



AI Dependency and Student Well-Being: The Moderating Role of Personality Traits in Social, Psychological, and Educational Outcomes

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ABSTRACT

Artificial intelligence (AI) tools like ChatGPT, Copilot, and Gemini have significantly transformed how university students learn, write papers, conduct research, and manage academic stress. While these benefits are evident, concerns about over-reliance on AI and its social, psychological (self-esteem), and educational impacts remain. This study examined the relationship between AI dependency and the social, psychological, and educational challenges faced by university students. It also explored the Big Five personality traits as moderators to assess how they influence the relationship between AI dependency and students' challenges in Pakistan. The quantitative phase (N = 350) used survey data, including the GenAI Dependency Scale, the Big Five Inventory, the Social Connectedness Scale, the Rosenberg Self-Esteem Scale, and the Educational Stress Scale for Adolescents. Findings indicated that AI dependency was negatively associated with social connectedness ($r = -.219, p < .001$) and positively associated with educational stress ($r = .325, p < .001$), with a less significant relation to self-esteem. Additionally, agreeableness moderated the relationship between AI and social connectedness, while multiple personality traits moderated the relationship between AI and self-esteem. The results highlight AI's dual role as an academic aid and a potential source of disengagement. Recommendations are provided for students, teachers, counselors, universities, and policymakers to promote responsible, balanced, and psychologically healthy use of AI in higher education.

Introduction

Artificial intelligence (AI) drastically impacts human behavior, social interactions and institutional process worldwide especially in the technological advancement era of twenty-first century. The usage of AI tools in higher education has increased due to remote learning initiatives, increased digitalization and global expansion of internet accessibility. Students increasingly adopt AI powered tools for exam preparation, writing assistance, information retrieval and problem solving. Although AI has the potential to enhancing efficiency and accessibility but scholars have raised concern regarding consequences of excessive dependence on AI tools, specifically in the developing countries where digital literacy is unknown to people uneven (Kasneci et al., 2023). The growing reliance on AI may influence student's learning habits, cognitive functions and psychological well-being, making it a pinpoint area of academic inquiry.

In developing countries, like Pakistan, AI is still the focus of attention and student's engagement increases through freely available AI Chatbots and online tutoring system. In Pakistani universities, students often face challenges related to academic work overload, competition, limited educational resources and performance-oriented evaluation system. In such situation, AI tools may be considered feasible and convenient way to handle such stress. Sometime, this reliance can be adaptive but it may worsen the social, educational and psychological outcomes (Huang et al., 2024).

Artificial Intelligence in Education

Artificial intelligence has become a vital part of the education system, affecting learning processes and educational practice. It can generate human-like content, provide academic assistance and solve complex problems. Most students used these tools for assignments writing, exam preparation and research support due to its accessibility and feasibility. Scholars worry that unregulated use of generative AI may lead to reduced critical thinking and originality (Bewersdorff et al., 2023). The ease with which students easily generate responses according to their own needs can lead to shifting attention from personal learning to machines, potentially leading to reshape student's academic expectation.

Concept of AI Dependency

The concept of AI dependency emerges from theoretical bases of earlier research on challenging technology use, including smartphone addiction, internet addiction and digital dependency. Researchers argue that AI is not intrinsically addictive, but their attractive features like efficiency, instant feedback, perceived intelligence and emotional satisfaction can promote over-reliance, especially for those people experiencing low self-efficacy and low self-esteem (Brand et al., 2019). Unlike traditional technologies, AI system actively pretends human cognitive task, which may further confuse the boundary between support and replacement in learning process. Perceived usefulness and trust also highlight AI dependency. Student who perceives AI as reliable, unbiased and accurate may develop excessive trust on AI outcomes, leading them to accept information (Shin, 2022). Such over trust can be harmful in educational context, where biases, inaccuracies and superficial explanations lead to problematic AI use.

Personality Factors and AI Use

Personality refers to stable pattern of thoughts, behaviors and emotions that assess how individuals observe and respond to their surroundings (McCrae & Costa, 2008). Personality factors play a dynamic role in shaping how individuals' interaction with technology, including AI system in educational context. Personality traits named as Big Five Personality traits consist of Conscientiousness, Extraversion, Openness, Agreeableness and Neuroticism (Costa & McCrae, 2008) are the best predictors of coping mechanism, learning strategies, academic motivation and technology use behavior in educational settings. As artificial intelligence become over indulge in student's academic and personal lives, it would be necessary to understand how personality traits influence AI use and reliance is essential for explaining individual differences in student's social, educational and psychological challenges.

One of the personality factors neuroticisms, characterized by instability of emotion, anxiety and susceptible to stress. Student with a high neuroticism may have negative attitude toward oneself including fear of failure, academic exhaustion, burnout, low emotional regulation and low self-efficacy which may foster excessive reliance on AI tool as coping mechanism (Elhai et al., 2020). Conscientiousness, including self-directed behavior, self-discipline and organized behavior. Individuals higher in conscientiousness have a better time management skills, self-regulation and persistence in learning task, enable them to less reliable on the AI tools (Marengo et al., 2024). Openness to experience including creativity, exploration and curiosity has a more complicated relationship with AI use. Student high in openness may be more susceptible to use AI technologies and process technologies into their learning domains. Excessive reliance on AI induced content may ultimately stop creativity by promoting appropriate outcomes and diminishes originality (Kasneci & Kasneci, 2026). Therefore, it is difficult to differentiate between dependent AI use and adaptive AI use. Agreeableness and extraversion also influence relationship with AI tools, particularly in collaborative learning context. Extraverted people use AI less as a substitute for human interaction and more as a supplementary tool for interaction and mediating learning experience. In contrast, introverted people may depend more heavily on AI tools to avoid social interaction, which can ultimately reduce communication, social withdrawal and diminished peer interaction (Heffer et al., 2019). Agreeableness often characterized by acceptance, cooperation and trust, may foster student's tendency to accept AI output leading to uncritical acceptance of AI-generated information (Shin, 2021).

Social Challenges Among Students

Social development is a core principle of determining overall student's educational experiences, significantly in collectivist culture where collaboration, communication and interaction play an important role in student's cognitive and academic growth through shared experiences, students may develop a sense of interpersonal skills, sense of belongingness and construct knowledge. Educational scholar emphasize that learning is inherently a social process, shaped by communication with teachers, peers and social community. However traditional pattern of social interaction may change due to over-reliance on AI.

In Pakistani culture, where group affiliation and interpersonal relationship are central to social identity. Pakistani culture traditionally relies on peer instructions for emotional reassurance and academic support. Effective communication requires constant feedback, and social engagement. When students rely on AI tools for draft-written work, articulate ideas and solve academic problems their cognitive effort starts to decline, ultimately lead to destructive decision making and critical thinking.

Psychological Challenges Among Students

Students' academic success, social functioning, and overall quality of life depends upon psychological overall well-being. University students practice significant mental health challenges due to performance expectations, academic pressure, and transitional stressors associated with evolving adulthood (Abdullah et al., 2025). Recent research highpoints psychological distress, including stress, anxiety and depression in relation to increasing dependance on artificial intelligence (AI) tools within educational settings (Bukhari et al., 2025).

The psychological constructs such as imposter syndrome(a psychological pattern in which an individual doubts their skills, talents, or accomplishments and has a persistent internalized fear of being exposed as a "fraud) have been found to have a strong empirical association with AI dependency, wherein lessened self-efficacy and self-doubt have been empirically associated with psychological distress among students (Ahmad et al., 2026). Although AI can reduce some cognitive load, its adoption can also impact academic stress by sparking pressure for performance, moral considerations and validity issues (Pang et al., 2025).This align with stress appraisal, whereby students use AI both as a helping tool and psychological burden, especially when academic outcomes are mediated by technology.

