An Empirical Investigation on Psychosocial Determinants of AI Dependence

Aviral Srivastava, Dr. Aishvarya Upadhyay

DAV PG College (BHU)

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ABSTRACT

Aim To examine how gender, self-efficacy, attachment styles, and social influence AI dependence among college students.

Background Artificial Intelligence (AI) has become increasingly important in daily life, and researchers have identified psychological factors as significant determinants of AI dependence.

Methods A total of 154 college students aged between 18 and 28 were selected. Data was collected through a questionnaire, and participants' AI Usage, Self-Efficacy, Attachment style, and Dependency were assessed through scales based on the Technology Acceptance Model (extended TAM), New General Self-Efficacy Scale (NGSES), Experience in Close Relationship Revised Scale (ECR-R), and Scale for Dependence on Artificial Intelligence (DIA). AI-Self Efficacy was measured through the AI-Self Efficacy Scale (AISES).

Results

An independent samples t-test revealed that males ($M = 14.06$, $SD = 3.77$, $n = 88$) had significantly higher AI dependence than females ($M = 12.33$, $SD = 4.36$, $n = 46$) ($t = 2.28$, $p < .05$), with no significant difference between general or AI self-efficacy and gender. A moderate positive correlation was observed between DAI and AISES subscales. DAI showed significant positive correlations with AISE-AS.

Conclusion

Males showed higher AI-dependency, while attachment styles were not significantly related. Human-like interaction and perceived trust in AI predicted AI Dependence.

Keywords: Artificial Intelligence (AI), Psychological factor, Gender differences, College Students, AI-dependency

INTRODUCTION

The rapid advancement in technology has led to an increase in the usage of AI in various facets of life, including education (Yilmaz & Karaoğlan Yilmaz, 2023*)*.AI has given significant competitive advantages to those who have knowledge about its utilization and could be used to create new innovative products and services (Makridakis, 2017*)*. It has been found that factors such as personal ability, social influence, perceived usefulness, trust, and various other factors play an important role in the acceptance of AI tools. (Dahri and Yahaya,2024). As AI continues to evolve, it is important to examine its psychosocial influence on its adoption and AI dependence among users.

Self-efficacy is an important factor in this human-technology interaction, defined as an individual's belief in their capacity to execute particular behaviour to meet specific goals (Bandura, 1977, 1986, 1997). This belief significantly impacts an individual's approach to the goal, measurement, and sources of self-efficacy have been extensively studied (Heslin & Klehe, 2008), and standardized instruments such as the New General Self-Efficacy Scale (NGSES) (Chen & Gully, 2001) were developed.

It was found that in previous studies, familiarity and skill in using computer programs contribute to the development of general computer self-efficacy (Iverson, Brooks, Ashton, Johnson, & Gualtieri, 2009). The emergence of AI, a new Self efficacy has also emerged: AI self-efficacy, which refers to an individual's confidence in their ability to effectively interact and utilize AI systems. The development of the validation of scale AISES (Wang and Chuang,2023) is important for assessing AI efficacy. The AI-Self efficacy is dependent on AI attitude, interest, and anthropic factors of AI and even on social influence (Hong,2021).

Beyond Self-efficacy, other psychological dimensions like Attachment style also cause an impact on AI (Wu et al., 2025). Attachment style, which has been studied in interpersonal relations, is also important in the study of human-AI interaction: for example, Gillath et al. (2020) found that individuals with anxious attachment report *lower* trust in AI, while attachment security can increase trust (Gillath, Ai, Branicky, Keshmiri, Davison, & Spaulding, 2020). These styles may influence how individuals bond, trust, and become dependent on AI tools. Attachment styles were assessed using the Experiences in Close Relationships – Revised (ECR-R) (Fraley, Waller, and Brennan, 2000).

The extended TAM construct provides an efficient framework for predicting user acceptance of new technologies, emphasizing the significance of factors like perceived usefulness and perceived ease of use (Baitekov, 2023). TAM bridges the users' psychological intentions with their practical evaluations of a technology's usefulness and ease of use, while remaining adaptable to different contexts. Social influence is an important factor in technology adoption. (Dahri and Yahaya,2024).

