific Needs

Oronzo Parlangeli
DISPOC
University of Siena
Siena, Italy
oronzo.parlangeli@unisi.it

Francesco Currò
DISPOC
University of Siena
Siena, Italy
francesco.curro2@unisi.it

Margherita Bracci
DISPOC
University of Siena
Siena, Italy
margherita.bracci@unisi.it

Enrica Marchigiani
DISPOC
University of Siena
Siena, Italy
enrica.marchigiani@unisi.it

Lorenzo Reina
DI
University of Pisa
Pisa, Italy
HTLAB
Università Cattolica del Sacro Cuore
Milano, Italy
lorenzo.reina@phd.unipi.it

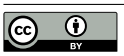
Paola Palmitesta
DISPOC
University of Siena
Siena, Italy
paola.palmitesta@unisi.it

Abstract

The rapid diffusion of Artificial Intelligence (AI) is transforming everyday practices, raising concerns about emerging forms of excessive use and technological dependency. The present study, based on an online questionnaire with 306 participants aged 18–30, examined how the satisfaction of psychological needs relates to AI dependency. Drawing on Self-Determination Theory (SDT), need satisfaction was assessed both in everyday life and in the context of AI use, alongside a measure of AI dependency. Relationships among variables were examined using Structural Equation Modelling (SEM). Results revealed a contrasting pattern: basic psychological need satisfaction was negatively associated with AI dependency, whereas AI-specific need satisfaction showed a strong positive association. These findings suggest that generative AI may function not only as a compensatory resource for unmet needs, but also as a primary context for need satisfaction, thereby reinforcing dependency-related patterns of use. Contrary to expectations, the association between basic and AI-specific needs was weak, indicating that the two constructs operate as partially independent processes. Overall, the findings highlight the importance of distinguishing between basic and context-specific need satisfaction in understanding the psychological mechanisms underlying AI dependency.

CCS Concepts

• **Human-centered computing** → *HCI theory, concepts and models*; • **Applied computing** → *Psychology*; • **Computing methodologies** → *Artificial intelligence*.



This work is licensed under a Creative Commons Attribution 4.0 International License.
ECCE 2026, Siena, Italy
© 2026 Copyright held by the owner/author(s).
ACM ISBN 979-8-4007-2515-9/26/09
https://doi.org/10.1145/3822301.3822323

Keywords

AI use, AI dependency, Basic Psychological Needs, Autonomy, Competence, Relatedness, Self-Determination Theory (SDT)

ACM Reference Format:
Oronzo Parlangeli, Francesco Currò, Margherita Bracci, Enrica Marchigiani, Lorenzo Reina, and Paola Palmitesta. 2026. From Psychological Need Satisfaction to AI Dependency: The Divergent Roles of Basic and AI-Specific Needs. In *European Conference on Cognitive Ergonomics (ECCE 2026), September 15–18, 2026, Siena, Italy*. ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3822301.3822323

1 Introduction

The increasing diffusion of Artificial Intelligence (AI) technologies has made access to information more immediate and has expanded opportunities for support in learning and content production, contributing to the transformation of how individuals learn, work, and interact with technology [14].

Young adults, adolescents, and younger users represent a substantial proportion of individuals engaging with AI applications across a range of contexts, including education, digital communication, and social media platforms [2, 27, 59]. According to the latest Eurostat report on the use of Artificial Intelligence [16], based on a population sample aged between 16 and 74 years, 63.8% of individuals aged 16–24 in Europe report using AI technologies, compared to 36.2% of the overall population. The use of generative AI for private purposes is also more prevalent among younger users (44.2%) than in the general population (25.1%).

Within this context, the increasing use of advanced digital systems may contribute to the development of intensive usage patterns which, in some cases, may evolve into problematic use or forms of technological dependency. Research on behavioral addictions related to digital technologies has shown that excessive use of digital tools can be associated with loss of control, interference with daily activities, and negative consequences for psychological well-being [35, 40].

In the specific case of AI systems, some authors have highlighted the risk of overreliance, defined as an excessive trust in automated systems and machine-generated outputs, which may impair users' critical evaluation and decision-making processes [45].

In light of these considerations, there is a growing interest within the scientific community in examining the psychological and behavioral implications of intensive AI use, particularly among younger users [30].

Against this background, the present study aims to explore factors that may facilitate or hinder the emergence of intensive AI use and to examine the psychological consequences associated with these patterns of interaction. More specifically, the study investigates whether the satisfaction of basic psychological needs—namely autonomy, competence, and relatedness—as well as needs related to AI use, may reduce the tendency to rely excessively on such technologies, thereby decreasing the likelihood of developing problematic or dependency-like usage patterns.

2 Related Work

2.1 Attitudes Toward Artificial Intelligence

A variety of cognitive, psychological, social, and contextual factors can influence attitudes toward artificial intelligence (AI) and, consequently, individuals' propensity to use such technologies [26]. In this regard, the Technology Acceptance Model (TAM) explains how positive attitudes are shaped by perceptions of usefulness and the ability of technology to enhance performance or simplify tasks [10, 65].

Digital competence also plays a key role: individuals with higher levels of digital skills and greater exposure to emerging technologies tend to display more favorable attitudes toward AI [66, 67]. Additionally, merely perceiving a system as AI can increase trust and reliance, even when its actual performance does not differ from non-AI technologies [34]. This suggests that expectations associated with AI may foster reliance and cognitive delegation processes [38]. Generational differences further contribute to these dynamics, with younger individuals generally more inclined to adopt new technologies [49].

Psychological and dispositional factors are also relevant. Trust in technological systems is a key determinant of adoption, as higher levels of trust are associated with greater willingness to rely on automated outputs [37]. However, recent studies have questioned both the conceptualization of trust and the methodologies used in AI research, highlighting the need for further investigation [57]. Personality traits, particularly those described by the Big Five model [22, 44, 56, 62], also influence attitudes. For example, agreeableness is associated with more positive attitudes toward AI, whereas conspiratorial beliefs are linked to more negative ones [46, 61]. Similarly, openness to experience is positively associated with attitudes toward AI [23].

Risk perception and concerns about potential negative consequences, such as loss of control, privacy issues, and the impact of automation on employment, may also lead to more cautious attitudes [14]. In addition, social and cultural factors, including norms, media representations, and institutional context, can significantly shape AI acceptance [4].

Overall, attitudes toward AI emerge from the interaction of multiple individual, technological, and contextual factors, making their understanding crucial for analyzing AI adoption and promoting responsible use.

2.2 Attitudes Toward AI and Self-Determination Theory

Self-Determination Theory (SDT) identifies three basic psychological needs that guide human motivation and behavior: autonomy, competence, and relatedness [53]. Autonomy refers to the perception of acting freely and making one's own decisions; competence concerns the sense of personal effectiveness in dealing with tasks; and relatedness reflects the need to feel connected to others and to develop meaningful relationships. Within SDT, these needs represent fundamental theoretical components and play a key role in distinguishing between intrinsic and extrinsic motivation [12, 53].

In recent years, SDT has been widely applied across domains such as education, health, work, and, more recently, digital technology use [6, 53, 64]. With regard to artificial intelligence, several studies have begun to examine how the satisfaction of basic psychological needs influences interaction with AI systems. Evidence suggests that need satisfaction is associated with higher engagement, more positive attitudes, and greater acceptance of AI [5, 11, 41]. Conversely, when these needs are frustrated, individuals tend to perceive AI more negatively and with greater concern, highlighting the importance of perceived competence and social connectedness in technology acceptance.