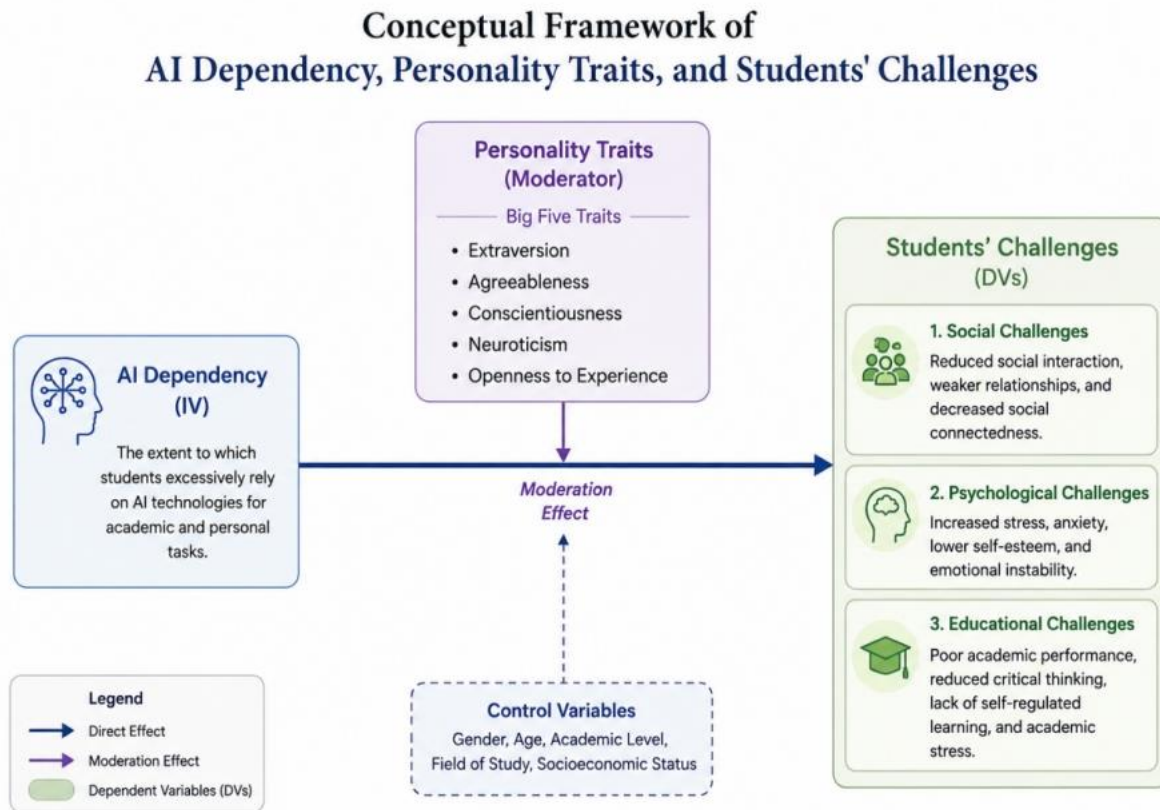
Educational Challenges and Academic Outcomes

Educational challenges are central to understanding the concept of AI adoption in Education. In Pakistani Universities, the adoption of AI is increasing due to performance-related stress, to enhance performance and efficiency (Du & Lv, 2024). However, researches evident that integration of AI tools may affect cognitive engagement and independent learning (Al-Zahrani, 2024). In Pakistan's competitive academic environment, where critical examination system and limited institutional resources increases more pressure, leave student vulnerable to adopt AI tools (Akhtar et al., 2023).

Academic integrity is one of the major concerns in educational departments. There is increased ambiguity between AI-assisted assignments and plagiarism detection (Khasawneh, 2024). Many Students perceive AI as an assistant tool rather than misconduct strategy because of limited institutional policies and inconsistent faculty guidance contribute to confusion surrounding ethical boundaries (Al-Ahmad et al., 2024). If the practice of structured framework & may not address the AI integration in education dependency may underestimate academic standards.

Study habits and time management may also be influenced by AI dependency. Pakistani studies on self-regulated learning support that student who rely on AI tools often show weaker planning, monitoring and reflective strategies. Self-regulated learning emphasizes the importance of independent cognitive effort in academic success (Panadero & Broadbent, 2018). When AI replaces human efforts rather than support these processes, the metacognitive abilities start to decline (Lim et al., 2023).

Figure 1



Note. IV = Independent Variable; M = Moderator; DVs = Dependent Variables

Figure 1 shows that the relationship between AI dependency (IV) and students' social, psychological and educational challenges (DVs) is moderated by personality factors (M).

Rationale of the Study

There are reasons which led to the present study. First, it aims to fill a gap in the empirical research on the social, psychological and educational implications of AI dependency on students, with a particular focus on the Pakistani context of higher education. Second, it aims to integrate the personality aspects that moderate, giving a more nuanced perspective on individual differences regarding outcomes concerning AI.

Significance of the Study

With the growing use of AI in education, learning, communication, and problem-solving, this study is essential in explaining the social, psychological, and educational difficulties that students are facing despite the tools they have given with the constructive role of AI. The study highlights the moderating effect of personality traits, emphasizing how AI vulnerability can deepen or buffer the effects on individuals. The findings will provide valuable insights for teachers, counsellors, and policy makers to inform pedagogical practices that train students with the skills to use AI responsibly and efficiently, promote emotional health and wellbeing, and improve academic engagement.

Objectives of the Study

1. To examine the relationship between AI dependency, personality traits and challenges (social, psychological, and educational) among university students.
2. To predict the impact of AI dependency on challenges (social, psychological, and educational) encountered by university students.
3. To investigate whether personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism) moderate the relationship between AI dependency and students' social challenges, psychological challenges, and educational challenges among university students.

Hypotheses

H1: There will be a significant relationship between AI dependency and challenges (social, psychological, and educational) encountered by university students.

H2: AI dependency will significantly predict social challenges, psychological challenges, and educational challenges among university students.

H3: Personality traits (openness, conscientiousness, extraversion, agreeableness, neuroticism) will significantly moderate the relationship between AI dependency and students' social challenges, psychological challenges, and educational challenges among university students.

Literature Review

With the introduction of AI tools (e.g., ChatGPT, Copilot and Gemini), the way students learn, search for information, and do work is changing. These technologies offer instant feedback, perform higher-level cognitive skills and personalize learning, which affect learning and well-being. The impact of AI is not universal, though – it depends on the individual characteristics of the student, including their personality. The Big Five personality traits comprise of Openness, Conscientiousness, Extraversion, Agreeableness and Neuroticism are known to be significant when it comes to using technology. The use of artificial intelligence in higher education is growing, but empirical research is rare in the psychological and social realm in Pakistan. The latest research shows a worry about over reliant on AI, lowered critical thinking, and cheating in students (Abbas et al., 2025). International research, however, highlighted the learning-enhancing and cognitive-disengaging dual nature of AI and its contribution to techno-stress (Guo et al., 2024). Thus, it is essential to understand the interaction of AI usage and personality traits for addressing student's psychological, educational and social challenges.

Personality Traits and Social AI Engagement

Personality traits affect the impact of AI on social behavior. Extraverted students will be more inclined towards using AI in collaborative tasks as opposed to introverts and neurotic students who use AI to replace social interaction. According to McCrae and Costa (2008), those with an extraversion personality type are more likely to be socially engaged and may help mitigate the loneliness that can be caused by AI. Students with high scores on the Neuroticism and self-critical perfectionism subscales of the NEO personality inventory were more likely to be using AI tools for academic work, leading to less social interaction with peers. The trend indicates that AI can amplify social trends but not necessarily change them (Yang et al., 2024)

For students in Pakistan, it was found that those with more social anxiety preferred the use of AI for learning over working in groups, because it removes the pressure of interpersonal communication. This preference, however, was correlated with decreases in social competence as time went on (Khan et al., 2025)

Social and Behavioral Dimensions of AI Use

In addition to academic and psychological aspects, the application of artificial intelligence also holds relevance for students' social behaviors and interactions. There is a limited number of studies on the empirical level in Pakistan, but the few studies and models available in the literature offer a good degree of insight on the topic. Personalized AI technologies can either enhance group learning or individual learning habits. Students who have made extensive use of AI for tasks like writing assignments, for example, might also be less inclined to participate in discussions and group work. Such findings are corroborated by international research (Khan et al., 2025).

Students who use AI tools regularly for academic tasks are less engaged in the classroom and with peers. This phenomenon is especially likely to occur with introverts and neurotics, who may lean towards interacting with AI instead of fellow humans. On the other hand, the students that were high on extraversion and openness were more inclined to make use of AI in collaborative learning, either for discussion or knowledge sharing (Khan et al., 2025).

Psychological Domain: AI Use and Mental Health Outcomes

AI Dependency and Psychological Well-being

One of the greatest concerns for the usage of AI is its psychological effects, especially dependency and mental well-being. Abbas (2025) reported that the overreliance of AI tools on the part of Pakistani students led to high levels of learned helplessness and low self-confidence. This implies that reliance on AI could negatively impact the students' self-efficacy. Zhong et al. (2024) found needs frustration to be a strong mediator between personality traits and AI dependency, internationally. Students with a high level of neuroticism reported a higher level of emotional distress, and this heightened distress led to greater use of AI to cope with it. Likewise, Dwivedi et al. (2023) stated that although AI is providing emotional support to cognitive abilities, it can also create psychological dependency, especially for students with poor self-regulation. The dependency can make it less motivating to learn on your own and more dependent on outside help. Another contribution by Zhai et al. (2024) also found that overuse of AI can lead to emotional fatigue and a decrease in cognitive engagement, underscoring the potential downsides of AI integration in the psychological realm.