Dependence on AI refers to the over-reliance on an AI system for performing tasks. Dependence on AI becomes problematic when users start to prefer AI for everyday tasks, which leads to reduced autonomy and self-confidence. (Zhang and Zhao, 2024) It may also result in a decline in critical thinking and creativity. (Gerlich, 2025) The scale for dependence on artificial intelligence (DIA) is important to assess AI dependence. (Morales-García & Sairitupa-Sanchez, 2024)

With the increasing integration of AI in the academic and personal lives of students, understanding the impact of various psychosocial factors on AI dependence is important. While existing literature talks about the aspects, such as AI's impact on self-control, self-esteem, and problem-solving, a significant research gap persists in a comprehensive study of psychosocial factors- like gender and self-efficacy. Both general and AI attachment styles and social influence in Indian College students. This study is crucial for the overall understanding of human-AI interaction, and it also helps in effective, evidence-based strategies to promote healthy technology and to reduce potential negative outcomes. Therefore, this study examines the psychosocial determinants to fill the research gap, providing valuable insights into human AI interaction.

Methods:

Research Design and Procedure:

In this study, a cross-sectional quantitative research design was employed. The research was conducted on university students with the help of a self-reported questionnaire. The study employed an offline method of data collection through a hard copy of the self-reported questionnaire administered to the participants.

The participants from various disciplines are considered for the study, mainly undergraduate and postgraduate students. Participants were informed about the study's purpose, and they were assured of the confidentiality of their identity and data. Participants were given a questionnaire, and the process of filling out the questionnaire took 12 to 15 minutes. The questionnaire was filled in a single sitting.

Participation was entirely voluntary, and students retained the right to decline or withdraw from the study at any point without any consequences.

Participants:

The total number of participants for the study was 154; the data of 20 participants were removed due to incomplete self-reported questionnaires. The age range was 18 to 28, with the mean age of 21.40. And there are 46 female participants, who comprise 34% of the total sample, representing the structure of females in the study.

Instruments: In the present study, standardized and validated self-report measures are employed to measure psychological variables like self-efficacy, AI acceptance, dependency on AI, and attachment patterns. The following tools were used:

1. New General Self-Efficacy Scale (NGSES) General Self-efficacy was measured with the help of the New General Self-Efficacy Scale. The scale has 8 items that assess individual competence in various situations. The items were scored on a 5-point Likert scale ranging from 1(strongly disagree) to 5(strongly agree), with higher ratings indicating greater self-efficacy. (Chen & Gully, 2001)
2. AI Self-Efficacy Scale (AISES) AI self-efficacy was measured using the AISES, which measures individuals' confidence in collaborating with and applying AI tools. This scale has four sub-scales which are- Assistance (AISE-AS), Anthropomorphic interaction (AISE-AI), Comfort with AI(AISE-CF), and Technological Skills (AISE-TS). The items were scored on a 5-point Likert scale ranging from 1(strongly disagree) to 5(strongly agree), and the higher the score, the greater the levels of AI-related self-efficacy. (Wang and Chuang,2023)
3. Dependence on AI Scale The dependency on artificial intelligence was measured using the AISES scale, which measures the extent to which individuals rely on AI for their work and decision-making. The items were scored on a 5-point Likert scale ranging from 1(strongly disagree) to 5(strongly agree), with higher scores indicating greater dependency. (Morales-García & Sairitupa-Sanchez, 2024)
4. Technology Acceptance Model (extended TAM) for AI Acceptance of AI was developed from an extended version of the Technology Acceptance Model (extended TAM) (Lin et al., 2023), which was adapted for the measurement of ChatGPT acceptance in educational environments. It has subscales for the measurement of Personal Competence (extended TAM-PC), Social Influence (extended TAM-SI), Perceived AI Trust (extended TAM-PAI), Perceived Usefulness of AI (extended TAM-AIU), Perceived AI Enjoyment (extended TAM-AIE), Perceived Usefulness (extended TAM-PAII), Attitude towards ChatGPT (extended TAM-Ach), Metacognitive Self-Regulated Learning (extended TAM-SRL) (Dahri and Yahaya,2004).
5. Experiences in Close Relationships-Revised (ECR-R) Attachment styles were measured using the ECR-R scale, a scale that measures two dimensions: attachment anxiety and attachment avoidance. The 36 items are scored on a 7-point Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). (Fraley, Waller, and Brennan, 2000)

All the measures used in this study have had good psychometric properties in earlier studies. Adequate levels of reliability and validity, for example, internal consistency as evidenced by Cronbach's alpha, were established by their initial developers. These proved properties confirm the appropriateness of the measures for use in the current study.