At the same time, digital technologies can both support and hinder the satisfaction of psychological needs. For instance, excessive use may reduce direct social interactions and foster isolation [43, 48]. Moreover, advanced automation may undermine individuals' sense of competence and autonomy, potentially impairing independent decision-making [55]. Despite growing interest in these dynamics, existing research has rarely examined how basic psychological needs operate as protective or risk factors in the development of AI dependency.

2.3 From Need Satisfaction to AI Dependency

Recent research has increasingly focused on the psychological and behavioral factors underlying problematic or excessive use of generative AI systems, leading to the development of validated measures of AI dependency [15, 21, 42]. For instance, Goh et al. [21] conceptualize AI dependency in terms of metacognitive evaluations, such as cognitive preoccupation and awareness of negative consequences, combined with perceptions of restlessness and social isolation.

Understanding user–AI interaction requires considering how these systems operate across multiple levels of experience, evolving from simple tools into cognitive and relational partners. One line of research highlights how AI systems are designed to promote continuous and cyclical interactions through personalized feedback loops [33]. These dynamics can generate reinforcement mechanisms, as AI outputs are often perceived as relevant and rewarding, thereby encouraging repeated use. Such processes resemble behavioral addiction patterns, where intermittent rewards strengthen behavioral persistence [32, 33].

Another key mechanism involves cognitive offloading [1]. Frequent interaction with AI may lead individuals to externalize cognitive functions such as problem solving, decision-making, and self-reflection [31, 36]. This process has been described as the emergence of an "algorithmic self," in which self-understanding becomes mediated by AI-generated interpretations [29, 63]. As a result, increasing reliance on AI may reduce personal agency and weaken self-regulation capacities [54].

From an SDT perspective, AI systems may provide immediate and seemingly effective ways to satisfy basic psychological needs. For example, rapid and personalized responses can enhance perceived competence, while conversational interactions may simulate forms of relatedness [54]. However, evidence suggests that perceived competence does not necessarily increase dependency risk. Although more competent users may engage more with AI systems, they also tend to adopt more efficient strategies, reducing overall interaction time [9, 34, 60]. Consequently, competence may buffer the relationship between perceived risk and dependent use [54][53]. Regarding relatedness, some studies suggest that interactions with AI may partially substitute direct social relationships, potentially reducing motivation or skills needed for authentic social engagement [17, 58].

Despite these theoretical insights, research linking SDT to problematic AI use remains limited. Most studies have focused on technological or behavioral aspects of AI adoption, while the role of psychological needs in the development of dependency has received less attention [14]. It is therefore important to investigate how the satisfaction or frustration of autonomy, competence, and relatedness shapes individuals' relationship with AI, potentially fostering either balanced use or problematic patterns.

3 The Study

Grounded in Self-Determination Theory (SDT), the present study examines how the satisfaction of basic psychological needs and their technology-specific counterparts relate to generative AI dependency. In line with research on behavioral addictions, unmet psychological needs may increase the likelihood of relying on external sources to compensate for psychological deficits [35, 40]. H1. Basic psychological needs are negatively associated with generative AI dependency. Previous research suggests that general need satisfaction tends to extend to context-specific experiences, including interactions with AI technologies [5, 11, 41]. H2. Basic psychological needs are positively associated with technology-specific psychological needs. However, evidence regarding problematic AI use remains mixed, as need satisfaction may either promote efficient use or increase engagement depending on contextual factors [9, 34, 60]. Accordingly, the direction of this relationship remains theoretically ambiguous. For this reason, H3 is formulated as a non-directional hypothesis. H3. Technology-specific psychological needs are associated with generative AI dependency. Building on these assumptions, it is plausible that AI-specific need satisfaction acts as an intervening mechanism through which general psychological needs influence dependency-related outcomes. H4. Technology-specific psychological needs mediate the relationship between basic psychological needs and generative AI dependency. The hypotheses of the present study are graphically represented in

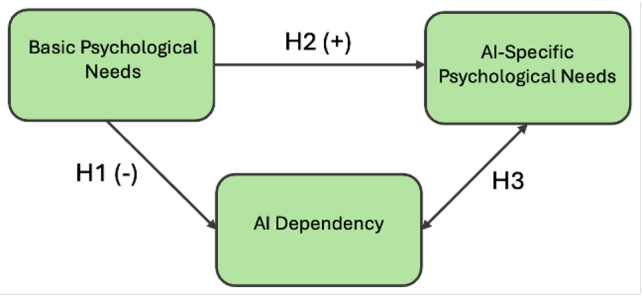


Figure 1: Hypothesized structural model. Basic psychological needs are expected to positively predict AI-specific psychological needs (H2) and negatively predict AI dependency (H1). AI-specific psychological needs are expected to be associated with AI dependency (H3). The indirect effect (H4) is represented by the path from basic psychological needs to AI dependency through AI-specific psychological needs.

Figure 1. In addition to the main analyses, a set of individual and usage-related variables were examined in preliminary analyses to explore their associations with generative AI dependency. Gender was included due to potential differences in technology use and psychological experiences reported in prior research [7]. Age was considered given that younger individuals tend to show higher levels of technology adoption and AI use [16, 49]. Finally, familiarity with AI and daily time spent using AI tools were included, as they have been associated with more intensive usage patterns [35, 66, 67].

4 Method

4.1 Sample characteristics

The sample comprises 306 participants, including 182 females (60%) and 120 males (39%); 4 participants chose not to disclose their gender ("other"; 1%). The participants range in age from 18 to 30 years (Mf= 22.6; SDf= 3.10; Mm=22.7; SDm= 2.99; Mo=20.5; SDo= 2.08). The participants are mainly students (N= 237; 77.4%), workers (N=35; 11.4%), working students (N=32; 10.5%), and not occupied or studying (N= 2; 0.7%). Among the participants, 185 have a high school diploma or lower (60.5%), 2 have a bachelor's degree (0.7%), 117 have a master's degree (38.2%), and 2 have a PhD or specialization (0.7%). Participants completed a voluntary, anonymous self-report questionnaire administered online between January and March 2026. A snowball sampling method was employed to recruit participants.

Upon accessing the questionnaire, which was implemented on the Google Forms platform, participants were provided with information about the aims of the study and were required to give their informed consent before proceeding. The completion time for the questionnaire was approximately 5–10 minutes.

The questionnaire was structured into three sections. Section 1 collected socio-demographic information, including gender, age, education, and occupation. Section 2 focused on participants' use of artificial intelligence applications, including familiarity with AI, time spent using such tools, types of applications used, and

purposes of use. Section 3 included three validated scales, which are described in detail in the following section.

The study was approved by the Ethical Research Committee of the University of Siena (CAREUS 8/2026/0052276).

4.2 Measures

The general satisfaction of psychological needs was assessed using the Italian version of the Satisfaction of Basic Psychological Needs Scale (SBPNS) [20]. The scale consists of 12 items measuring three dimensions: autonomy, competence, and relatedness, with four items per subscale. Responses are rated on a 5-point Likert scale ranging from 1 (not true at all) to 5 (very true). Examples of items are: “I feel free to decide for myself how to do my things” (autonomy); "I feel good at doing many things" (competence); "People are generally pretty friendly towards me" (relatedness). In the present study, the scale demonstrated good internal consistency for autonomy (α = 0.86), and acceptable internal consistency for competence (α = 0.75) and relatedness (α = 0.76).

