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Dependency on Generative AI as predictor of Self-Efficacy in Writing and Defending Academic Texts Among University Students

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ARTICLE INFO	ABSTRACT
Submission: July 06, 2026 Revised: July 22, 2026 Accepted: August 10, 2026 Available Online: August 24, 2026 Keywords: <i>Generative Artificial Intelligence. Self-efficacy. University students.</i> Corresponding author: Misbah Arshad Email: misbah.arshad@uog.edu.pk	The current study investigated the relationship between the dependency on Generative Artificial Intelligence (GenAI) and self-efficacy in writing and defending academic texts among university students. The sample for this cross-sectional research design was university students across various degree levels. To measure the study variables Self-Efficacy for Writing and Defending Academic Texts Scale and the Generative AI Dependency Scale were used. The results revealed a significant negative relationship between overall GenAI dependency and total academic text self-efficacy. Specifically, the withdrawal dimension of AI dependency exhibited inverse associations with both writing self-efficacy and oral defense self-efficacy. Comparative analyses revealed that male students reported higher writing self-efficacy than female students. Moreover, significant differences were observed across academic qualification levels, with postgraduate students demonstrating higher self-efficacy in academic writing compared to undergraduate students. The results indicate that although cognitive involvement with AI has no direct negative impact on writing confidence, behavioral reliance and withdrawal symptoms share a strong negative relationship with students' confidence in drafting and defending scholarly work and orally justifying scholarly work. Consequently, higher education institutions must balance technological assistance with interventions that safeguard students' independent academic competence and defense readiness.

Introduction

The quick rise of Generative Artificial Intelligence (GenAI) has changed education, changing how university students work with research thinking critically and writing academically. Different from search engines, powerful GenAI services like ChatGPT put together complicated books, make text, improve grammar and help with writing papers going from extra tools to main parts of the academic work (Organization for Economic Co-operation and Development [OECD], 2026). Even though GenAI has benefits for teaching like making it faster to think of ideas, making language better and giving instant help with writing (Peterson, 2026) its quick spread has caused worries about students using it too much. Using AI-generated content can make students' thinking skills weaker, their ability to think on their own less and their honesty in work when difficult thinking tasks are given to machines (Deep & Chen 2025; Kaabi, 2025). Dependence on Generative AI is seen as a pattern of using it much with less control, thoughts that keep coming back feeling bad when not using it and still using it even when it leads to bad results (Tate et al. 2023 as cited in Revesai, 2025). Looking at how it affects student's ability to take charge of their learning has become very important to study.

Self-efficacy, an idea in Bandura's Social Cognitive Theory, is about a person's belief in their ability to do things needed to reach certain goals (Bandura, 1997). Students with self-efficacy are more motivated to keep going and are stronger when facing school problems (Artino, 2012). Writing self-efficacy is about how a student feels confident in organizing thoughts following rules for writing and sharing ideas in text (Li et al., 2024). Being good in school is more than just writing. Students also need to speak and defend their work during exams like thesis defenses and viva. To understand these needs, Collado et al. (2023) Made the Self-Efficacy for Writing and Defending Academic Texts (SEWDAT) Scale showing that doing well in school needs both writing and speaking confidence.

Bouzar et al. (2024) found a positive correlation between engagement with ChatGPT and writing self-efficacy with the help of feedback features of GenAI and how using it can lead to a sense of accomplishment. However, Zhang et al. (2024) found a negative impact of AI dependency on independent critical thinking. This finding was further supported by Jia et al. (2025), who revealed a positive relationship between GenAI dependency and false self-efficacy. The contradicting nature of these findings was further clarified by Abbas et al. (2026), which revealed that while AI support increased efficiency, it negatively impacted understanding of the students by reduced conceptual integration. This study further elaborated that the impact of AI mediated learning is influenced by the regulation of factors including trust, effort and autonomy.

The current study is based on Bandura's (1997) idea, which says that self-efficacy comes from doing tasks on your own. In writing that happens when students think of ideas, check evidence, bring together books and fix their work. When students use GenAI much for these thinking parts they don't get real chances to learn and they start to think that the success is because of the tool, not their own work (Bandura, 1997). Also researchers say there is a difference between using AI as a helper or as something that replaces thinking (Guo et al., 2024). As a crutch AI takes over the thinking. This difference is important during speaking exams, where AI can't do the thinking and deep knowledge that is needed in a viva.