Data Analysis

The collected data were analyzed with the help of Statistical Package for the Social Sciences (SPSS) v. 31. Firstly, the data were screened for missing values and outliers. Questionnaires with incomplete responses were also excluded from the final analysis.

Descriptive analysis, such as means, standard deviation, and frequency, was calculated to summarize participant demographics and the central tendencies of variables, including AI dependence, general self-efficacy, AI self-efficacy, attachment styles, and various extended TAM constructs.

Inferential statistical analyses were conducted to address the research objectives:

- Gender differences in dependence on AI, general self-efficacy, and AI self-efficacy were assessed using an independent samples t-test.

- To examine the relation between dependence on artificial intelligence and several psychosocial factors, such as extended TAM constructs, attachment styles, and self-efficacy assessments, Pearson's correlation coefficient was calculated.
- Multiple linear regression analysis was performed to determine the extent to which general self-efficacy, AI self-efficacy, attachment styles, and extended TAM constructs predicted dependence on AI.

RESULTS

The final sample consisted of 134 college students aged between 18 and 28 years (M = 21.40, SD = 2.63), with 89 males (65.93%) and 46 females (34.07%). Descriptive statistics for variables and their subscales: General Self-Efficacy (NGSES), AI Self-Efficacy (AISES), Dependence on AI (DAI), Attachment Styles (ECR-R), and the extended TAM construct are performed.

An independent samples t-test was conducted to determine the impact of gender differences in dependence on AI (Table.1). The results indicated that males (M = 14.06, SD = 3.77, n = 88) had a significantly higher mean score on the Dependence on Artificial Intelligence (DAI) scale compared to females (M = 12.33, SD = 4.36, n = 46).

The difference in means was statistically significant (*t* =2.28, *p* < .05), with a mean difference of 1.73 (95% CI [0.22, 3.24]).

Table.1 Independent Samples t-test

Group	n	Mean (M)	SD	Mean Diff.	t (df)	p-value	95% CI	Cohen's d	Significance
Males	88	14.06	3.77						
Females	46	12.33	4.36	1.73	t(80.79) = 2.28	.025	[0.22, 3.24]	0.435	p < .05

The Pearson correlation analysis among the various constructs, encompassing general self-efficacy, AI-specific self-efficacy dimensions, dependence on AI, components of the Technology Acceptance Model (extended TAM), and attachment styles, yielded several salient relationships within our sample of 134 participants. A comprehensive statistical overview of these correlations is presented in Tables 2.1 and 3.1

General Self-Efficacy (NGSES) and Other Variables:

General self-efficacy (NGSES) demonstrated no statistically significant correlations with any of the AI-specific self-efficacy dimensions (AISE-AS, AISE-AI, AISE-CF, AISE-TS), nor with dependence on AI (DAI). Furthermore, NGSES did not exhibit significant associations with any of the AI-Technology Acceptance Model (extended TAM) constructs. Across all these pairings, the observed correlations did not meet the thresholds for statistical significance at either the p<0.001 or p<0.005 levels.

AI Self-Efficacy and Other Variables:

Table 2.1 Significant Positive Correlations between AI Self-Efficacy and extended TAM Constructs (N=134)

AI Self-Efficacy Dimension	extended TAM Construct	r-value	p-value
AISE-AS	extended TAM-PC	0.374	<0.001
AISE-AS	extended TAM-SI	0.393	<0.001
AISE-AS	extended TAM-PAI	0.393	<0.001
AISE-AS	extended TAM-AIU	0.393	<0.001