Personality Traits and Emotional Regulation in AI Use

Students' emotional reactions to AI technologies are greatly shaped by personality traits. Negative emotional outcomes have been consistently associated with neuroticism. Sahar and Hassan (2025) suggested that the higher the neuroticism level, student stress level would be higher, and the enjoyment of using AI tools would be lower. However, those who are conscientious and open showed higher emotional control and adaptive use of AI (Kasneci & Kasneci, 2026). The psychological results of these students were more positive when the AI was used as a learning tool and not a crutch. Ali et al (2024) in the Pakistani context, revealed that the emotional intelligence of students decreased the relation between the usage of AI and the stress faced by Pakistani students due to using AI, in which the high level of emotional intelligence of students is related to low stress of using AI. Moreover, self-determination theory (SDT) indicates that self-determination, specifically autonomy and competence, are important factors in psychological wellbeing (Ryan & Deci, 2020). Tools that interfere with these needs can have negative emotional impacts, particularly on vulnerable students, when used with AI.

Psychological Impacts of AI and Personality Interaction

The psychological influence of AI use by students is an evolving research field, particularly in terms of differences in personality. Similarly, Abbas (2025) also found that learned helplessness and lower self-confidence is highly linked to frequent use of AI amongst student in Pakistan. Moreover, students who feel evaluation systems are unfair may be more likely to use AI as a coping mechanism. Zhong et al. (2024) additionally examined the psychological process between personality and dependence on AI. They found that the relationship between neuroticism and AI reliance is mediated by needs frustration, which they defined as the thwarting of the autonomy, competence and relatedness needs. Students with high neuroticism were more likely to feel negative emotions and this led to a greater reliance on AI tools to aid their academic work. Similarly, Sahar and Hassan (2025) discovered that the use of AI technologies caused an increase in the level of stress and decrease in enjoyment among neurotic students. This indicates that the psychological effect of AI use is not always beneficial when it comes to academic stress, and that it is dependent on person-to-person

differences in emotional control. The emotional regulation of students can be a challenge, and they may feel pressured by AI when it isn't helping. In a global context, Dwivedi et al. (2023) proposed a new framework called "techno-psychological adaptation" that provides an understanding of how people adapt psychologically to new technologies. Using this model, AI can have positive effects (increased engagement), or negative effects (emotional exhaustion, anxiety). Additionally, Zhai et al. (2024) found that an increase in over-reliance on generative AI was correlated with a reduction in the critical thinking ability and cognitive engagement of students with low self-regulation. The results of these findings highlight how vital it is to take into account personality traits in assessing the psychological impacts of AI in education. AI can improve learning, but can also be a contributor to maladaptive psychological outcomes, particularly those of vulnerable populations of students.

Educational domain

Personality Characteristics and Educational Use of AI

The increasing dimensions of research highpoints the importance of personality in persuading students' understandings of AI in the learning domain. The existing body of literature shows that personality plays a significant role in shaping students' experience of using AI in educational contexts. Abbas (2025) conducted a quantitative study to assess the association between big five personality traits and AI usage among the Pakistani students. The results showed that conscientiousness showed a negative relationship with excessive use of AI tools, indicating that students with a higher conscientiousness incline to opt for problem-solving on their own. Neuroticism, on the other hand, was positively related to AI dependence, suggesting that students with emotional instability are more likely to use AI to feel better and/or to complete tasks. Moreover, greater reliance on AI was associated with decreased academic self-efficacy and greater levels of learned helplessness.

To validate these results, Sahar and Hassan (2025) examined the motivational factors of the use of AI by students in university in Pakistan. Their findings showed that higher scores on neuroticism were associated with lower scores on intrinsic motivation and expectancy-value beliefs to use AI. Students with a neuroticism trait were more prone to use AI instrumentally, suggesting a superficial participation in academic activities. In contrast, there was weak but positive correlation between openness and extraversion with exploratory and collaborative uses of AI. These relationships are also supported by studies from around the world.

AI Use and Academic Performance

Artificial Intelligence (AI) technologies are having a deep and multifaceted effect on students' learning achievements, especially in modern learning settings that make use of technology and devices. One of the main advantages of AI lies in its ability to provide personalized learning experiences. The use of AI in education systems had an extraordinary effect on enhancing students' learning performance, adaptive learning paths, providing personalized feedback, and immediate academic support (Ain & Azam, 2025). Similarly, Kasneci et al. (2023) found that with proper use, AI tools such as generative models like ChatGPT can improve learning proficiency and understanding. Their research identified how AI can aid students in comprehending complex topics, brainstorming, and structuring academic material. Abbas (2025) argued that, in the Pakistani context, there was a negative correlation between the use of excessive AI and academic performance, especially in self-regulated students.

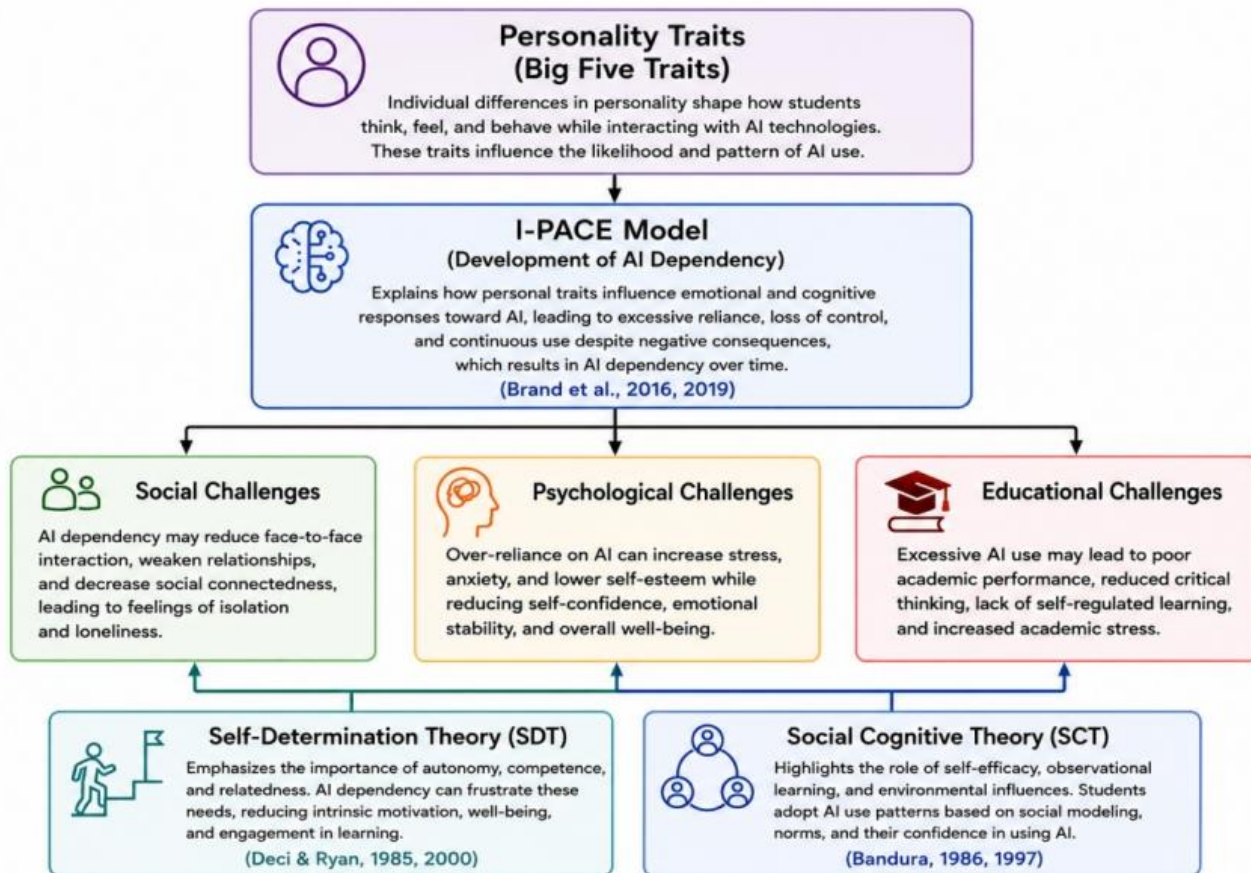
Personality Traits and Academic Achievement in AI Contexts

In an AI-assisted learning environment, the academic achievements of the students are strongly influenced by their personality traits, which influence their motivation, self-regulated learning, and engagement with the learning task. Conscientiousness has consistently been the best predictor of academic outcomes of the Big Five personality traits. Conscientious individuals are organized, persistent, disciplined and goal oriented – they are able to manage their learning effectively even in technologically mediated learning. The researchers – Watson et al. (2008) – have reported that time management, effort regulation and strategic learning – all of which are very important to success in school – are very strongly predicted by conscientiousness. These are even more essential in the era of AI powered learning where students need to learn when and how to use AI tools, but not so much that they can't. This is evidence of the theoretical approach, in the Pakistani context.