To assess the satisfaction of psychological needs in relation to AI use, we employed the Basic Psychological Needs Scale for Technology Use (BPNS-TU) [41]. The scale comprises four subscales (autonomy, competence, relatedness to others, and relatedness to technology), each consisting of three items. Responses are provided on a 5-point Likert scale. Examples of items are: "When I use Artificial Intelligence, I feel like I am in control" (autonomy); "When I use Artificial Intelligence, I feel empowered in my own abilities" (competence); "When I use Artificial Intelligence, I feel less alone" (relatedness to others); “I have a friendly feeling with AI” (relatedness to technology). The Italian version of the scale was obtained using a back-translation procedure, involving independent translation into Italian followed by reverse translation into English by a native speaker. The scale demonstrated satisfactory internal consistency: good for autonomy (α = 0.87) and competence (α = 0.84); acceptable for relatedness to others (α = 0.71) and relatedness to technology (α = 0.73).

Dependency on generative AI was measured using the Generative Artificial Intelligence Dependency Scale (GAIDS) [21]. The scale includes 11 items across three subscales: cognitive preoccupation, negative consequences, and withdrawal. Items are rated on a 5-point Likert scale ranging from 1 (not at all) to 5 (very much). Examples of items for the three subscales are: “I feel an urge to use generative AI, even when it may not be necessary” (preoccupation, 3 items); “I have trouble completing work or other responsibilities without generative AI” (negative consequences. 4 items); “I get frustrated or irritable when I am unable to use generative AI” (withdrawal, 4 items). The Italian version of the scale was developed using a back-translation procedure. Internal consistency in the present study was good (α = 0.89), particularly for negative consequences (α = 0.81) and withdrawal (α = 0.91), and acceptable for cognitive preoccupation (α = 0.74).

4.3 Data analysis

Analyses were organized around the study hypotheses. Descriptive statistics characterized participants’ familiarity with, time spent on, and uses of AI tools. Because all scales departed from normality (Shapiro–Wilk test, $p < .001$), gender differences across the SBPNS, BPNS-TU, and GAID domains were examined with Wilcoxon rank-sum tests and rank-biserial effect sizes; these comparisons were exploratory. H1 was tested with a multiple linear regression predicting GAID scores from daily AI usage, age, and familiarity, applying heteroscedasticity-consistent (HC3) standard errors given non-normal, heteroscedastic residuals (Breusch–Pagan test, $p < .001$). H2 was addressed through Spearman rank-order correlations among the three scales. H3 and H4 were tested via structural equation modeling (SEM), following the two-step procedure of Anderson and Gerbing [3]: a confirmatory factor analysis (CFA) first established measurement-model adequacy, after which the structural paths were estimated. Because the indicators were ordinal Likert-type items, all models were estimated in lavaan [52] using the WLSMV estimator on the polychoric correlation matrix, and the scaled versions of all fit indices are reported. Model fit was evaluated against the criteria of Hu and Bentler [28]: CFI and TLI $\geq$ .95 ($\geq$ .90 acceptable), RMSEA $\leq$ .06 ($\leq$ .08 acceptable), and SRMR $\leq$ .08; the X^2 statistic is reported for completeness only, given its sensitivity to sample size. As the initial measurement model fit poorly, it was respecified by inspecting standardized loadings and modification indices, leading to removal of the BPNS-TU Autonomy subscale; this respecification was data-driven and the revised model is therefore partly exploratory. Convergent validity and reliability were assessed via average variance extracted (AVE > .50) and composite reliability (ω > .70). To address concerns about common method variance arising from the single-session, self-report design, a Harman single-factor test was conducted by constraining all indicators to load on a single common factor and comparing its fit with that of the hypothesized measurement model.

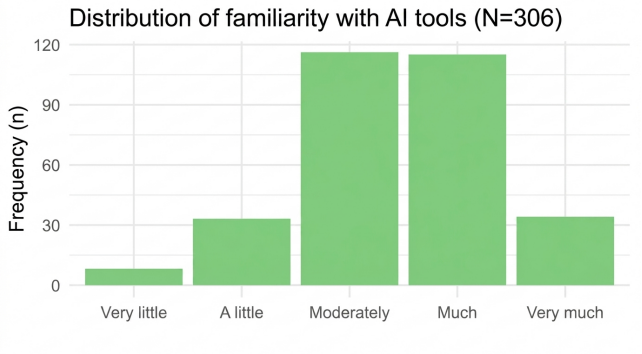


Figure 2: The distribution of familiarity with AI tools.

5 Results

5.1 Familiarity with AI tools, daily time spent on AI tools and AI’s main uses

Participants’ familiarity with AI tools and their daily usage patterns were examined. The majority reported moderate (37.9%), high (36.7%), or very high (11.1%) levels of familiarity (Figure 2).

Daily usage, however, was more evenly distributed, with 25.2% reporting low use, 28.4% relatively low use, and 31.7% moderate use (Figure 3).

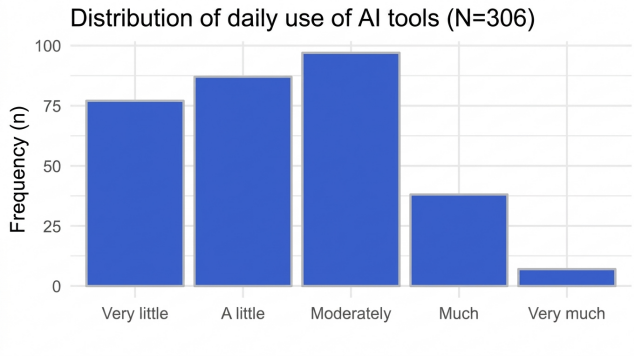


Figure 3: The distribution of daily time spent on AI tools.

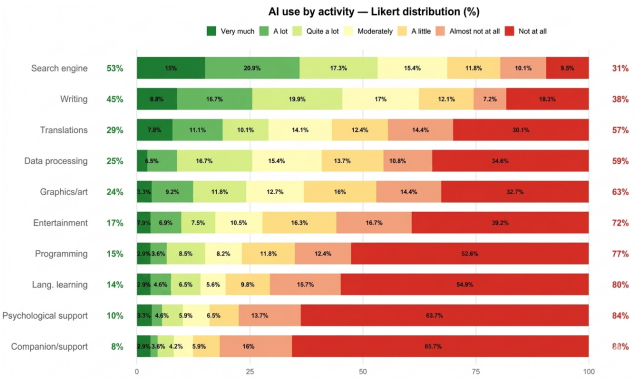


Figure 4: Distribution of self-reported generative AI use across activities (% of participants per response category). Bars display the full Likert distribution, from "Very much" to "Not at all". Green values on the left indicate the combined proportion of frequent users (the three highest categories), and red values on the right indicate the combined proportion reporting little or no use (the two lowest categories). Activities are ordered from most to least frequently used.

Participants reported using generative AI across a variety of activities, with marked differences in frequency by task (Figure 4). Productivity-oriented uses, particularly as a search engine substitute and for writing-related tasks, were the most widely adopted, followed by creative and learning tasks at intermediate levels. In contrast, relational and emotional uses (companion, emotional support, psychological coaching) were reported by very few participants, suggesting that generative AI remains largely confined to cognitive and instrumental purposes in this sample. This pattern is particularly relevant given the centrality of relatedness within the self-determination theory framework underlying this study.