AISE-AS	extended TAM-AIE	0.353	<0.001
AISE-AS	extended TAM-PAII	0.310	<0.001
AISE-AS	extended TAM-Ach	0.284	<0.001
AISE-AS	extended TAM-SRL	0.294	<0.001
AISE-AS	extended TAM-IC	0.284	<0.001
AISE-AI	extended TAM-PC	0.296	<0.001
AISE-AI	extended TAM-SI	0.279	<0.001
AISE-AI	extended TAM-PAI	0.308	<0.001
AISE-AI	extended TAM-AIU	0.415	<0.001
AISE-AI	extended TAM-PAII	0.253	<0.005
AISE-AI	extended TAM-Ach	0.293	<0.001
AISE-CF	extended TAM-PC	0.440	<0.001
AISE-CF	extended TAM-SI	0.351	<0.001
AISE-CF	extended TAM-PAI	0.516	<0.001
AISE-CF	extended TAM-AIU	0.493	<0.001
AISE-CF	extended TAM-AIE	0.252	<0.005
AISE-CF	extended TAM-PAII	0.423	<0.001
AISE-CF	extended TAM-Ach	0.466	<0.001
AISE-TS	extended TAM-PC	0.336	<0.001
AISE-TS	extended TAM-SI	0.329	<0.001
AISE-TS	extended TAM-PAI	0.298	<0.001

AISE-AS (Assistance): A strong and consistent pattern of significant positive correlations emerged between AISE-AS and multiple extended TAM constructs. These associations, all significant at $p<0.001$, included extended TAM-PC ($r=0.374$), extended TAM-SI ($r=0.393$), extended TAM-PAI ($r=0.393$), extended TAM-AIU ($r=0.393$), extended TAM-AIE ($r=0.353$), extended TAM-PAII ($r=0.310$), extended TAM-Ach ($r=0.284$), extended TAM-SRL ($r=0.294$), and extended TAM-IC ($r=0.284$).

AISE-AI (Anthropomorphic Interaction): Significant positive correlations were also observed between AISE-AI and several extended TAM components. These included extended TAM-PC ($r=0.296$, $p<0.001$), extended TAM-SI ($r=0.279$, $p<0.001$), extended TAM-PAI ($r=0.308$, $p<0.001$), extended TAM-AIU ($r=0.415$, $p<0.001$), extended TAM-PAII ($r=0.253$, $p<0.005$), and extended TAM-Ach ($r=0.293$, $p<0.001$).

AISE-CF (Comfort with AI): A robust pattern of significant positive associations was found between AISE-CF and various extended TAM constructs. Specifically, AISE-CF correlated positively with extended TAM-PC ($r=0.440$, $p<0.001$), extended TAM-SI ($r=0.351$, $p<0.001$), extended TAM-PAI ($r=0.516$, $p<0.001$), extended TAM-AIU ($r=0.493$, $p<0.001$), extended TAM-AIE ($r=0.252$, $p<0.005$), extended TAM-PAII ($r=0.423$, $p<0.001$), and extended TAM-Ach ($r=0.466$, $p<0.001$).

AISE-TS (Technological Skills): Significant positive correlations were identified between AISE-TS and select extended TAM components, namely extended TAM-PC ($r=0.336$, $p<0.001$), extended TAM-SI ($r=0.329$, $p<0.001$), and extended TAM-PAI ($r=0.298$, $p<0.001$).

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Table: 3.1 Significant Positive Correlations of Dependence on AI (DAI) with AI Self-Efficacy and extended TAM Constructs (N=134)

Primary Construct	Correlated Construct	r-value	p-value
Dependence on AI (DAI)	AISE-AS (Assistance)	0.360	<0.001
Dependence on AI (DAI)	AISE-AI (Anthropomorphic Interaction)	0.336	<0.001
Dependence on AI (DAI)	AISE-CF (Comfort with AI)	0.336	<0.001
Dependence on AI (DAI)	extended TAM-PC (Personal Competence)	0.292	<0.001
Dependence on AI (DAI)	extended TAM-SI (Social Influence)	0.329	<0.001
Dependence on AI (DAI)	extended TAM-PAI (Perceived AI Trust)	0.298	<0.001
Dependence on AI (DAI)	extended TAM-AIE (Perceived AI Enjoyment)	0.277	<0.005
Dependence on AI (DAI)	extended TAM-PAII (Positive Attitude towards ChatGPT)	0.244	<0.005
Dependence on AI (DAI)	extended TAM-SRL (Self-Regulation in Learning)	0.261	<0.005
Dependence on AI (DAI)	extended TAM-IC (Intention to Use ChatGPT)	0.263	<0.005

Dependence on AI: Dependence on AI (DAI) demonstrated significant positive correlations with several AI self-efficacy dimensions: AISE-AS ($r=0.360$, $p<0.001$), AISE-AI ($r=0.336$, $p<0.001$), and AISE-CF ($r=0.336$, $p<0.001$). These results suggest that a greater reliance on AI is associated with higher AI self-efficacy across various AI-related domains Table 3.1

DAI also exhibited significant positive correlations with multiple extended TAM constructs, including extended TAM-PC ($r=0.292$, $p<0.001$), extended TAM-SI ($r=0.329$, $p<0.001$), extended TAM-PAI ($r=0.298$, $p<0.001$), extended TAM-AIE ($r=0.277$, $p<0.005$), extended TAM-PAII ($r=0.244$, $p<0.005$), extended TAM-SRL ($r=0.261$, $p<0.005$), and extended TAM-IC ($r=0.263$, $p<0.005$).