AI Use, Critical Thinking and Academic Integrity

Critical Thinking and Academic integrity are among the key issues related to AI's use. Dwivedi et al. (2023) state that generative AI tools can be used to enable academic dishonesty, if not used properly. Zhai et al. (2024) determined that students who depend on AI tend to have weaker problem-solving abilities and critical thinking. This is an issue of concern for the long-term educational costs of using AI. Rauf et al. (2024) found that students in Pakistan have raised their point of view about the fairness and integrity of AI tools in assessments, indicating the importance of establishing clear institutional policies.

Theoretical Frameworks



Methodology

The target population consisted of university students enrolled in public and private universities across Pakistan. Using a convenience sampling technique, a total of 350 participants (both male and female, aged 18–26 years) were selected for the quantitative phase. Inclusion criteria required students to be regular users of AI tools such as ChatGPT, Grammarly, or other generative AI applications for academic or personal purposes. Participants who reported no exposure to AI tools were excluded.

Instruments:

Generative AI Dependency Scale (GAD-Scale; Goh, 2025)

Generative AI dependency scale assesses individuals' reliance on generative AI tools such as chatbots and AI assistants for completing tasks and obtaining information. The 10-item scale uses a 5-point Likert response format (1 = strongly disagree to 5 = strongly agree), where higher scores indicate greater dependency on generative AI technologies.

Big Five Inventory (BFI-44; John & Srivastava, 1999)

Personality traits were assessed using the Big Five Inventory (BFI-44) inventory contains 44 items that measure the five personality dimensions: openness, conscientiousness, extraversion, agreeableness, and neuroticism. Participants respond using a 5-point Likert scale, with higher scores indicating stronger expression of the respective personality traits.

Social Connectedness Scale (SCS; Lee & Robbins, 1995)

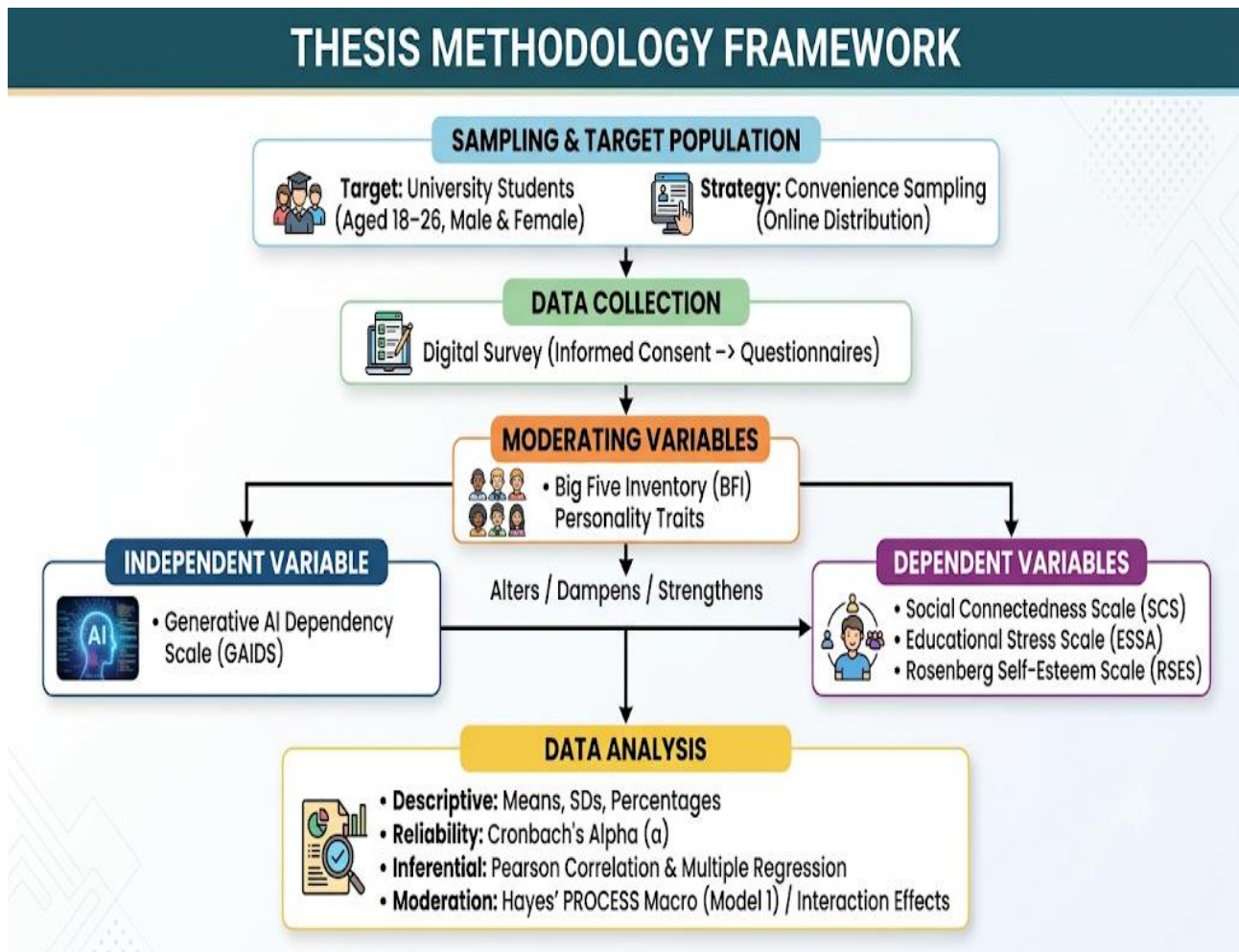
Social connectedness was measured using the Social Connectedness Scale developed by Lee and Robbins (1995). The 20-item scale assesses individuals' sense of belongingness and emotional connection with others. Participants respond using a 6-point Likert scale, where higher scores represent a stronger sense of social connectedness.

Rosenberg Self-Esteem Scale (RSES; Rosenberg, 1965)

Self-esteem scale consists of 10 items measuring global self-worth and self-acceptance. Responses are recorded on a 4-point Likert scale, with higher scores indicating higher levels of self-esteem.

Educational Stress Scale for Adolescents (ESSA; Sun et al., 2011)

Educational stress scale contains 16 items assessing academic stress across dimensions such as study pressure, workload, and worry about grades. Participants respond on a 5-point Likert scale, where higher scores indicate greater educational stress.



Procedure:

After obtaining permission from relevant university authorities, data were collected from 350 students enrolled in different universities using a convenience sampling technique. Participants were informed about the purpose of the study and assured that their participation was voluntary and their responses would remain confidential. Data were collected through a self-administered questionnaire consisting of two sections. The first section included demographic information such as age, gender, and academic program, while the second section comprised five standardized scales: the Generative Artificial Intelligence Dependency Scale (10 items), Big Five Inventory (44 items), Social Connectedness Scale (20 items), Rosenberg Self-Esteem Scale (10 items), and the Educational Stress Scale for Adolescents (16 items). Participants completed the questionnaire either in person or through an online form, which took approximately 15–20 minutes to complete, and the collected responses were later coded and prepared for statistical analysis.

Data Analysis

The collected data were analyzed using IBM SPSS Statistics. Initially, descriptive statistics (means, standard deviations, and frequencies) were computed to summarize the demographic characteristics of the participants and the main study variables. Reliability analysis was conducted using Cronbach's alpha to assess the internal consistency of each scale. Pearson correlation analysis was then performed to examine the relationships among the study variables. Finally, regression analysis was conducted to determine the impact of independent variable on the three dependent variables. The significance level for all statistical tests was set at $p < .05$. This design is mostly appropriate for examining complex relationships, such as using the personality traits as a moderator to assess the relationship between generative AI dependency and students' psychological, social, and educational outcomes.

RESULTS

Table 1: Correlational analysis of variables (N=350)

	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9
1.GENAI	2.65	.71	-	-.219**	.070	.325**	.088	-.104	.044	-.005	.065
2.SCS	3.61	.52		-	-.147**	-.198**	.395**	.151**	.126*	-.167**	-.007
3.RSES	2.44	.33			-	.088	-.098	-.288**	-.432**	.215**	-.258**
4.ESSA	3.06	.62				-	.051	.080	.016	.216**	.246**
5.Extr	3.05	.48					-	.108*	.122*	-.035	.176**
6.Agree	3.28	.49						-	.329**	.026	.398**
7.Concient	3.09	.52							-	-.234**	.319**
8.Neuro	3.12	.51								-	.145**
9.Open	3.26	.48									-

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

GENAI = generative AI dependency; SCS = social connectedness; RSES = Rosenberg self-esteem; ESSA = educational stress; Extr = extraversion; Agree = agreeableness; Concient = conscientiousness; Neuro= neuroticism; Open = openness.