The present study was designed to explore the association between Generative AI dependency and self-efficacy in writing and defending texts among university students. This study specifically looks at whether higher levels of Generative AI dependency are linked to lower confidence in writing and defending academic manuscripts on their own. Previous research explored AI use writing self-efficacy and academic performance separately. In Pakistan the use of Generative AI in education sector has increased quickly helping students who are trying to meet English language requirements and academic writing standards (Majeed et al., 2022; Qadeer, 2025). However, while there have been studies on writing anxiety and general AI use, little research has looked at students' confidence in defending work that is done with AI. With the increase in Generative AI use, filling this gap will help understand the effects of relying on Generative AI and will give real data to help set rules for using AI properly in higher education.

Method

Study Design and Participants

This cross-sectional correlational research explored the relationship of Generative Artificial Intelligence and self-efficacy about writing and defending their work. The participants in this study were university students from various public and private sector universities in Pakistan. There were 1104 students participated in the study.

Measures

The instruments that were used in the study were: demographic form, the Generative AI Dependency Scale and the Self-Efficacy for Writing and Defending Academic Texts Scale.

Demographic Form: This form was made based on what people wrote and it included, gender, age, semester, program, degree, public or private sector university.

Generative AI Dependency Scale (GAIDS): The Generative AI Dependency Scale was developed by Goh and his team in 2025. This scale was used to measure how people depend on Generative AI tools. It has 11 questions with rating from 1 to 5. The scale has three parts: how much people think about Generative AI, what bad things happen when they use it and what happens when they stop using it. The score high shows that the dependency on Generative AI is high.

Self-Efficacy for Writing and Defending Academic Texts Scale (SEWDAT): This scale was developed by Collado and his colleagues in 2023. This scale is used to find out how confident students are when they write about what they learned and when they talk about what they learned. The Self-Efficacy for Writing and Defending Academic Texts Scale has 8 questions that people answer by giving a score from 1 to 5. The Self-Efficacy for Writing and Defending Academic Texts Scale is divided into two parts: one part looks at how confident participants are, when they write and the other part looks at how confident people are when they talk about what they learned.

Procedure and Ethical Consideration

There were total 1104 participants took part in the study. The participants were approached electronically through social media and google forms were shared in many groups among various universities. Moreover, the data were also collected physically through hardcopies of the measures. The permission at every stage was granted from the authorities and from the participants as well. It took almost 15 to 20 minutes to finish the survey. The data was compiled and analyzed by using Excel and IBM SPSS. The current study follows the American Psychological Association guidelines. All the participants, who took part in this study agreed to share their information before we gathered it. People who took part in the study were informed what our study was about and what we were going to do. We kept everything about the people who took part in the study secret. The researchers ensure the anonymity and confidentiality of the participants, who took part in it. The participants were also ensured that, if they want to quit at any time, they can without any penalty. The collected information about the participants were kept safe and only used it for the research purpose.

Results

The data set was screened for missing values, multivariate outliers, and assumptions of normality before preceding hypothesis testing. For analysis, a total of $N = 1104$ valid responses were retained. The descriptive statistics and correlation analysis among variables GEN AI Dependency and Academic self-efficacy were computed.

Table 1: Descriptive Statistics and Pearson Correlation for Variables of Generative AI Dependency and Academic self-efficacy ($N=1104$)

Variables	(M)	(SD)	1	2	3	4	5	6	7
Total S.E	26.6	6.26	---						
Writing S.E	16.2	4.28	.94 ^{***}	---					
Oral S.E	10.4	2.71	.83 ^{***}	.58 ^{***}	---				
GAID Total	32.3	8.63	-.08 ^{**}	-.09 ^{**}	-.04	---			
GAID: Compulsion	9.0	2.81	.03	.02	.05	.80 ^{***}	---		
GAID: Negative consequences	12.3	3.56	-.04	-.04	-.03	.85 ^{***}	.57 ^{***}	---	
GAID: Withdrawal	11.0	3.93	-.16 ^{***}	-.17 ^{***}	-.10 ^{**}	.86 ^{***}	.52 ^{***}	.56 ^{***}	---

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

As shown in Table 1, the mean score for generative AI dependency total is $M = 32.3$ ($SD = 8.63$), while total academic self-efficacy is $M = 26.6$ ($SD = 6.26$). A statistically significant positive correlation between writing self-efficacy and total self-efficacy, $r = .94$, $p < .001$ was shown by Pearson correlation analysis. Moving on studies show oral self-efficacy has statistically significant positive association with total self-efficacy, $r = .83$, $p < .001$ and writing self-efficacy, $r = .58$, $p < .001$. On the other hand, Generative AI dependency total has a significant weak negative relationship with total self-efficacy, $r = -.08$, $p < .01$, and writing self-efficacy, $r = -.09$, $p < .01$. Moreover, generative AI dependence subscale withdrawal has statistically significant negative association with total self-efficacy, $r = -.16$, $p < .001$. Whereas Generative AI dependence compulsion subscale and total self-efficacy has non-significant correlation, $r = .03$, $p > .05$, along Generative AI dependence subscale negative consequences and total self-efficacy, $r = -.04$, $p > .05$.