Multiple Linear Regression Predicting Dependence on AI (DAI)

Predictor	B	SE_B	beta	t	p
Model Summary					
R2					
Adjusted R2					
F(16, 119)				3.578	< .001
Predictors					
AISE-AI (Anthropomorphic Interaction)	0.24	0.08	0.274	3.018	.003**
extended TAM-PAI (Perceived AI Trust)	-0.43	0.14	-0.415	-3.130	.002**
Other predictors not significant					

Note. N = 134. AISE-AI = AI-specific self-efficacy for anthropomorphic interaction.

extended TAM-PAI = Perceived AI Trust from the AI-Technology Acceptance Model.

**p < .01

Among all the predictors:

Anthropomorphic Interaction (AISE-AI) was a significant **positive predictor** of AI dependence, *($\beta = 0.242, p<0.005$)*, suggesting that individuals who perceive AI as more human-like tend to be more dependent on it.

Perceived AI Trust (extended TAM-PAI) was a significant **negative predictor**, *($\beta = -0.433, p<0.001$)*, indicating that higher trust in AI functionality is associated with a lower level of dependence.

Other predictors, including general self-efficacy, emotional assistance, comfort with AI, technological skill, perceived enjoyment, attitude, intention, and attachment dimensions, do not significantly contribute to the model ($p > .05$).

DISCUSSION

The aim of this study was to explore the psychological factors influencing AI Dependence, such as General Self-efficacy, AI self-efficacy, extended TAM variables, and attachment among Indian college students. The findings from the study offer important insights into the relationship among various psychosocial factors and AI dependence.

The study identified a notable gender disparity in reliance on AI. It demonstrated that males exhibited a greater dependence on AI, evidenced by their higher average scores relative to females; this distinction has a small to medium effect size. Research indicates that women tend to have a less favorable attitude toward AI, engage with AI technologies less frequently, possess lower perceived knowledge of AI, and report higher levels of AI-related anxiety (Otis et al., 2025; Russo, 2025). This could create a psychological landscape where women are less likely to form a strong reliance or dependence on AI technologies. This finding highlights the need for more gender specific studies of AI interaction. Though no significant gender difference was observed for NGSES and AI-Self Efficacy, it was found in earlier research that women have lower General self-efficacy and AI-Self Efficacy compared to males (Asio and Sardina, 2025; Otis et al., 2025).

There was no significant correlation found between General Self-Efficacy (NGSES) and Dependence on AI(DAI) in the current study, which does not align with the previous research, as a significant relation was found between academic self-efficacy and dependence on AI, and a moderate relation was there. (Estrada-Araoz, 2024)

The correlational analysis underlines the influence of AI-specific self-efficacy on AI dependence and various other psychosocial aspects. Individuals who had greater efficacy in using AI for Assistance (AISE-AS), engaging in Anthropomorphic Interaction (AISE-AI), and overall

Comfort with AI (AISE-CF) showed a significant positive correlation with higher dependence on AI. This indicates that individuals with a higher dependence on AI also tend to report increased personal competence, social influence, trust, perceived usefulness, enjoyment, positive attitudes, self-regulation, and intention to use AI. This establishes Bandura's self-efficacy theory, suggesting that confidence in one's ability to effectively interact with and utilize AI systems directly contributes to their integration and reliance (Bandura 1977,1986,1997). Research indicates that an increase in the usage of AI, such as generative AI, can increase efficiency and confidence, enhancing self-efficacy (Liang et al., 2023b; Yilmaz and Yilmaz, 2023), and the use of AI may lead to dependence on AI, which weakens students' ability to solve problems independently. (Octaberlina et al., 2024; Zhang et al., 2024)

