Artificial Intelligence Dependency and Student Learning Outcomes: The Mediating Role of Cognitive Engagement and Self Efficacy

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***Abstract*—Generative Artificial Intelligence (GenAI) has quickly permeated the higher education sphere, affecting how students learn. While using such technologies can provide ample and individualized assistance right away, the reliance on AI can potentially change the outcomes of student learning as well. This paper studies the correlation between our dependence on the use of AI and educational achievement, taking cognitive engagement and self-efficacy as mediators. A survey of a group of 412 representatives of higher education institutions was conducted. The gathered data was analyzed with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM) with 5000 bootstrapping replications. According to the results of research, AI dependence can have a strong influence on learning outcomes, level of cognitive engagement, and self-efficacy. In addition, cognitive engagement and self-efficacy serve as significant mediators in the connection between AI dependence and learning outcomes.**

***Index Terms*—Generative Artificial Intelligence; AI Dependency; Cognitive Engagement; Self-Efficacy; Learning Outcomes; Higher Education.**

I. INTRODUCTION

The rising use of Generative Artificial Intelligence (GenAI) in universities has opened a new landscape of learning for students through personalized education, real-time feedback, and academic assistance. However, an increase in the reliance on the available AI resources may change the way in which learners tackle their educational activities independently and how effectively they cope with them. Consequently, researching the influence of AI on education presupposes a dualistic approach to the matter where both the magnitude of AI usage and the psychological and cognitive mechanisms involved should be considered. Thus, cognitive engagement and self-efficacy are essential for studying whether AI facilitates learning or leads to over reliance on technology.

1.1. Generative Artificial Intelligence in Education

Generative Artificial Intelligence (GAI) is a unique and strong type of artificial intelligence. It is used for the purpose of creating material that seems human in response to various types of inquiries and commands made utilizing deep learning models (Lim et al., 2023). ChatGPT is among the most well-known tools in this field and has won its users over due to its amazing ability to give answers similar to those of humans and to interact in different languages. The complexities of GAI have caused controversies regarding the role of conventional activities of people in energy production (Holly, 2023; Stokel-Walker, 2023) and issue of ethics.

1.2. Opportunities and Challenges of GAI in Learning

In the educational sphere, GAI has shown its effectiveness in practice in a very short period of time. Educators have different attitudes toward using GAI. Whereas people like Noam Chomsky criticize GAI calling it “high-tech plagiarism” and “the way of skipping learning,” many teachers believe that GAI can improve the process of teaching and learning in terms of personalized tutoring, automatic essay grading (Terwiesch, 2023), interactive learning adaptive studying, and providing several examples and explanations. Some institutions, for example New York City public schools (Lukpat, 2023), banned the use of ChatGPT. Nevertheless, banning GAI may cause more negative results as the banning

may lead to the Streisand Effect and psychological resistance. These two phenomena make GAI more popular in case of its ban and increase students' resistance to rules and regulations. Promoting the understanding of GAI technologies, teaching students how to use these tools properly, and discussing their advantages and disadvantages present a more effective solution than simply banning their use.

1.3. GAI Interaction and Student Learning Outcomes

This work takes a positive and inclusive approach to the issue of GAI use and investigates how the student-GAI interaction is related to the student's learning success. While students can make use of GAI to generate various forms of content, this does not imply that such use leads to success in the studies. Many theoretical works have examined the issue; however, empirical evidence is still missing. Therefore, one of the research goals of this study is to establish empirical proof of the correlation between student and GAI interaction and learning success.

Moreover, this study explores how student-GAI interaction quality is associated with their educational achievement. On one hand, due to the ease of access to GAI tools (e.g., ChatGPT, built on GPT3.5, is free to use), it would be like providing a cost-effective way to students to obtain an array of highly capable personal assistants working across multiple domains! Thus, with such powerful "personal helpers," students may come to think that GAI has enabled them to tackle more complex issues and perform even more challenging tasks due to the belief that they can develop their self-efficacy in the course of interacting with GAI. On the other hand, due to interactivity in real time and instant feedback provided by GAI solutions, students may be encouraged to take part in educational activities in a more active manner. GAI interaction is not constrained by time and space nor does it require students to wait for their teacher's response.

1.4. Self-Efficacy and Cognitive Engagement as Mediating Factors

Additionally, those students who have higher self-efficacy will probably show increased cognitive engagement. They are more inclined toward different learning tasks because they have a strong conviction of being able to complete them with success and are ready to invest energy into knowledge gain. Thus, it is suggested that self-efficacy and cognitive engagement together are able to mediate the connection between students' interaction with GAIs and their academic results.

II. REVIEW OF LITERATURE

Shi et al (2026) highlight that Generative AI (GenAI) changed the way students learn by giving them personalized ideas and the chance to learn in a dynamic environment. At the same time, not much is known about the ways GenAI has affected students' engagement and well-being. The survey of 750 students from Central China was conducted to understand the impact of student-teacher, student-content, student-student, and student-AI interactions on students' engagement and well-being via different elements of self-efficacy. Partial least square structural equation modelling (PLS-SEM) was used to verify the concepts outlined above, while fuzzy-set qualitative comparative analysis (fiscal) was utilized to determine complicated causal schemes. The results of the studies demonstrated that dimensional self-efficacy was the mediator in the relationship between both students-students interaction and students-AI interaction and the two outcomes mentioned above. Academic self-efficacy was the mediator in the case of student-teacher interaction and two outcomes, while the emotional self-efficacy had the mediating effect in the case of student-content interaction. In addition, fiscal demonstrated that there were various causal chains affecting engagement and well-being.