Table 2: Linear Regression Estimating Academic Self-efficacy from Generative AI dependency (N=1104)

Variables	B	Std. Error	Beta	p
(Constant)	28.4***	.73		<.001
GEN AI Total	-.06**	.022	-.08	.009
R ²	.006			

Note. *** $P < .001$

Table 2 presents the effect of Generative AI dependence on self-efficacy in writing and defending oral text. The independent variable demonstrated 0.6% variance in dependent variable with $F(1,1102) = 6.786$, $p < 0.01$, that is shown by value of $R^2 = .006$. Dependency on GENAI ($\beta = -.08$, $t = -2.61$, $p = .009$) negatively predicted Self-Efficacy according to results.

Table 3: Independent Samples t- test Comparing Gender Differences Across all Variables

Variables	Females		Males		p	t (1102)	Cohen's d
	M	SD	M	SD			
Total S.E	26.1	6.28	27.64	6.11	<.001	-3.97	.26
Writing S.E	15.91	4.28	16.81	4.23	.001	-3.26	.21
Oral S.E	10.13	2.73	10.83	2.61	<.001	-4.00	.26
GAID Total	31.1	8.40	32.10	9.07	.073	-1.80	.16
GAID Compulsion	8.86	2.74	9.21	2.93	.054	-1.93	.12
GAID: Negative consequences	12.28	3.44	12.46	3.82	.46	-.74	.05
GAID: Withdrawal	10.82	3.83	11.29	4.11	.07	-1.81	.12

To analyze gender differences across academic self-efficacy and generative AI dependency, an independent samples t test was carried out. Table 3 shows significant mean difference in total self-efficacy, $t(1102) = -3.97$, $p < .001$, $d = .26$, with males ($M = 27.64$, $SD = 6.11$) scoring higher than females ($M = 26.1$, $SD = 6.28$). likewise, males reported significantly higher scores in both writing self-efficacy $t(1102) = -3.26$, $p = .001$, and oral self-efficacy, $t(1102) = -4.0$, $p < .001$, stating a predictable pattern of higher academic self-efficacy among male participants. In contrast, no statistically significant difference was observed in total Generative AI Dependency between males ($M = 32.10$, $SD = 9.07$) and females ($M = 31.1$, $SD = 8.40$). Further analysis of sub scales shows no meaningful distinction over compulsion, $t(1102) = -1.93$, $p = .054$, $d = .12$, negative consequences $t(1102) = -.74$, $p = .46$, $d = .05$, and withdrawal, $t(1102) = -1.81$, $p = .07$, $d = .12$.

Table 4: Mean, Standard Deviation and Multiple One-Way Analysis of variance in variables of Self-Efficacy and Generative AI Dependency across educational levels

Variables	ADP		BS		PGD		MS/MPHIL		PHD	
	M	SD	M	SD	M	SD	M	SD	M	SD
Total S.E	25.7	6.7	26.3	6.2	31.8	4.1	30.0	6.2	34.3	4.8
Writing S.E	16.2	4.68	16.0	4.2	20.0	1.8	18.6	4.25	21.5	2.8
Oral S.E	9.5	3.1	10.3	2.7	11.8	2.5	11.4	2.6	12.8	2.4
GAID Total	31.8	8.5	32.4	8.5	25.3	3.4	32.2	9.4	23.3	9.7
GAI Compulsion	9.0	2.5	9.01	2.8	7.5	1.3	9.04	3.1	6.6	3.21

GAID: Negative consequences	12.5	3.3	12.4	3.5	9.5	3.42	12.6	3.7	9.3	3.7
GAID: Withdrawal	10.3	3.98	11.05	3.9	8.3	.50	10.6	4.2	7.5	3.6

Note. *** $P < .001$

Table 4 shows mean and standard deviation values for variables of academic self-efficacy and generative AI dependency across education levels. Findings indicate that participants with higher educational level have higher mean academic self-efficacy with PHD students stating the highest mean score ($M = 34.3$, $SD = 4.8$) prior to PGD ($M = 31.8$, $SD = 4.1$), MS/MPHIL ($M = 30.0$, $SD = 6.2$), BS ($M = 26.3$, $SD = 6.2$) and ADP Students ($M = 25.7$, $SD = 6.7$). On the other hand, Generative AI dependency mean scores were higher in BS students ($M = 32.4$, $SD = 8.5$) whereas low dependency scores were reported by PHD ($M = 23.3$, $SD = 9.7$) and PGD students ($M = 25.3$, $SD = 3.4$).