The various dimensions of AI self-efficacy had a positive correlation with several domains of the AI-Technology Acceptance Model (extended TAM), which include Personal Competence (extended TAM-PC), Social Influence (extended TAM-SI), Perceived AI Trust (extended TAM-PAI), Perceived Usefulness of AI (extended TAM-AIU, extended TAM-PAII), Perceived AI Enjoyment (extended TAM-AIE), Attitude towards ChatGPT (extended TAM-Ach), and Intention to use ChatGPT (extended TAM-IC). The noteworthy positive correlations between the dimensions of AI self-efficacy and extended TAM (Wang & Chuang, 2023; Dahri & Yahaya, 2024) highlight the importance of competence and trust in promoting AI acceptance. Furthermore, it underscores that self-efficacy is a strong predictor of AI dependence, consistent with the relationships identified in this study. (Morales García et al. 2024)

Furthermore, Dependence on AI (DAI) also had a significant positive correlation with nearly all extended TAM constructs, supporting that greater reliance on AI is related to positive attitudes and perceptions of its utility and acceptance. The detailed correlation Tables 3.1 and 3.2 reveal that DAI was significantly correlated with numerous other extended TAM constructs with comparable or stronger magnitudes. For example, extended TAM-PC and extended TAM-PAI also showed significant positive correlations with DAI, emphasizing various factors linked to AI-dependence. Consistent with prior research on technology acceptance, our study reveals a positive correlation between greater AI reliance and users' positive attitudes toward its utility and acceptance (Davis, 1989; Hoffman et al., 2018). Essentially, when individuals perceive AI as both beneficial and reliable, they instinctively incorporate it more deeply into their workflows. However, this advantageous integration comes with a notable warning. Although heightened trust is typically favorable, it may inadvertently diminish when the technology's functions are influenced by human biases, which could result in an unhealthy dependency that undermines sound decision-making, as explored in relation to suitable levels of automation dependency that undermines sound decision-making, as explored in relation to suitable levels of automation (Parasuraman & Riley, 1997).

The multiple linear regression analysis offered a clearer understanding of what directly predicts AI dependence. The overall statistical model was meaningful, accounting for roughly 32.5% of the differences observed in DAI scores.

Within this model, Anthropomorphic Interaction (AISE-AI) or how much individuals see AI as human-like, emerged as a significant positive predictor of AI dependence ($\beta = 0.242$, $p<0.01$). This suggests a direct relation: the more human-like people perceive AI to be, the more they tend to rely on it. This finding aligns well with the common psychological tendency for people to connect with or lean more heavily on things that show human-like traits. Various studies on Chatbots have found similar results in which users are more likely to rely on AI chatbots when they exhibit human-like traits (Moriuchi, E.,2021; Cheng, S., et al., 2022).

Conversely, Perceived AI Trust (extended TAM-PAI) was found to be a significant negative predictor of AI dependence ($\beta = -0.433$, $p = .002$). This outcome might seem unexpected: it suggests that when people have more trust in AI's ability to work well and reliably, they depend on it less. One way to understand this is that individuals who truly trust AI see it as a dependable tool that helps them achieve more, rather than something they need to constantly check or lean on excessively. Studies on human automation interaction have found that trust should lead to appropriate reliance, where users leverage the automation effectively without over-relying or under-relying (Lee, J. D., & See, K. A.,2004). Determining the right degree of automation is essential. As people's confidence in AI technologies grows, there is an evident inclination to lessen direct supervision. Nevertheless, if the AI is not completely reliable, and especially when human biases impact its results, this reduction in oversight could cultivate an unregulated reliance that might result in less favorable or harmful consequences (Nolemi, 2024). This distinction separates a constructive dependency on a valuable tool from a detrimental over-dependency that could undermine an individual's autonomy and self-confidence.

It is important to note that general self-efficacy (NGSES) and various subcomponents of AI self-efficacy, such as Assistance (AISE-AS) and Comfort with AI (AISE-CF), while showing a strong correlation with DAI in bivariate evaluations, did not appear as significant independent factors in the multivariate regression analysis. This indicates that their impact on DAI may be influenced by other factors incorporated in the broader model.