The result showed that AI dependency has significant negative correlation with social connectedness ($r = -.22$, $p < .01$) and significant positive correlation with educational stress ($r = .33$, $p < .01$). AI dependency has non-significant relationship with self-esteem ($r = .07$, $p > .05$).

Table 2: Simple Linear Regression Analyses Predicting Social Connectedness, Self-Esteem, and Educational Stress from AI Dependency (N = 350)

Outcome Variable	B	SE	β	t	p	95% CI	R ²
Social Connectedness	-0.16	0.04	-0.22	-4.20	< .001	[-0.235, -0.085]	.05
Self-Esteem	0.03	0.03	0.07	1.31	.190	[-0.016, 0.081]	.01
Educational Stress	0.28	0.04	0.33	6.41	< .001	[0.194, 0.367]	.11

Note. $N = 350$. Predictor = AI Dependency. B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; CI = confidence interval. All coefficients represent the effect of AI Dependency on each outcome variable.

The results revealed that AI dependency significantly predicted **social connectedness** ($\beta = -.22$, $t(348) = -4.20$, $p < .001$), explaining **5%** of the variance ($R^2 = .05$). AI dependency also significantly predicted **educational stress** ($\beta = .33$, $t(348) = 6.41$, $p < .001$), accounting for **11%** of the variance ($R^2 = .11$). However, AI dependency did not significantly predict **self-esteem** ($\beta = .07$, $t(348) = 1.31$, $p = .190$), explaining only **1%** of the variance ($R^2 = .01$).

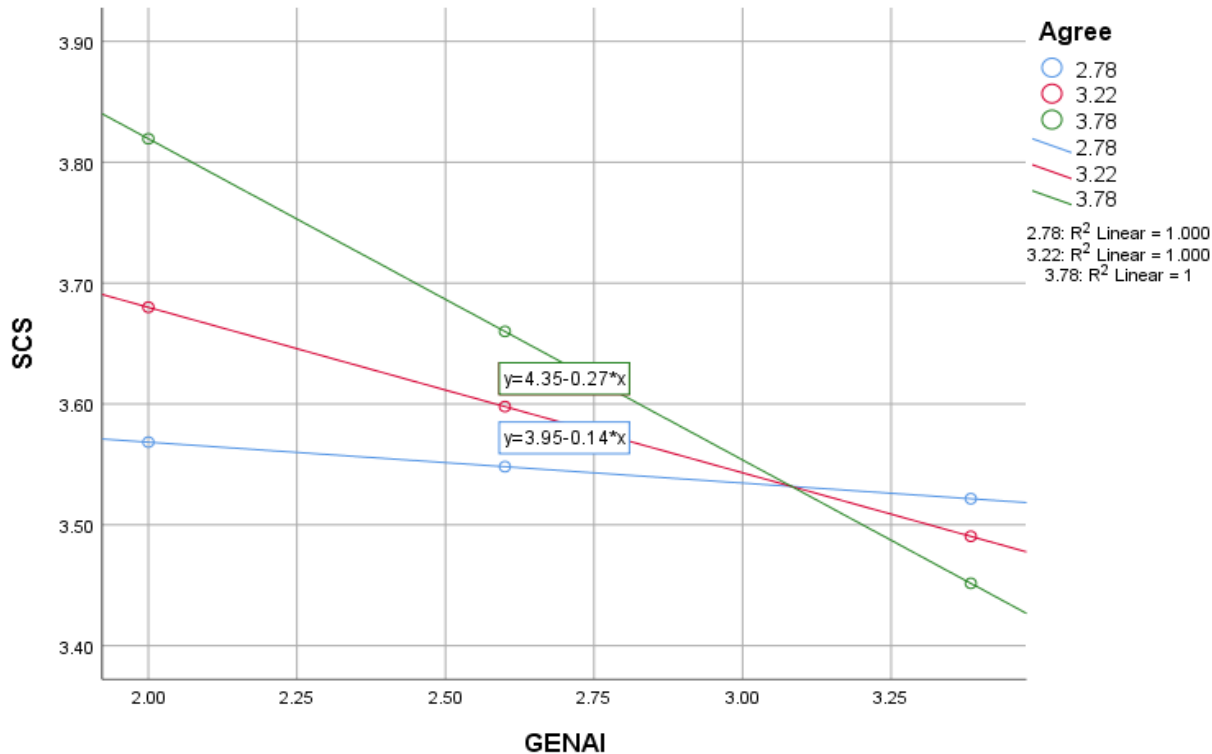
Table 3: Moderation of Agreeableness on the Relationship Between AI Dependency and Social Connectedness ($N=350$)

Predictor	B	SE	t	p	95% CI	
					LL	UL
Constant	1.65	0.68	2.43	.016	0.32	2.98
AI Dependency (IV)	0.61	0.26	2.35	.019	0.10	1.12
Agreeableness (Moderator)	0.71	0.20	3.53	< .001	0.32	1.11
AI $\times$ Agreeableness	-0.23	0.08	-2.96	.003	-0.39	-0.08
R^2	.09					
F	11.09					
ΔR^2	.02					

Note. $N = 350$. CI = confidence interval.

The interaction between AI dependency and agreeableness was significant ($B = -0.23$, $p = .003$), indicating that agreeableness moderates the association between AI dependency and social connectedness.

Figure 2: Moderation of Agreeableness on the Relationship Between AI Dependency and Social Connectedness ($N=350$)



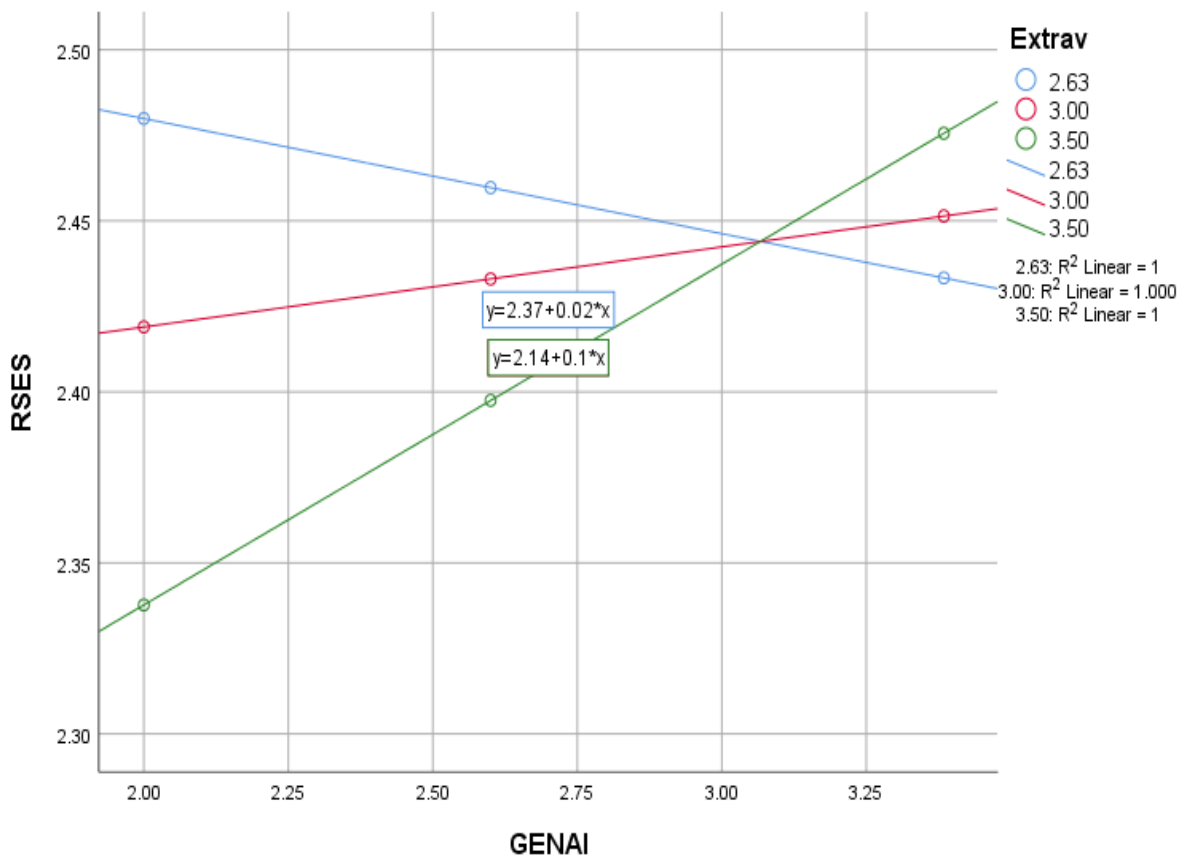
Note. GENAI = generative AI dependency; SCS = social connectedness ; agree = agreeableness

Table 4: Moderation of Extraversion on the Relationship Between AI Dependency and Self-Esteem (N=350)

Predictor	B	SE	t	p	95% CI	
					LL	UL
Constant	3.77	0.45	8.44	< .001	2.90	4.65
AI Dependency (IV)	-0.43	0.17	-2.58	.010	-0.76	-0.10
Extraversion (Moderator)	-0.47	0.14	-3.24	.001	-0.75	-0.18
AI × Extraversion	0.15	0.05	2.83	.005	0.05	0.26
R^2	.04					
F	4.58					
ΔR^2	.022					

Note. N = 350. CI = confidence interval.