5.2 Gender Differences

We analyzed data from the SBPNS, BPNS-TU, and GAID scales. For each domain, we calculated the mean, standard deviation, and scores for males and females, and reported the p-value from the Wilcoxon rank sum test. This nonparametric test was chosen because all scale distributions were non-normal (Shapiro-Wilk test, $p < 0.001$). Total scores were derived for the entire sample, excluding the four participants who did not report their gender in comparisons between females and males. Most gender differences were non-significant, with some notable exceptions. On the SBPNS, none of the three dimensions (Autonomy, Competence, Relatedness) showed significant differences between females and males, as indicated by similar mean values and high p-values (0.2–0.8). On the BPNS-TU scale, significant gender differences were found for Autonomy ($p = 0.001$) and Competence ($p = 0.002$), with males scoring higher (3.7±0.9 and 3.1±0.9) than females (3.3±1.1 and 2.8±1.0). Relatedness to Technology also differed significantly ($p=0.009$), again higher in males, whereas Relatedness to Others was not significant ($p=0.4$). On the GAID scale, only the Preoccupation dimension showed a significant difference ($p=0.011$), with males slightly higher (1.9±0.8 vs 1.7±0.8). Negative Consequences, Withdrawal, and the Total score did not reach significance. Overall, males scored significantly higher than females in Autonomy, Competence, Relatedness with Technology, and Preoccupation with AI, with small effect sizes (rank-biserial correlation 0.17–0.22). No gender differences were found in basic psychological needs in general contexts.

5.3 Generative Artificial Intelligence Dependency

To examine H1, a multiple linear regression was conducted with daily AI tool usage, age, and AI tool familiarity as predictors of GAID scores. Given evidence of non-normality of residuals (Shapiro-Wilk test, $p < .001$) and heteroscedasticity (Breusch-Pagan test, $p < .001$), heteroscedasticity-consistent standard errors (HC3) were applied [39]. The overall model was significant, $F(3, 302) = 22.86$, $p < .001$, $R^2 = .185$. As shown in Figure 3, all three predictors emerged as significant independent contributors, with daily time spent on AI tools as the strongest ($B = 0.19$, $p < .001$), followed by age ($B = -0.04$, $p = .002$) and familiarity with AI tools ($B = 0.09$, $p = .041$).

5.4 Relationships Between Basic Needs, Technology Needs, and AI Dependency

A correlation analysis revealed coherent patterns across the three scales. As expected, domains within the same scale were positively correlated, with BPNS dimensions showing moderate-to-strong associations (e.g., autonomy–competence, $\rho = .62$) and BPN-TU domains displaying weaker but consistent interrelations (e.g., autonomy–competence, $\rho = .48$). At the inter-scale level, basic psychological needs were only weakly associated with technology-specific needs (e.g., autonomy–autonomy-TU, $\rho = .39$; competence–competence-TU, $\rho = .31$), and no significant correlations emerged with AI-related forms of relatedness. This suggests that general need satisfaction only partially translates into need satisfaction in AI contexts. Technology-specific psychological needs were positively associated with all dimensions of AI dependency, with correlations ranging from weak to moderate (e.g., relatedness to others with cognitive preoccupation, $\rho = .44$; competence with negative consequences, $\rho = .28$). In contrast, basic psychological needs showed largely non-significant associations with AI dependency, with the exception of a small negative correlation between autonomy and negative consequences ($\rho = -.21$). Overall, these findings indicate that AI-specific need satisfaction is more closely linked to

dependency-related outcomes than general need satisfaction, while the association between the two need domains remains limited.

5.5 Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM)

To examine the hypotheses (H3-H4), a structural equation modelling (SEM) approach was employed to test the proposed relationships among basic psychological needs, technology-specific psychological needs, and dependency on generative AI within a self-determination theory framework [13]. Following the two-step procedure recommended by Anderson and Gerbing [3], a confirmatory factor analysis (CFA) was first performed to assess measurement model adequacy before estimating structural paths.

The initial CFA model, in which all subscales served as first-order indicators of their respective second-order latent constructs, demonstrated poor fit: X^2 (547) = 1711.619, p < .001; CFI = .879; TLI = .869; RMSEA = .084, 90% CI [.079, .088]; SRMR = .123. Prior CFAs conducted separately for each scale had already indicated that the BPNS-TU Autonomy subscale exhibited a weak loading on its intended factor (λ = .530). This pattern was corroborated in the full measurement model, where the same subscale showed a large modification index indicating cross-loading onto the general basic psychological needs factor (MI = 599.325, standardized EPC = .576), confirming insufficient discriminant validity between perceived autonomy in AI use and general autonomy satisfaction. Rather than reflecting a measurement failure, this overlap may indicate that autonomy in AI use is not experienced as a technology-specific need but as an extension of general autonomy satisfaction; a finding that aligns with SDT, which considers autonomy the most universal and domain-transcendent of the three basic needs [13]. Consequently, the BPN-TU Autonomy subscale was removed from the measurement model, and the CFA was re-estimated.

The revised measurement model demonstrated good fit: X^2 (452) = 893.453, p <.001; CFI = .949; TLI = .944; RMSEA =.057; SRMR = .085 (Figure 5). CFI, TLI, and RMSEA met recommended thresholds; although the SRMR was marginally above the .08 criterion, the overall pattern of fit indices consistently supported model adequacy [28]. All standardized factor loadings were statistically significant (p < .001). Convergent validity was supported by AVE values exceeding the .50 threshold for all factors (range = .501–.845) [19]. Composite reliability estimates (ω) were satisfactory across all factors (range = .759–.906). Structural paths were then estimated within this validated measurement framework, specified as the hypothesized mediation model (Figure 1), in which basic psychological needs (F1) could influence AI dependency (F3) both directly and indirectly through AI-specific psychological needs (F2). Basic needs positively predicted AI-specific needs (a = .20, p = .001) and negatively predicted dependency directly (c = −.34, p < .001), whereas AI-specific needs strongly and positively predicted dependency (b = .78, p < .001). The indirect effect of basic needs on dependency through AI-specific needs was positive and significant (a×b = .16, 95% CI [.06, .26], p = .002), opposite in sign to the direct effect, while the total effect remained negative (total = −.18, p = .010). This pattern reflects competitive (inconsistent) mediation, supporting H4: greater basic need satisfaction is directly associated with lower dependency, yet is also associated with slightly higher AI-specific need satisfaction,

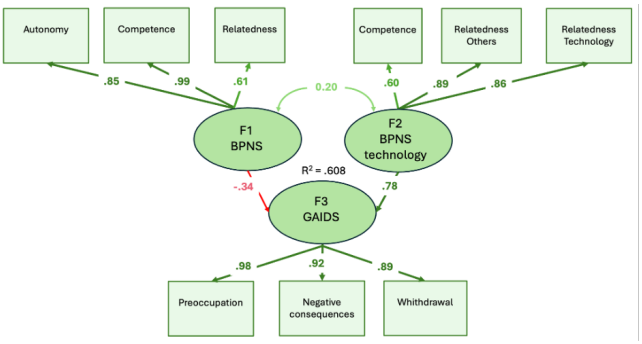


Figure 5: Final structural equation model linking basic psychological needs (BPNS = F1), technology-specific needs (BPNS-TU = F2), and Generative AI Dependency (GAIDS = F3).