Attachment Styles and AI Dependence A crucial finding was the absence of significant correlations between both Avoidance (ECR-AO) and Anxiety (ECR-AX) attachment styles and AI dependence (DAI), as well as other AI-related self-efficacy or extended TAM constructs. Moreover, neither attachment style significantly predicted DAI in the regression analysis.This suggests that, at least within this specific group of Indian college students and using the direct assessments applied, prevalent adult attachment styles do not seem to have a straightforward linear connection with AI dependence or its associated psychosocial elements.

This conclusion, while seemingly contrary to some intuitive expectations, resonates with the intricate insights of attachment theory in new scenarios. Traditional attachment theory mainly focuses on human-to-human relationships (Bowlby, 1969; Fraley et al., 2000), yet recent investigations have begun to assess its relevance in human-AI exchanges. Certain studies indicate that individuals with defined attachment styles may engage with AI in ways that reflect their interpersonal behaviors. For example, a positive association has been found between anxious attachment and the likelihood of adopting conversational AI for counseling, as individuals might perceive AI as a secure, nonjudgmental substitute for human therapists (Wu et al., 2025). Likewise, a stronger emotional attachment to chatbots has been associated with heightened emotional reliance on them (Fang, 2025). In contrast, avoidant attachment has occasionally shown little to no significant impact on the adoption of or trust in AI (Gillath, 2021; Wu et al., 2025).

It is essential to distinguish between adult attachment style and the development of particular "attachment-like" tendencies towards AI. While the measures for general adult attachment in our study (ECR-AO, ECR-AX) did not directly determine AI dependence, this does not rule out the potential for AI to serve specific attachment-related roles for some individuals, as proposed by new scales intended to evaluate experiences in human-AI relationships (Wu et al,2025). The lack of a direct linear correlation in our model may suggest that the effects of attachment styles on AI dependence are more intricate, possibly mediated by alternate psychological factors or specific interaction behaviors not captured during the assessment.

Theoretical and Practical Implications:

These findings contribute significantly to the theoretical understanding of human-AI interaction, specifically the various dimensions of AI self-efficacy that are significant in shaping AI dependence. The inverse relationship between perceived AI trust and dependence offers a novel theoretical insight, suggesting that trust might act as a buffer against problematic over-dependence. The study also fills the identified research gap by providing a comprehensive assessment of psychosocial factors in an Indian college student context.

From a practical standpoint, these results could be helpful in the design, development, and promotion of AI systems. The finding that human-like features in AI predict greater dependence suggests a key challenge: while these features can certainly make AI more engaging, they might also, by accident, lead to users relying on it too much. Therefore, those who create AI should carefully think about the right balance. They need to weigh making AI easy and pleasant to use through these human-like traits against the risk of encouraging an unhealthy level of reliance.

On the other hand, actively building trust in AI systems and clearly communicating that trust could be a good way to reduce problematic dependence. This would help users see AI as a dependable tool that gives them power, rather than something they feel forced to use all the time. Teachers and policymakers could use these ideas to create specific programs. These programs would aim to help students use AI in a healthy and balanced way, build critical understanding of AI, and make sure that using AI actually improves, rather than reduces, their independence and self-belief.

Limitations and Future Research: Each study has its own limitations and scopes for further research. Firstly, the cross-sectional design used in this research does not establish a causal relationship between various factors. To comprehend how reliance on AI evolves and develops over time, it is essential to conduct longitudinal studies that track individuals over an extended period of time.

Secondly, this study relies completely on self-report questionnaires for all information. This means there's a chance of common method bias, where the way the data was collected might influence the results. Future studies could get around this by using more objective ways to measure AI use or by observing people's behavior, not just asking questions.

Third, the sample only included college students in India. This means findings might not apply to people in other age groups, different cultures, or various job settings. Future research should aim to include more varied and representative groups of people.

Fourth, while the statistical model explained dependence on AI (accounting for 32.5% of the differences in DAI scores, with an adjusted R^2 of .234), a large part remains unexplained.

Finally, general self-efficacy and attachment styles didn't show significant relationships in direct analyses. While these factors hold significance, their direct impact on AI dependence might be more intricate than initially perceived. Future investigations should consider whether their effects are indirect, potentially mediated by other psychological or social factors, or if particular contexts influence how they relate to AI dependence. Additionally, future studies could focus on other psychological characteristics, examine variations in AI usage for educational versus personal reasons, and utilize qualitative approaches such as interviews to achieve a richer and more comprehensive insight into the complex dynamics between humans and AI.

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