Table 5: Post hoc Analysis

Variables	$F(4,1099)$	η^2	Post hoc
Total S.E	9.7***	0.034	1<2<3>4<5
Writing S.E	10.13***	0.036	1>2<3>4<5
Oral S.E	5.01***	0.018	1<2<3>4<5
GAID Total	3.79**	0.014	1<2>3<4>5
GAID Compulsion	2.4*	0.009	1<2>3<4>5
GAID: Negative consequences	2.8*	0.01	1>2>3<4>5
GAID: Withdrawal	3.10*	0.011	1<2>3<4>5

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

The analysis of results indicated mean difference across educational levels on total self-efficacy with $F(4,1099) = 9.7$, $p < .001$. PHD students have a higher level of self-efficacy as compared to PGD and MS/MPHIL. The value was .034 ($< .20$) which showed very small effect size. The Post HOC comparison also reported that PHD students have higher Academic self-efficacy than other education levels. In contrast, results indicated mean difference across educational levels on generative AI dependency $F(4,1099) = 3.79$, $p < .01$. post HOC Comparison also stated BS students have higher level of dependency on generative AI as compared to other education levels which indicated very small effect size of .014 ($< .20$).

Discussion

The present investigation aimed to examine the relationship between generative AI dependency and self-efficacy in writing and defending academic texts in university students. This study aligns to the existing literature specifying a significant negative relationship between academic self-efficacy and AI reliance, which can yield to unhealthy dependency (Estrada Araoz et al., 2025; Zhang et al., 2024; Rodriguez et al., 2024). However, our findings about the writing subscale of academic self-efficacy indicate a contradiction with some of the previous studies. Barendregt (2026) stated a neutral impact of AI support interventions in different phases of writing process on overall independent writing self-efficacy of students. On the other hand, Eshelman (2024) reported an increase in students' writing self-efficacy due to feedback features of AI. These contradictions can be explained by considering that students' writing self-efficacy is influenced by additional factors such as academic stress, performance expectations as stated by Zhang et al. (2024), and their abilities to think critically and comprehend digital information as reported by Haliq et al. (2025). Similarly, the oral self-efficacy subscale exhibited a non-significant negative correlation with total generative AI dependency, continuing to reinforce the tendency of decreased academic self-efficacy due to reliance or dependency on generative AI (Estrada Araoz et al., 2025; Zhang et al., 2024; Rodriguez et al., 2024).

While total generative AI dependency remains a statistically significant predictor of total academic self-efficacy in this study, only its withdrawal sub-scale is a statistically significant negative correlate across total academic self-efficacy and both of its sub scales. This interesting finding shifts attention towards the psychological experience of disconnecting from generative AI use in cases of dependency or addiction, which can range from mild reactions such as irritability and anxiety to more severe grief reactions (Kelly et al., 2026). As casual engagement with AI evolves into compulsive use, this psychological distress appears to negatively impact academic self-efficacy among students based on the findings of our study. Other sub scales of generative AI dependency do not present statistically significant correlations with total self-efficacy and its subscales. However, a noticeable difference shows

cognitive preoccupation (salience and compulsive use) forming a positive correlation with total academic self-efficacy (and its subscales) while negative consequences subscale forming a negative correlation with the total academic self-efficacy (and its subscales).

The strange positive correlation can be explained by the phenomenon of how compulsive use of generative AI makes it appear as a support system for our everyday life (Kelly et al., 2026). The cognitive preoccupation highlights the positive scaffolding impact of generative AI, as established by Guo et al. (2024). This perceived support buffers the academic stress among students. The psychological well-being among students is evidently found to form a significant positive relationship with academic self-efficacy (Chikampa et al., 2025). The negative correlation however, can be explained by how concerns about AI reliance and reduced critical thinking has made people realize the need for regulations on AI usage in academia (Vieriu & Petrea, 2025). This attitude results in a precautionary use of generative AI which reduces its negative consequences and encourages students to utilize personal efforts for accomplishing challenging academic tasks. These enactive mastery experiences are established through the Bandura's (1997) framework of this study. Moreover, by distinguishing the use of AI as a scaffold, and as an intellectual crutch, this aligns with our aim to consider the dual impact of generative AI (Guo et al., 2024).