The interaction between AI dependency and extraversion was significant, $B = 0.15$, $t(346) = 2.83$, $p = .005$, showing that extraversion moderates the relationship between AI dependency and self-esteem.

Figure 3: Moderation of Extraversion on the Relationship Between AI Dependency and Self-Esteem (N=350)

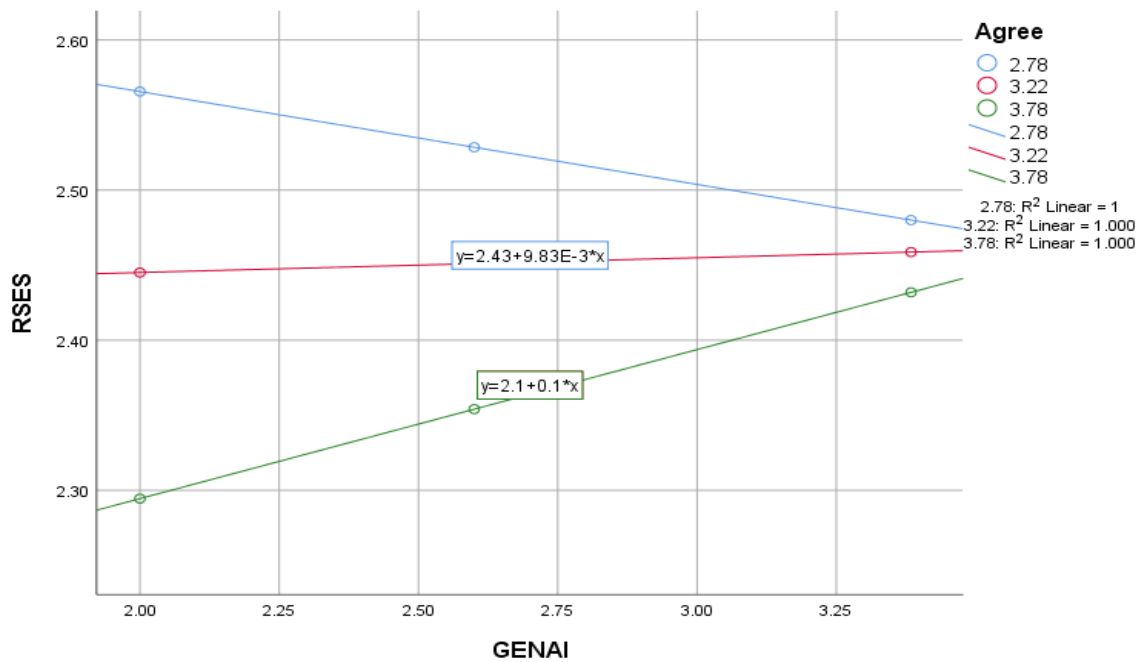
Note. GENAI = generative AI dependency; RSES = self-esteem; extrav = extraversion

Table 5: Moderation of Agreeableness on the Relationship Between AI Dependency and Self-Esteem (N=350)

Predictor	B	SE	t	p	95% CI	
					LL	UL
Constant	4.34	0.43	10.17	< .001	3.50	5.18
AI Dependency (IV)	-0.51	0.16	-3.12	.002	-0.83	-0.19
Agreeableness (Moderator)	-0.59	0.13	-4.66	< .001	-0.84	-0.34
AI × Agreeableness	0.16	0.05	3.27	.001	0.06	0.26
R^2	.11					
F	14.51					
ΔR^2	.027					

Note. N = 350. CI = confidence interval.

The interaction between AI dependency and agreeableness was significant, $B = 0.16$, $t(346) = 3.27$, $p = .001$, indicating that agreeableness moderates the association between AI dependency and self-esteem.

Figure 4: Moderation of Agreeableness on the Relationship Between AI Dependency and Self-Esteem (N=350)

Note. GENAI = generative AI dependency; RSES = self-esteem; agree = agreeableness

Table 6: Moderation of Conscientiousness on the Relationship Between AI Dependency and Self-Esteem (N=350)

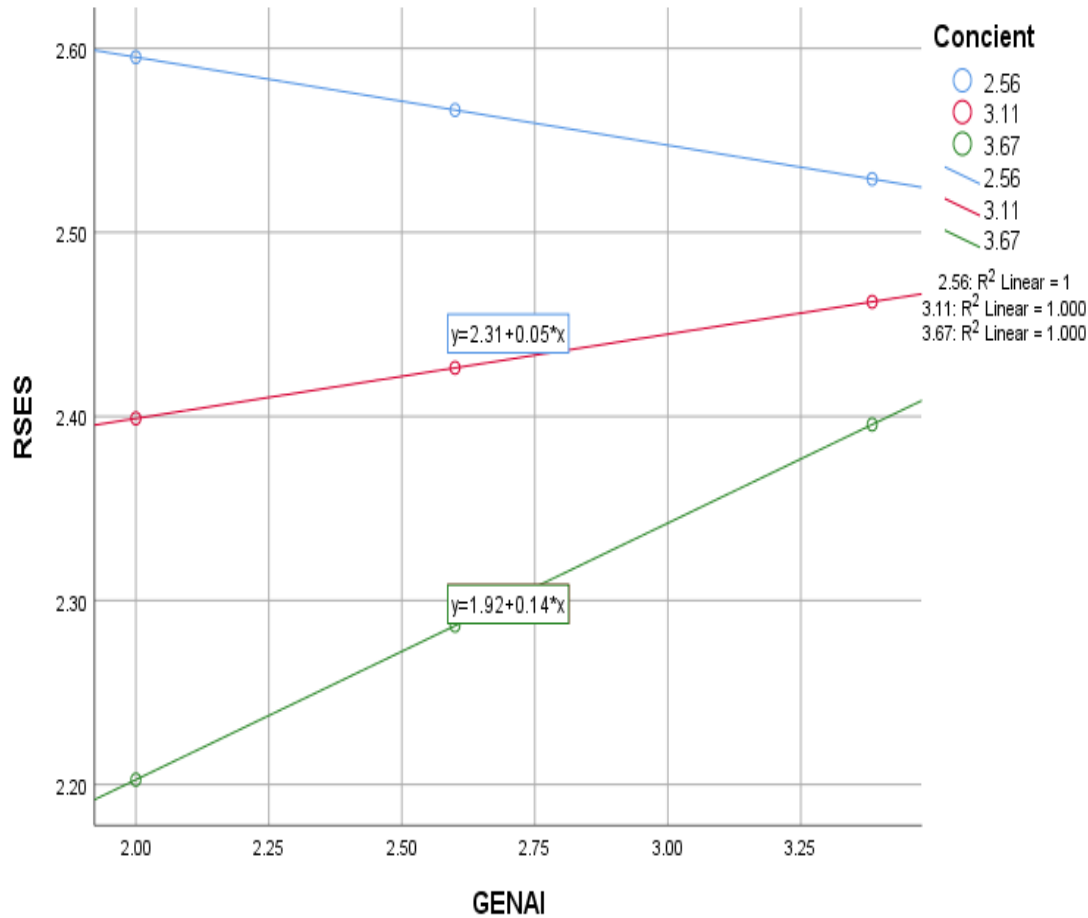
Predictor	B	SE	t	p	95% CI	
					LL	UL
Constant	4.46	0.33	13.31	< .001	3.80	5.11
AI Dependency (IV)	-0.48	0.13	-3.66	< .001	-0.74	-0.22
Conscientiousness (Moderator)	-0.69	0.11	-6.44	< .001	-0.90	-0.48
AI × Conscientiousness	0.17	0.04	4.03	< .001	0.09	0.25
R^2	.23					
F	34.57					

ΔR^2 .036

Note. N = 350. CI = confidence interval.

The interaction between AI dependency and conscientiousness was significant, $B = 0.17$, $t(346) = 4.03$, $p < .001$, indicating that conscientiousness significantly moderates the association between AI dependency and self-esteem.