Note. Rounded rectangles represent latent variables and rectangles represent observed indicators. Path coefficients are reported on the arrows. The path from F1 to F2 is the mediation path (a); AI dependency (F3) is predicted by basic psychological needs (F1, direct effect) and AI-specific psychological needs (F2). Negative paths are shown in red, positive paths in green. All structural paths were significant (p ≤ .001), and the indirect effect of F1 on F3 through F2 was positive and significant (a×b = .16, p = .002), opposite in sign to the direct effect, indicating competitive mediation. The model explains 60.8% of the variance in AI dependency (F3; R^2 = .608).

which in turn raises dependency, partially offsetting the protective direct effect. Together, F1 and F2 accounted for 60.8% of the variance in dependency (R^2 = .608). Because the BPNS-TU Autonomy subscale was removed from the measurement model, this indirect pathway reflects AI-specific competence and relatedness, but not AI-specific autonomy. As a check for common method variance, a single-factor model in which all items loaded on one common factor fit the data poorly (X^2(464) = 4378.83, p< .0001; CFI = .546; TLI = .514; RMSEA = .166; SRMR = .189), markedly worse than the hypothesized measurement model (CFI = .949, RMSEA = .057). This indicates that a single method factor cannot account for the observed structure, suggesting that common method variance is unlikely to be the primary driver of the results, although it cannot be ruled out entirely given the self-report design.

6 Discussion

The results presented here attempt to provide an overview of generative AI dependency by combining behavioral indicators with underlying motivational processes. Daily AI use emerged as the strongest predictor of dependency, consistent with dose–response patterns observed in behavioral addictions [25, 68]. The immediacy and personalization of AI outputs may function as a form of variable-ratio reinforcement, sustaining repeated engagement over time. Notably, dependency levels among moderate users were comparable to those of heavier users, suggesting that dependency-related processes may emerge at intermediate levels of engagement. Although this pattern requires replication, it highlights the potential for AI systems to foster habitual use even in the absence of intensive exposure.

Beyond usage frequency, familiarity with AI was also associated with dependency, indicating that increased confidence and ease of use may lower the threshold for repeated interaction. Age showed a negative association with dependency, with younger individuals reporting higher GAID scores irrespective of usage levels. This aligns with prior evidence on greater susceptibility to problematic technology use among younger populations [35], as well as with neurodevelopmental accounts emphasizing ongoing maturation of cognitive control systems [8]. No gender differences were observed in overall dependency, although males reported higher levels of cognitive preoccupation. This localized effect suggests that gender differences may operate at the level of specific dependency components rather than the global construct. Although very few participants reported using generative AI for explicitly relational or emotional purposes (Figure 3), AI-specific relatedness was among the strongest correlates of dependency. This is consistent with comparable student samples, where chatbot use is widespread but explicit help-seeking is rare [51]. The BPNS-TU relatedness items capture a felt sense of connection while using AI, feeling less alone, perceived reciprocity, a friendly disposition toward the system, rather than deliberate emotional use; such relatedness can thus emerge even during instrumental use and predict dependency without implying that users turn to AI for companionship. Social desirability and the predominantly student, academic sample may further reduce reports of explicit relational use.

Despite their significance, usage-related variables accounted for a limited proportion of variance in dependency ($R^2 = .185$), underscoring the need to consider deeper psychological mechanisms. Correlational evidence indicated that general need satisfaction only weakly translated into AI-related need satisfaction, and that relational experiences with AI were largely independent from broader social connectedness. At the same time, technology-specific psychological needs were consistently associated with all dimensions of AI dependency, whereas general needs showed minimal direct associations. This pattern points to a functional dissociation between offline and AI-mediated need satisfaction.

The structural model further clarified these dynamics. Consistent with H1, basic psychological need satisfaction was significantly and negatively associated with AI dependency, consistent with SDT-based accounts of compensatory technology use [12]. In contrast, and in line with H3, technology-specific psychological needs showed a strong positive association with dependency, indicating that perceiving AI as a primary source of competence and relatedness is strongly associated with greater dependency. Together, these predictors accounted for a substantial proportion of variance in the AI dependency latent factor ($R^2 = .608$). This estimate should, however, be interpreted with caution. Because it derives from a latent-variable model, in which structural coefficients are disattenuated for measurement error, it is expected to exceed the variance that would be explained using observed scores; and because all constructs were assessed through self-report in a single session, shared method variance may have further inflated the associations. The value should therefore be read as evidence that a need-based framework is informative for understanding AI dependency, rather than as a precise estimate of explanatory power generalizable beyond this sample.

Crucially, the two need systems exerted opposing influences on dependency. Consistent with H4, AI-specific need satisfaction significantly mediated the relationship between basic needs and dependency; however, this indirect path was positive whereas the direct path was negative, indicating competitive mediation. Basic need satisfaction is therefore directly protective against dependency, but to the extent that it spills over into AI-specific need satisfaction it marginally increases it. This divergence reinforces the view that need fulfilment in AI contexts operates as a partially independent motivational system rather than a simple extension of offline functioning: AI may act not only as a compensatory resource for unmet needs, but also as an autonomous context of need satisfaction capable of reinforcing continued use. These structural relationships are correlational. Given the cross-sectional design, the strong association between AI-specific need satisfaction and dependency is equally compatible with the reverse account, in which heavier or more dependent AI use cultivates perceptions of AI as a source of competence and connectedness rather than the other way around. The competitive mediation pattern should likewise be read as a structure of associations, not a causal sequence.

Additional implications arise from the measurement model. The exclusion of the BPNS-TU autonomy subscale due to cross-loading with general autonomy raises important conceptual and methodological questions. While this pattern may reflect the domain-transcendent nature of autonomy within SDT [12], it may also indicate limitations in operationalizing autonomy as a context-specific construct (cf. [47]). Future research should therefore further examine whether autonomy can be meaningfully distinguished across contexts, or whether it functions as a more global psychological resource.

Overall, the present findings suggest that AI dependency cannot be fully understood in terms of usage intensity alone, but requires consideration of how and where psychological needs are satisfied. The distinction between basic and AI-specific need satisfaction provides a novel lens for understanding human–AI interaction, pointing to the possibility that dependency emerges not only from unmet needs, but from the increasing capacity of AI systems to fulfill them.

7 Conclusion

These findings may have important implications for the design of generative AI systems. Digital technologies appear to provide a framework for psychological need satisfaction [50, 53], while design features aimed at maximizing engagement may reinforce persistent use patterns [18, 25]. In this sense, generative AI systems may not simply support task completion, but also shape users' motivational experiences by providing immediate and personalized feedback.

If AI increasingly serves as a source of competence and social connectedness, such mechanisms may inadvertently contribute to dependency-related outcomes. This is particularly relevant in light of the reinforcing nature of interactive systems, where repeated engagement can be sustained even in the absence of explicit user intentions. Designers should therefore balance engagement with features that support user autonomy and self-regulation, avoiding manipulative design practices [24].

More broadly, these findings suggest that the psychological architecture of AI systems should be considered alongside their functional capabilities, as design choices may directly influence not only how often users engage with these tools, but also the quality and regulation of such engagement.

8 Limitations

Some limitations of the present study should be acknowledged.

First, the design is cross-sectional, so the associations observed among basic need satisfaction, AI-specific need satisfaction, and AI dependency cannot be interpreted in causal or temporal terms. The reverse direction is equally consistent with the data: rather than AI-specific need satisfaction fostering dependency, more frequent or dependent AI use may itself cultivate perceptions of competence and connectedness with AI; conversely, dependency could erode the satisfaction of basic psychological needs rather than result from its absence. Longitudinal and experimental designs are needed to establish the direction of these effects.