Study findings showed significant differences for demographic correlates in relation to academic self-efficacy. The results revealed that male university students have a higher level of academic self-efficacy than female university students. This finding aligns with the same variable study of Peruvian university students which suggested that males reported to have greater confidence to handle challenging academic situations, therefore leading to more positive perceptions about their academic abilities (Estrada Araoz et al., 2025). These differences can be further explained through social and psychological factors including stress, self-imposed demands, and social norms. (Morán-Soto & González-Peña, 2022). Despite a systematic review of gender differences regarding the usage of AI tools for learning in higher education students suggesting that female students have stronger concerns about AI dependency when using AI tools as compared to male students, this study however revealed no significant differences across genders in generative AI dependency. The results reinforced the idea that AI is becoming deeply integrated with the academic experiences of everyone regardless of their gender, even if contradicting studies suggest an uneven adoption of AI tools across genders with females being more cautious and selective (Abusa'aleek & Alenizi, 2024; Freeman, 2025, as cited in Matobobo, 2026).

Additionally, through a one-way ANOVA, study variables were found to have significant variation across five distinct academic levels including ADP, BS, PGD, MS/MPHIL and PHD students. Post-hoc comparisons showed that as the degree level increased (PGD, MS/MPHIL and PHD), not only total academic self-efficacy increased, both of its dimensions: writing self-efficacy and oral self-efficacy also increased. Conversely, lower degree levels (undergraduates) exhibited higher generative AI dependency as compared to higher degree levels (PHD), confirming an inverse trend. Although a non-linear drop is observed at PGD level, these results are consistent with Estrada Araoz et al. (2025), if the chronological age pattern across different degree levels is held constant. Estrada Araoz et al. (2025) observed an age pattern among students stating that older students with their maturity and previous experiences to handle academic demands have a higher academic self-efficacy as compared to younger students. On the other hand, younger students are more accustomed to AI due to growing up in a digitized environment and hence more prone to reliance on AI as opposed to older students.

Study findings highlight the need for interventions targeting two domains. First, promoting AI dependency literacy among students to make them aware of the negative consequences of AI. This approach will ensure a conscious use of generative AI reducing any risks of compulsive behaviors. Second, an institutionalized effort is demanded to incorporate lower education degree levels with academic self-efficacy through intervention programs. Further research is needed to investigate other factors like perceived social support, individual competencies and coping strategies for academic pressure. Furthermore, a longitudinal research design to study these variables would provide developmental insights that are not accomplishable through a cross-sectional research design.

Limitation and Future Directions

The current research offered important findings regarding the correlation between Generative AI Dependency and academic self-efficacy. Despite these findings, several limitations must be acknowledged. To begin with, the research used a cross-sectional design (data collected at a single point in time) thus the design cannot establish cause and effect relationships. It is not possible to prove whether higher AI dependency influences the self-efficacy or if existing self-efficacy causes changes in varying AI usage patterns. Secondly, Data were collected utilizing self-report questionnaires that are subject to social desirability bias and response bias. Additionally, Group sample size imbalances across educational levels can affect statistical power, homogeneity of variance and post

HOC comparison. Moreover, unmeasured confounding variables such as prior digital literacy, instructor attitude toward AI and personal motivation could account for variance in both AI dependency and academic self-efficacy.

Conclusion

The current study aims to investigate the association between university students' generative AI dependency and academic self-efficacy. As university students excel from undergraduate degree levels to post graduate level, they have to acquire skills for writing and defending their academic texts. Undergraduate students are more likely to develop AI dependency because of increased digitization of their surroundings and limited academic writing and oral skills. Various social and psychological factors such as gender, stress, social demands and norms not only contribute to the development of academic self-efficacy but also play a role in attitudes towards the use of generative AI tools. Students experiencing cognitive preoccupation reported to have positive association with academic self-efficacy due to perceived support provided by these systems. However, increased reporting for negative consequences highlights the growing concerns regarding generative AI tools and a need for regulating them. Withdrawal remains an essential component drawing parallels between AI dependency and other addictive behaviors in the public health domain. The results highlight a need to separate the instrumental use of generative AI tools from viewing them as compensatory support systems. Future studies need to investigate other psychological and social factors to broaden the literature on the dual impacts of generative AI, which thus will lead to effective training, dependency prevention and skills development initiatives.

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