Figure 5: Moderation of Conscientiousness on the Relationship Between AI Dependency and Self-Esteem (N=350)



Note. GENAI = generative AI dependency; RSES = self-esteem; concient = conscientiousness

Table 7: Moderation of Openness on the Relationship Between AI Dependency and Self-Esteem (N=350)

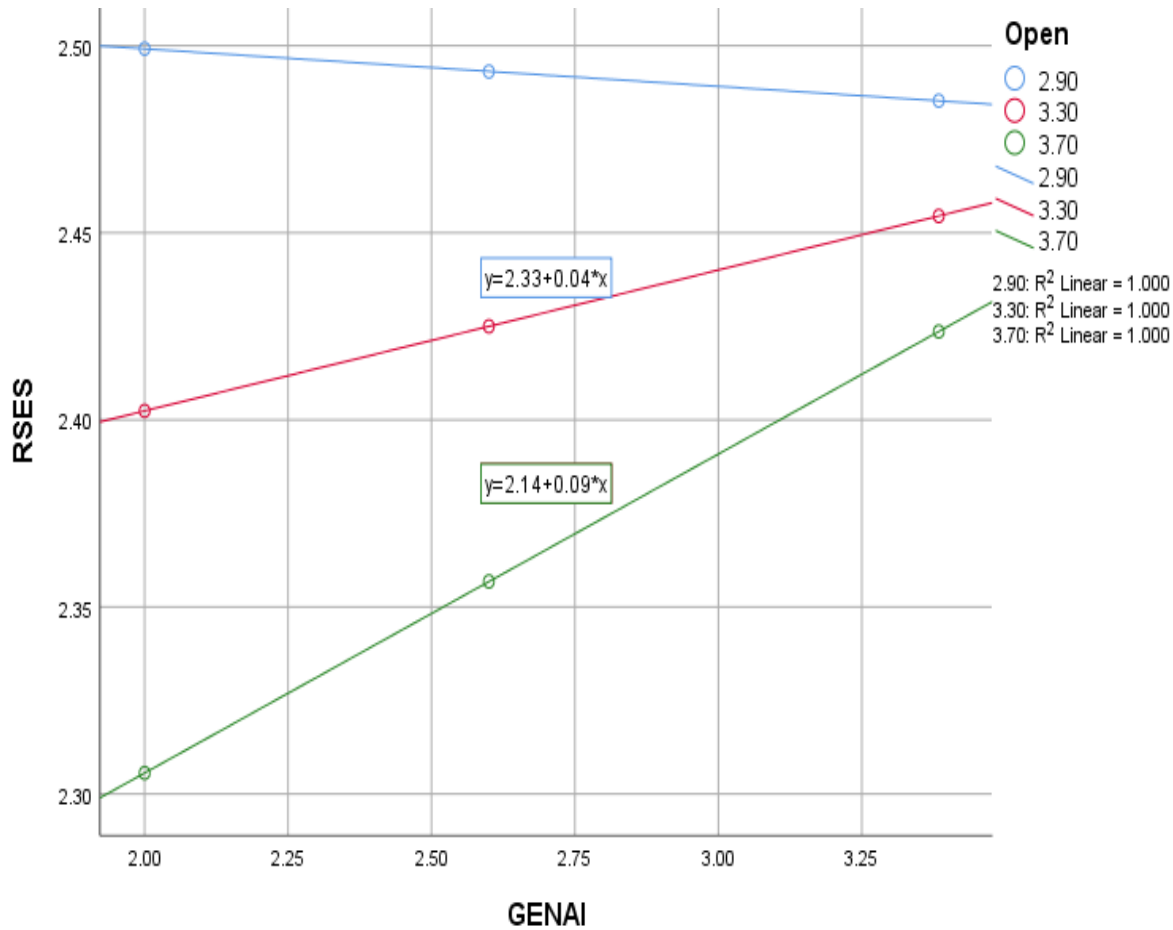
Predictor	B	SE	t	p	95% CI	
					LL	UL
Constant	3.91	0.43	9.19	< .001	3.07	4.75
AI Dependency (IV)	-0.36	0.16	-2.17	.031	-0.68	-0.03
Openness (Moderator)	-0.48	0.13	-3.77	< .001	-0.73	-0.23
AI × Openness	0.12	0.05	2.44	.015	0.02	0.22
R^2	.30					
F	11.41					

ΔR^2	.016
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Note. N = 350. CI = confidence interval.

Importantly, the interaction between AI dependency and openness was significant, $B = 0.12$, $t(346) = 2.44$, $p = .015$, indicating that openness moderates the association between AI dependency and self-esteem.

Figure 6: Moderation of Openness on the Relationship Between AI Dependency and Self-Esteem (N=350)



Note. GENAI = generative AI dependency; RSES = self-esteem; open = openness

Table 8: Summary of moderation analysis of Personality Traits with AI dependency and students' challenge (N=350)**Moderation Effects: Significant vs. Non-Significant**

Green solid line (—) = Significant moderation ($p < .05$) | Red dashed line (- - -) = Non-significant moderation ($p > .05$)

Outcome Variable	Moderator (Interaction)	B	SE	t	p	ΔR^2	Effect	Significance Indicator
SCS	Extraversion	-0.15	0.08	-1.81	.072	.009		Not Significant
SCS	Agreeableness	-0.23	0.08	-2.96	.003	.023		Significant
SCS	Conscientiousness	-0.14	0.07	-1.94	.053	.010		Not Significant
SCS	Neuroticism	0.14	0.08	1.81	.071	.009		Not Significant
SCS	Openness	-0.15	0.08	-1.95	.052	.010		Not Significant
Self-Esteem	Extraversion	0.15	0.05	2.83	.005	.022		Significant
Self-Esteem	Agreeableness	0.16	0.05	3.27	.001	.027		Significant
Self-Esteem	Conscientiousness	0.17	0.04	4.03	< .001	.036		Significant
Self-Esteem	Neuroticism	-0.06	0.05	-1.20	.230	.004		Not Significant
Self-Esteem	Openness	0.12	0.05	2.44	.015	.016		Significant
ESSA	Extraversion	0.04	0.10	0.37	.710	.0004		Not Significant
ESSA	Agreeableness	0.01	0.09	0.10	.920	.0000		Not Significant
ESSA	Conscientiousness	0.07	0.08	0.81	.421	.0017		Not Significant
ESSA	Neuroticism	-0.01	0.09	-0.16	.873	.0001		Not Significant
ESSA	Openness	0.09	0.09	0.98	.327	.0023		Not Significant

-0.40 -0.20 0 0.20 0.40
Effect Size (B)

Legend

- Significant moderation ($p < .05$)
 - - - Non-significant moderation ($p > .05$)

Notes

- SCS = Social Connectedness
- ESSA = Educational Stress
- Green solid lines indicate significant moderation effects.
- Red dashed lines indicate non-significant moderation effects.

Discussion

This study designed to explore the association between the use of artificial intelligence and personality traits with general social, psychological and educational difficulties of university students. The use of AI tools is influenced by academic pressures, personality, expectations with regards to the institutions and peer culture, and the perceived availability of human support. The quantitative results confirmed the relationships between AI dependency, social connectedness, self-esteem and educational stress and

personality traits in measurable way. The descriptive results showed that the overall dependency on AI was low to moderate, social connectedness was moderate, and the education-related stress level was moderate with moderate levels of self-esteem. The trend indicates that the usage of AI is becoming a regular part of students' lives, though the majority of students in this sample might not be considered to be highly relying on it. However, there were social and educational implications, even with moderate dependency. The majority of the respondents were undergraduate students, with the majority using ChatGPT as their main AI tool. Academic usage was the most frequent use of AI followed by problem solving and coding. What matters here is the overall, as it shows that the students see AI mainly as a means to enhance their studies, rather than for entertainment or socializing. The frequency data also highlighted that a substantial proportion of students were spending more than two hours per day with AI, hinting at the possibility that some learners may have integrated AI into their learning process.

The first major finding was that there was a significant and negative association between AI dependency and social connectedness. Correlation between the use of AI and social connectivity was statistically significant, although small to moderate. AI dependency also significantly predicted lower social connectedness (as confirmed by regression analysis). Helps to justify the claim that over-dependence on AI could restrict opportunities for meaningful peer interaction, teacher consultation, and collaborative learning.

Our results on negative association between AI dependency and social connectedness are also well supported by the recent research. A quantitative survey study was conducted with 450 emerging adults (18-29 years) in Universities of Islamabad and Rawalpindi by Nayyar and Maqsood (2026). They found that when people think the AI chatbots (such as Replika or ChatGPT) are caring and empathetic, they tend to be more emotionally dependent on the artificial personalities. Importantly, these correlated directly with reported less loneliness, less contact with friends and family, and less face-to-face contact. Students who thought that AI "understood" them were also more likely to refrain from real human relationships, thus directly supporting our finding.