Second, the study relied on a self-report questionnaire, which may be subject to common method bias, social desirability, and inaccuracies in participants' self-perceptions, particularly regarding their actual use of AI and dependency-related behaviors. Relatedly, the proportion of variance explained by the structural model (R^2 = .608) is likely an upper-bound estimate: latent-variable disattenuation and the single-session, self-report design both tend to inflate structural associations, and the value may be lower in samples assessed with multi-method or multi-wave designs.

Third, the sample was recruited using a snowball sampling method and consisted exclusively of young adults aged between 18 and 30 years. While this population is highly relevant given its frequent use of AI technologies, the findings may not be generalizable to more diverse populations.

A notable limitation concerns the exclusion of the BPN-TU Autonomy subscale, which was removed following evidence of insufficient discriminant validity with the general autonomy construct assessed by the BPNS. Although this decision was guided by systematic evaluation of the measurement model and is theoretically interpretable within SDT [13], it was not specified a priori. The revised structural model should therefore be considered exploratory.

Finally, although validated scales were employed, the Italian versions of some instruments were obtained through a back-translation procedure and may require further validation in different samples and contexts. The absence of independent psychometric validation, in conjunction with the current internal consistency estimates (α/ω = .71–.91), permits the use of these results as preliminary.

Acknowledgments

AI tools (Grammarly, 2026) were used exclusively for proofreading purposes, to enhance the clarity and fluency of the English discourse, while the authors take full responsibility for the scientific content and final wording.

References

[1] Al-Zahrani Abdulrahman M. 2024. Balancing Act: Exploring the Interplay Between Human Judgment and Artificial Intelligence in Problem-solving, Creativity, and Decision-making. *IgMin Research* 2, 3 (March 2024), 145–158. doi:10.61927/igmin158

[2] Duha Ali, Yasin Fatemi, Elahe Boskabadi, Mohsen Nikfar, Jude Ugwuoke, and Haneen Ali. 2024. ChatGPT in Teaching and Learning: A Systematic Review. *Education Sciences* 14, 6 (June 2024), 643. doi:10.3390/educsci14060643

[3] James C. Anderson and David W. Gerbing. 1988. Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin* 103, 3 (May 1988), 411–423. doi:10.1037/0033-2909.103.3.411

[4] Theo Araujo, Natali Helberger, Sanne Kruikemeier, and Claes H. De Vreese. 2020. In AI We Trust? Perceptions about Automated Decision-Making by Artificial Intelligence. *AI & SOCIETY* 35, 3 (Sept. 2020), 611–623. doi:10.1007/s00146-019-00931-w

[5] Jenna Bergdahl, Rita Latikka, Magdalena Celuch, Iina Savolainen, Eerik Soares Mantere, Nina Savela, and Atte Oksanen. 2023. Self-Determination and Attitudes toward Artificial Intelligence: Cross-national and Longitudinal Perspectives. *Telematics and Informatics* 82 (Aug. 2023), 102013. doi:10.1016/j.tele.2023.102013

[6] Christoph Buck, Eileen Doctor, Jasmin Hennrich, Jan Jöhnk, and Torsten Eymann. 2022. General Practitioners' Attitudes Toward Artificial Intelligence–Enabled Systems: Interview Study. *Journal of Medical Internet Research* 24, 1 (Jan. 2022), e28916. doi:10.2196/28916

[7] Zhihui Cai, Xitao Fan, and Jianxia Du. 2017. Gender and Attitudes toward Technology Use: A Meta-Analysis. *Computers & Education* 105 (Feb. 2017), 1–13. doi:10.1016/j.compedu.2016.11.003

[8] B.J. Casey, Sarah Getz, and Adriana Galvan. 2008. The Adolescent Brain. *Developmental Review* 28, 1 (March 2008), 62–77. doi:10.1016/j.dr.2007.08.003

[9] Shalini Chandra, Anuragini Shirish, and Shirish C. Srivastava. 2022. To Be or Not to Be . . . Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents. *Journal of Management Information Systems* 39, 4 (Oct. 2022), 969–1005. doi:10.1080/07421222.2022.2127441

[10] Fred D. Davis. 1989. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly* 13, 3 (Sept. 1989), 319–340. doi:10.2307/249008

[11] Triparna De Vreede, Mukhunth Raghavan, and Gert-Jan De Vreede. 2021. Design Foundations for AI Assisted Decision Making: A Self Determination Theory Approach. In *Hawaii International Conference on System Sciences*. hdl:10125/70630 doi:10.24251/HICSS.2021.019

[12] Edward L. Deci and Richard M. Ryan. 2000. The "What" and "Why" of Goal Pursuits: Human Needs and the Self-Determination of Behavior. *Psychological Inquiry* 11, 4 (Oct. 2000), 227–268. doi:10.1207/S15327965PLI1104_01

[13] Edward L Deci and Richard M Ryan. 2014. The importance of universal psychological needs for understanding motivation in the workplace. *The Oxford handbook of work engagement, motivation, and self-determination theory* 13 (2014), 13–32.

[14] Yogesh K. Dwivedi, Nir Kshetri, Laurie Hughes, Emma Louise Slade, Anand Jeyaraj, Arpan Kumar Kar, Abdullah M. Baabdullah, Alex Koohang, Vishnupriya Raghavan, Manju Ahuja, Hanaa Albanna, Mousa Ahmad Albashrawi, Adil S. Al-Busaidi, Janarthanan Balakrishnan, Yves Barlette, Sriparna Basu, Indranil Bose, Laurence Brooks, Dimitrios Buhalis, Lemuria Carter, Soumyadeb Chowdhury, Tom Crick, Scott W. Cunningham, Gareth H. Davies, Robert M. Davison, Rahul Dé, Denis Dennehy, Yanqing Duan, Rameshwar Dubey, Rohita Dwivedi, John S. Edwards, Carlos Flavián, Robin Gauld, Varun Grover, Mei-Chih Hu, Marijn Janssen, Paul Jones, Iris Junglas, Sangeeta Khorana, Sascha Kraus, Kai R. Larsen, Paul Latreille, Sven Laumer, F. Tegwen Malik, Abbas Mardani, Marcello Mariani, Sunil Mithas, Emmanuel Mogaji, Jeretta Horn Nord, Siobhan O'Connor, Fevzi Okumus, Margherita Pagani, Neeraj Pandey, Savvas Papagiannidis, Ilias O. Pappas, Nishith Pathak, Jan Pries-Heje, Ramakrishnan Raman, Nripendra P. Rana, Sven-Volker Rehm, Samuel Ribeiro-Navarrete, Alexander Richter, Frantz Rowe, Suprateek Sarker, Bernd Carsten Stahl, Manoj Kumar Tiwari, Wil Van Der Aalst, Viswanath Venkatesh, Giampaolo Viglia, Michael Wade, Paul Walton, Jochen Wirtz, and Ryan Wright. 2023. Opinion Paper: "So What If ChatGPT Wrote It?" Multidisciplinary Perspectives on Opportunities, Challenges and Implications of Generative Conversational AI for Research, Practice and Policy. *International Journal of Information Management* 71 (Aug. 2023), 102642. doi:10.1016/j.ijinfomgt.2023.102642

[15] Ahmed Abdelwahab Ibrahim El-Sayed, Samira Ahmed Alsenany, Maha Gamal Ramadan Asal, and Ibrahim Alasqah. 2025. Development and Validation of Artificial Intelligence Addiction Scale for Researchers: A Methodological Study. *Journal of Nursing Management* 2025, 1 (Jan. 2025), 8458533. doi:10.1155/jonm/8458533

[16] Eurostat. 2025. Individuals - Use of Generative AI Tools. doi:10.2908/ISOC_AI_IAIU

[17] Cathy Mengying Fang, Auren R. Liu, Valdemar Danry, Eunhae Lee, Samantha W. T. Chan, Pat Pataranutaporn, Pattie Maes, Jason Phang, Michael Lampe, Lama Ahmad, and Sandhini Agarwal. 2025. How AI and Human Behaviors Shape Psychosocial Effects of Extended Chatbot Use: A Longitudinal Randomized Controlled Study. arXiv:2503.17473 [cs.HC] doi:10.48550/arXiv.2503.17473

[18] Brian J Fogg. 2002. Persuasive technology: using computers to change what we think and do. *Ubiquity* 2002, December (2002), 2.