Similarly, Sajjad (2024) used cross sectional survey design to examine attitude of 617 students of universities located in southern Punjab (Multan and Bahawalpur). The research found that social isolation was a significant factor in excessive use of ChatGPT, and importantly, that excessive use of ChatGPT was a factor in higher levels of social isolation among peers and family. It created a vicious circle as follows: lonely students ask for assistance from AI or want to be with it, but when they use AI, they are less inclined to interact with others, which in turn causes their social connections to become weaker. This is a cyclical pattern, which lends support to the own cross-sectional finding.

The second major finding was that AI dependency was significantly and positively related to educational stress. AI dependency accounted for a significant amount of variance in educational stress ($p < .001$). There are two ways to interpret the relationship. First, students who are already stressed about their academic performance may be more likely to be using AI due to the need for immediate assistance. Second, it can lead to increased stress if students feel uncertain about the accuracy, originality, academic integrity or their own competence without using AI. This result is consistent with the I-PACE model that views problematic use of technology as a joint product of affective responses, personal dispositions, cognitive responses, and executive control. AI might be used by students experiencing stress because of the quick response time and reducing cognitive load. This is an ongoing process and, if it is maintained, the dependence on AI can be reinforced and its use can become a habit. Over time, students may become more accustomed to academic risk and may turn to short cuts for their learning. This can be an extra burden on students' shoulders, as they might feel less confident and competent in solving problems independently, especially during exams or in speaking situations, or in places where using AI is not allowed. In this way, a dependence on AI can be a root cause and result of educational stress.

In the context of Pakistan's higher education system, Sajjad (2024) conducted a survey of 617 students from universities in the southern region of Punjab and discovered that academic workload was a strong determinant of excessive use of ChatGPT. Students who were under a lot of academic pressure resorted to the use of AI as a coping mechanism, but it was a stress all its own.

Likewise, Zaib (2026) investigated the effect of 385 students in the academic writing of The Islamia University of Bahawalpur and revealed that the cognitive load reduction caused by AI tools in academic writing can sometimes paradoxically result in heightened dependency-related stress when students do not have access to these tools.

Most impressively, Qayyum (2026) performed a phenomenological study on 32 university students from Pakistan, and reported cognitive-offloading and erosion of self-confidence in the absence of AI assistance, with students explicitly stating that they felt anxious and stressed when required to perform in the absence of AI assistance.

The third significant discovery was that reliance on AI was not a strong predictor of people's self-esteem. There was a positive and non-significant correlation between AI dependence and self-esteem. This indicates that the use of AI is unlikely to have a straightforward linear relationship with students' self-worth in the global context. AI use could also help students build competence by providing explanations and feedback for some students. For some, over-dependence can lead to a loss of confidence in their ability to work independently. So, there's no reason to believe the nonsignificant relationship is devoid of psychological significance. Instead, it implies that self-esteem is multifaceted and can be impacted indirectly by the use of AI, such as through self-efficacy, perceived competence, academic performance, social comparisons and personality characteristics.

Regarding our second finding, we found that there was a positive correlation in the case of self-esteem, although it was not statistically significant based on the AI dependency. Ahmad and Hassan (2025) conducted a survey of 520 Pakistani university students on AI use and self-esteem and, once again, did not find a significant enough association between the two. There were also opposing effects, as some students felt more confident in their academic performance with the aid of AI, whereas others felt like they were not doing well or that AI made them feel vulnerable, they said.

Batool and Riaz (2024) provided a theoretical account of it. They examined 380 young adults in Faisalabad and found that dependency on AI (like the desire for social validation through algorithms) has two counteracting effects: AI can give short-term "ego boosts" by giving positive reinforcement, but it can also result in upward social comparisons, which decrease self-worth. These conflictual factors can neutralize the other, and leave a near zero net correlation. In the cross-cultural study across India, South Korea and the United States ($n = 1,200$) Sharma and Lee (2025) found that the positive correlation between AI chatbot dependency and self-esteem is weak and non-significant in all three cultures when loneliness is included in the analysis.

The moderation results add to the comprehension of individual variability. The effects of personality traits on the relationship between AI dependency and educational stress were not significant. This indicates a possibly broad pathway of the stress across personality profiles. In other words, when students rely heavily on AI, the association with educational stress appears regardless of whether they are more extraverted, agreeable, open, conscientious or neurotic. Academic stress can be significant and impact students at a wide level, particularly in competitive university settings where grades, deadlines and performance expectations are all significant. There were some relationships between social connectedness and self-esteem that were moderated by personality traits, however. This means that personality plays a greater role in determining social and psychological interpretations of the use of AI than in determining the stress relationship.

Agreeableness had significant moderation effects for social connectedness. The results showed that the social aspects of personality affect the relationship between dependency on AI and social experience. A possible interpretation is that the initial social networks might be stronger for students who are high in extraversion or agreeableness, but over-reliance on AI could lead to a greater contrast due to the decrease in typical social interaction patterns. Another interpretation would be that students with social orientations could utilize AI in collaborative environments, but then the reliance of AI may hinder face-to-face interactions when AI becomes the primary source of answers. Qualitative interviews provide support to the idea that there is a correlation between students' personality and their use of AI. Participants mentioned introversion, laziness, anxiety, organization, and trust as factors influencing their use of AI, checking AI output, or relying on human assistance.

The AI dependency relationship was significantly moderated by the factor of self-esteem, openness, extraversion, agreeableness and conscientiousness. The findings reveal that the use of AI does not impact students' psyches equally. AI can be used more ethically by conscientious students, who can verify answers and incorporate AI into their organized study routines. Students with a positive attitude to openness can leverage AI to explore and brainstorm new concepts instead of simply copying and pasting content. Extraverted students can use the AI assistance in addition to the discussion, and agreeable students can be sensitive to feedback and ethical issues.

As a result, these factors can modulate or alter the psychological significance of using AI. In contrast, neuroticism did not significantly moderate self-esteem in this sample, although it was related to educational stress and self-esteem in the correlation matrix. This suggests that general stress and self-evaluation are more strongly linked to the dependency pathway on the AI than is the dependency pathway on the AI itself.

Recommendations

Universities

- Advance clear AI-use policies
- Define appropriate assistance,
- Prohibited practices and costs of misuse.
- Policies should be educational rather than only punitive.

Counsellors

- Screen excessive AI reliance as a possible indicator of
 - academic stress, avoidance coping, low confidence or social isolation.
- Provide support for time management, study skills and anxiety reduction.

Students

- Students should use AI as learning assistant, not as a replacement for personal efforts.
- Assistance includes getting ideas and framework but final work should be written in own words.

Teacher

- Design assignments that require process evidence, reflection, classroom discussion, oral explanation and application to local contexts.
- This reduces passive copying and encourages deeper learning.

Future researcher

- Use longitudinal and experimental designs to clarify whether AI dependency causes stress and social disconnection or whether stressed and isolated students become more dependent on AI.

Policy makers

- Support responsible AI frameworks for Pakistani higher education, including teacher training, student guidance, data privacy standards and equitable access to digital resources.

Limitations of the Study

Causal relationships cannot be confirmed in the study, because the study design was cross sectional. The results indicate relationships between AI dependency, personality traits and student outcomes, but do not confirm that AI dependency actually leads to a decrease in social connectedness or increase in educational stress. Data were obtained using self-report questionnaires that can be influenced by social desirability, memory bias, and/or misunderstandings of questions. Students can account for AI usage in ways that lead to underreporting and/or overreporting their usage based on their definitions and understandings of dependency and academic integrity. The results of this study may not be applicable to school students, working adults or students in countries with varying education culture or AI policies. AI dependency is a relatively new field. Emerging capabilities are emotion-engaging, multimodal AI use, agentic AI systems, and AI-assisted social communication, which could become additional dimensions of a future scale.

Future Research Directions

Longitudinal studies are recommended to identify whether dependence on AI grows over time and if AI predicts changes in academic stress, self-esteem, and social connectedness and performance later in life. Students who use AI to explain, students who use AI to generate answers, and students who use traditional study methods can be compared in experimental studies. This would help explain what kind of uses of AI are conducive to learning and what kind are not conducive to learning.

Further studies need to address other psychological factors including perfectionism and emotional regulation, fear of failure, procrastination and the perception of loneliness, and academic self-efficacy. These factors can help to understand the formation of reliance on AI. One of the other areas that should be explored is the difference across disciplines. Students with backgrounds in computer science, engineering, psychology, and business and humanities have different ways of using AI in their studies and academic integrity issues. The next study in Pakistan should involve students from multiple provinces, public and private universities, and urban and rural students to gain greater generalizability and gain a better understanding of the culture.

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