[19] Claes Fornell and David F. Larcker. 1981. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research* 18, 1 (Feb. 1981), 39. jstor:3151312 doi:10.2307/3151312

[20] Laura Girelli, Fabio Alivernini, Fabio Lucidi, Mauro Cozzolino, Giulia Savarese, Maurizio Sibilio, and Sergio Salvatore. 2018. Autonomy Supportive Contexts, Autonomous Motivation, and Self-Efficacy Predict Academic Adjustment of First-Year University Students. *Frontiers in Education* 3 (Nov. 2018), 95. doi:10.3389/feduc.2018.00095

[21] Adalia Y.H. Goh, Andree Hartanto, and Nadyanna M. Majeed. 2025. Generative Artificial Intelligence Dependency: Scale Development, Validation, and Its Motivational, Behavioral, and Psychological Correlates. *Computers in Human Behavior Reports* 20 (Dec. 2025), 100845. doi:10.1016/j.chbr.2025.100845

[22] Lewis R Goldberg. 1981. Language and individual differences: The search for universals in personality lexicons. *Review of personality and social psychology* 2, 1 (1981), 141–165.

[23] Simone Grassini, Sebastian Oltedal Thorp, Alexander Sævild Ree, Aleksandra Sevic, and Enrico Cipriani. 2025. Distinct Predictors of Positive Attitudes toward Artificial Intelligence and General Technology: Big Five Traits, Gender, and Age. *Behaviour & Information Technology* (Dec. 2025), 1–14. doi:10.1080/0144929X.2025.2598623

[24] Colin M. Gray, Yubo Kou, Bryan Battles, Joseph Hoggatt, and Austin L. Toombs. 2018. The Dark (Patterns) Side of UX Design. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*. ACM, Montreal QC Canada, 1–14. doi:10.1145/3173574.3174108

[25] Mark Griffiths. 2005. A 'Components' Model of Addiction within a Biopsychosocial Framework. *Journal of Substance Use* 10, 4 (Jan. 2005), 191–197. doi:10.1080/14659890500114359

[26] Stefano Guidi, Lorenzo Reina, Francesco Currò, Enrico Cipriani, Simone Grassini, and Oronzo Parlangeli. 2026. Ecce Histor_IA. The Role of Narratives, Usage Contexts, and Tasks in Influencing Attitudes towards Artificial Intelligence. *Behaviour & Information Technology* (Jan. 2026), 1–13. doi:10.1080/0144929X.2025.2606832

[27] Alexa Hasse, Sandra Clio Cortesi, Andres Lombana, and Urs Gasser. 2019. Youth and Artificial Intelligence: Where We Stand. *SSRN Electronic Journal* (2019). doi:10.2139/ssrn.3385718

[28] Li-tze Hu and Peter M. Bentler. 1999. Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria versus New Alternatives. *Structural Equation Modeling: A Multidisciplinary Journal* 6, 1 (Jan. 1999), 1–55. doi:10.1080/10705519909540118

[29] Jeena Joseph. 2025. The Algorithmic Self: How AI Is Reshaping Human Identity, Introspection, and Agency. *Frontiers in Psychology* 16 (July 2025), 1645795. doi:10.3389/fpsyg.2025.1645795

[30] Elif Karamuk. 2025. The Automation Trap: Unpacking the Consequences of Over-Reliance on AI in Education and Its Hidden Costs. In *Advances in Computational Intelligence and Robotics*, Manuel B. Garcia, Joanna Rosak-Szyrocka, and Aras Bozkurt (Eds.). IGI Global Scientific Publishing, 147–170. doi:10.4018/979-8-3373-0122-8.ch007

[31] Fatma Gizem Karaoglan Yilmaz, Ramazan Yilmaz, Ahmet Berk Ustun, and Hatice Uzun. 2025. Exploring the Role of Cognitive Flexibility, Digital Competencies, and Self-Regulation Skills on Students' Generative Artificial Intelligence Anxiety. *Computers in Human Behavior: Artificial Humans* 5 (Aug. 2025), 100187. doi:10.1016/j.chbah.2025.100187

[32] Ahmed T. Kbaiah and Abdulqadir J. Nashwan. 2024. Beyond the Image: Artificial Intelligence's Role in Refining and Transforming Radiology Nursing. *Avicenna* 2024, 1 (March 2024). doi:10.5339/avi.2024.3

[33] Chokri Kooli, Youssef Kooli, and Eya Kooli. 2025. Generative Artificial Intelligence Addiction Syndrome: A New Behavioral Disorder? *Asian Journal of Psychiatry* 107 (May 2025), 104476. doi:10.1016/j.ajp.2025.104476

[34] Thomas Kosch, Robin Welsch, Lewis Chuang, and Albrecht Schmidt. 2022. The Placebo Effect of Artificial Intelligence in Human–Computer Interaction. *ACM Transactions on Computer-Human Interaction* 29, 6 (Dec. 2022), 1–32. doi:10.1145/3529225

[35] Daria Kuss and Mark Griffiths. 2017. Social Networking Sites and Addiction: Ten Lessons Learned. *International Journal of Environmental Research and Public Health* 14, 3 (March 2017), 311. doi:10.3390/ijerph14030311

[36] Mohamed Lahby. 2024. *Empowering Digital Education with ChatGPT: From Theoretical to Practical Applications*. CRC Press.

[37] J. D. Lee and K. A. See. 2004. Trust in Automation: Designing for Appropriate Reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society* 46, 1 (Jan. 2004), 50–80. doi:10.1518/hfes.46.1.50_30392

[38] Jiaxuan Li, Mingxing Han, and Qinjian Yuan. 2026. The Surprising Paradox of AI Literacy: How Lower AI Literacy Can Lead to Higher Acceptance. *International Journal of Human–Computer Interaction* (Jan. 2026), 1–21. doi:10.1080/10447318.2025.2609912

[39] J Scott Long and Laurie H Ervin. 2000. Using heteroscedasticity consistent standard errors in the linear regression model. *The American Statistician* 54, 3 (2000), 217–224.

[40] Christian Montag and Peter Walla. 2016. Carpe Diem Instead of Losing Your Social Mind: Beyond Digital Addiction and Why We All Suffer from Digital Overuse. *Cogent Psychology* 3, 1 (Dec. 2016), 1157281. doi:10.1080/23311908.2016.1157281

[41] Laura Moradbakhti, Simon Schreibelmayr, and Martina Mara. 2022. Do Men Have No Need for "Feminist" Artificial Intelligence? Agentic and Gendered Voice Assistants in the Light of Basic Psychological Needs. *Frontiers in Psychology* 13 (June 2022), 855091. doi:10.3389/fpsyg.2022.855091

[42] Wilter C. Morales-García, Liset Z. Sairitupa-Sanchez, Sandra B. Morales-García, and Mardel Morales-García. 2024. Development and Validation of a Scale for Dependence on Artificial Intelligence in University Students. *Frontiers in Education* 9 (March 2024), 1323898. doi:10.3389/feduc.2024.1323898

[43] Niaz Makhdum Muhammad, Mitch Schneider, Allison Hill, and Douglas M Yau. 2019. How the use of iPad and smartphones creates social isolation. In *Society for Information Technology & teacher education international conference*. Association for the Advancement of Computing in Education (AACE), 1060–1065.

[44] Jiyoung Park and Sang Eun Woo. 2022. Who Likes Artificial Intelligence? Personality Predictors of Attitudes toward Artificial Intelligence. *The Journal of Psychology* 156, 1 (Jan. 2022), 68–94. doi:10.1080/00223980.2021.2012109

[45] Samir Passi and Mihaela Vorvoreanu. 2022. Overreliance on AI literature review. *Microsoft Research* 339 (2022), 340.

[46] Delroy L Paulhus and Kevin M Williams. 2002. The Dark Triad of Personality: Narcissism, Machiavellianism, and Psychopathy. *Journal of Research in Personality* 36, 6 (Dec. 2002), 556–563. doi:10.1016/S0092-6566(02)00505-6

[47] Jason W. Payne and Ulrich Schimmack. 2025. Need Satisfaction and Frustration Are Not Distinct in the Basic Psychological Need Satisfaction and Frustration Scales. *Psychological Assessment* 37, 8 (Aug. 2025), 371–382. doi:10.1037/pas0001395

[48] Dorian Peters, Rafael A. Calvo, and Richard M. Ryan. 2018. Designing for Motivation, Engagement and Wellbeing in Digital Experience. *Frontiers in Psychology* 9 (May 2018), 797. doi:10.3389/fpsyg.2018.00797

[49] Marc Prensky. 2001. Digital Natives, Digital Immigrants Part 1. *On the Horizon* 9, 5 (Sept. 2001), 1–6. doi:10.1108/10748120110424816

[50] Andrew K. Przybylski, C. Scott Rigby, and Richard M. Ryan. 2010. A Motivational Model of Video Game Engagement. *Review of General Psychology* 14, 2 (June 2010), 154–166. doi:10.1037/a0019440

[51] Gavin N. Rackoff, Zhenyu Z. Zhang, and Michelle G. Newman. 2025. Chatbot-Delivered Mental Health Support: Attitudes and Utilization in a Sample of U.S. College Students. *DIGITAL HEALTH* 11 (Jan. 2025), 20552076241313401. doi:10.1177/20552076241313401

[52] Yves Rosseel. 2012. Lavaan: An *R* Package for Structural Equation Modeling. *Journal of Statistical Software* 48, 2 (2012). doi:10.18637/jss.v048.i02

[53] Richard M. Ryan and Edward L. Deci. 2018. *Self-Determination Theory: Basic Psychological Needs in Motivation, Development, and Wellness* (paperback edition ed.). The Guilford Press, New York London.

[54] Mohammed Salah, Fadi Abdelfattah, Hussam Alhalbusi, and Muna Al Mukhaini. 2024. Me and My AI Bot: Exploring the 'AIholic' Phenomenon and University Students' Dependency on Generative AI Chatbots - Is This the New Academic Addiction? doi:10.21203/rs.3.rs-3508563/v2

[55] Nathan E Sanders and Bruce Schneier. 2023. How ChatGPT hijacks democracy. *The New York Times* 15 (2023), 2023.

[56] Astrid Schepman and Paul Rodway. 2023. The General Attitudes towards Artificial Intelligence Scale (GAAIS): Confirmatory Validation and Associations with Personality, Corporate Distrust, and General Trust. *International Journal of Human–Computer Interaction* 39, 13 (Aug. 2023), 2724–2741. doi:10.1080/10447318.2022.2085400

[57] Tim Schrills, Thomas Franke, Steffen Hoesterey, and Eileen Roesler. 2026. Questioning Trust in AI Research: Exploring the Influence of Trust Assessment on Dependence in AI-assisted Decision-Making. *Behaviour & Information Technology* 45, 8 (May 2026), 1644–1660. doi:10.1080/0144929X.2025.2553153

[58] Steven Siddals, John Torous, and Astrid Coxon. 2024. "It Happened to Be the Perfect Thing": Experiences of Generative AI Chatbots for Mental Health. *npj Mental Health Research* 3, 1 (Oct. 2024), 48. doi:10.1038/s44184-024-00097-4

[59] Olivia Sidoti, Eugenie Park, and Jeffrey Gottfried. 2025. About a quarter of U.S. teens have used ChatGPT for schoolwork – double the share in 2023. Pew Research Center. (2025). https://www.pewresearch.org/short-reads/2025/01/15/about-a-quarter-of-us-teens-have-used-chatgpt-for-schoolwork-double-the-share-in-2023/

[60] Mengmeng Song, Xinyu Xing, Yucong Duan, Jason Cohen, and Jian Mou. 2022. Will Artificial Intelligence Replace Human Customer Service? The Impact of Communication Quality and Privacy Risks on Adoption Intention. *Journal of Retailing and Consumer Services* 66 (May 2022), 102900. doi:10.1016/j.jretconser.2021.102900

[61] Jan-Philipp Stein, Tanja Messingschlager, Timo Gnambs, Fabian Hutmacher, and Markus Appel. 2024. Attitudes towards AI: Measurement and Associations with Personality. *Scientific Reports* 14, 1 (Feb. 2024), 2909. doi:10.1038/s41598-024-53335-2

[62] Ernest C. Tupes and Raymond E. Christal. 1992. Recurrent Personality Factors Based on Trait Ratings. *Journal of Personality* 60, 2 (June 1992), 225–251. doi:10.1111/j.1467-6494.1992.tb00973.x

[63] Grace Leonora Turtle, Roy Bendor, Elisa Giaccardi, and Blazej Kotowski. 2024. Queering AI: Undoing the Self in the Algorithmic Borderlands. doi:10.48550/ARXIV.2410.03713

[64] Anja Van Den Broeck, D. Lance Ferris, Chu-Hsiang Chang, and Christopher C. Rosen. 2016. A Review of Self-Determination Theory's Basic Psychological Needs at Work. *Journal of Management* 42, 5 (July 2016), 1195–1229. doi:10.1177/0149206316632058

[65] Viswanath Venkatesh and Fred D. Davis. 2000. A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science* 46, 2 (Feb. 2000), 186–204. doi:10.1287/mnsc.46.2.186.11926

[66] Viswanath Venkatesh, Michael G. Morris, Gordon B. Davis, and Fred D. Davis. 2003. User Acceptance of Information Technology: Toward A Unified View1. *MIS Quarterly* 27, 3 (Sept. 2003), 425–478. doi:10.2307/30036540

[67] Bingcheng Wang, Pei-Luen Patrick Rau, and Tianyi Yuan. 2023. Measuring User Competence in Using Artificial Intelligence: Validity and Reliability of Artificial Intelligence Literacy Scale. *Behaviour & Information Technology* 42, 9 (July 2023), 1324–1337. doi:10.1080/0144929X.2022.2072768

[68] Kimberly S. Young. 1998. Internet Addiction: The Emergence of a New Clinical Disorder. *CyberPsychology & Behavior* 1, 3 (Jan. 1998), 237–244. doi:10.1089/cpb.1998.1.237