Yassine et al (2026) examine the rapid development of Artificial Intelligence (AI) has impacted education; nevertheless, the goal of higher effectiveness in students' learning process continues to be the primary objective of learners and educators. This research paper aimed to explore the key factors related to learning effectiveness in the era of AI, with the focus on the connections between the constructs of digital self-efficacy, digital attitude, cognitive engagement, and learning effectiveness. In this study, the two research methods were employed, namely structural equation modelling (SEM) and artificial neural networks (ANN) for studying the relationship between and the predictive success of the suggested model. The findings showed that there are significant direct and indirect relationships between the studied

variables. Cognitive engagement influenced the link between digital attitude to educational AI technologies and learning effectiveness, whereas self-efficacy in the area of AI moderated the influence of digital attitude on learning engagement. Besides, ANN analysis addressed the issue of complex and nonlinear relationship between the constructs and emphasized the importance of independent variables in the model, with the highest prediction power belonging to digital self-efficacy, whereas cognitive engagement and digital attitude came second.

Fang et al (2026) noted that the effects of artificial intelligence (AI) have become increasingly seen in learning and work practices; however, its connection with the innovative behaviour is still not fully understood. The goal of this study was to clarify the interplay between AI literacy and AI dependency and innovative behaviour through critical thinking awareness, self-regulated learning, and psychological need satisfaction. The research employed a cross-sectional survey design and 910 valid questionnaires were collected and administered through the Credamo platform with the use of gender and regional quotas. Structural equation modelling and bootstrap mediation analysis were used to explore the relationships outlined. The findings show that AI literacy and AI dependency have a positive relationship with innovative behaviour, with AI literacy having more influence. AI literacy shows significant indirect influence through higher critical thinking awareness, self-regulated learning, and fulfilment of psychological needs. The indirect impacts of AI dependency were less significant. The study analysed both variables jointly and offered a concept of purposeful AI dependency as a technology-based method of enhancing cognitive and operational capabilities.

Puttidech et al (2025) examine the impact of students' perception of artificial intelligence (AI) learning tools on their learning in calculus through the mediation of cognitive and emotional responses. This article is based on the principles of cognitive load theory and social cognitive theory, and examines how the perception of AI regarding its adaptability, accuracy of feedback, trust, and pedagogical value affects cognitive learning processes and academic performance. The information was collected through structured questionnaires answered by college teachers from nine Rajamangala Universities of Technology in Thailand. The Partial Least Squares Structural Equation Modeling method was used for the analysis. The findings showed that students' perception of AI as a learning tool had a major effect on their cognitive and emotional responses resulting in academic achievement. The model accounted for 75.7% of the variance in academic performance (R^2 = 0.757), indicating the great validity of the model. Moreover, it became evident that cognitive and emotional responses were mediators in the relationship between AI learning perception and academic achievement. The authors focus mainly on creating AI learning platforms that improve engagement, resilience, and confidence of students in learning calculus and STEM disciplines.

Jia et al (2025) examine that Generative artificial intelligence has demonstrated its efficacy in terms of aiding university students. However, too much of reliance on this technology may lead to the phenomenon of cognitive outsourcing and hinder the process of learning. Therefore, this research project studied the relationship between the level of reliance on GenAI by students and the extent to which they perceive teacher caring, as well as the effect GenAI will have over the students' academic success and self-efficacy. Namely, the purpose of this paper was to comprehend whether self-efficacy serves as a mediator within the relationship. The research was conducted taking into account media system dependency theory and 418 questionnaires among the students of public universities in China. The outcomes of the research indicate that the dependency on GenAI has led to the phenomenon of false effectiveness in terms of self-efficacy while having a negative impact on the students' academic success (Dunning-Kruger effect). According to the findings, perceived teacher caring has moderated the interaction between students' reliance on GenAI and their self-efficacy allowing them to overcome the Dunning-Kruger effect as teacher caring becomes more pronounced. Nonetheless, the effect on the students' academic success was weak.

Wu et al (2024) noted that identifying the relevant factors affecting self-directed learning ability among undergraduate students. Issues explored were related to a teacher's guidance and support, implementation of learning strategies, technology acceptance, motivation and having an experience with technology. Research applied the quantitative method

of the field study to collect data from the sample of 306 students in order to define the aspects essential for encouraging SDL among students. Results proved the effectiveness of self-efficacy and motivations as means of mediation within the analyzed framework. The findings offered insights into the fact that improvement in teacher's guidance and implementation of learning strategies lead to the gain of self-efficacy, acceptance of technology and motivation. Moreover, examples showed that generative AI applies to create individualized and flexible education opportunities and support teachers in providing smart education. Findings provided relevant contributions in deeper understanding of possible applications of generative AI in the field of higher education with respect to the factors affecting development of efficient educational technologies.

Capinding & Dumays (2024) aimed that conducted in this study examined the influence of the Artificial Intelligence (AI) system upon the students' learning experiences, the students' educational results, the teachers' recommendations concerning the future profession, the students' motivation, self-reliance and social interactions while being dependent on the usage of AI technologies. The descriptive-comparative design was employed to collect data from 194 learners who were chosen through such methods as stratified sampling. The results reveal that students were quite positive about the application of AI in their educational process since they reported that the usage of AI helped them to experience personalized learning, be engaged, become critical thinkers and improved their academic performance despite the fact that practical learning and test preparation were not perceived by the students positively. AI was also reported to provide useful assistance in the career guidance due to the fact that it helped the students to match their skills with various professions, choose suitable internships and provide them with different materials. Moreover, AI was reported to be helpful in motivation improvement through the use of gamified learning process and students' progress monitoring together with self-reliance through self-regulated learning and functioning as a critical thinker.

Liang et al (2023) highlight that current research was to analyse the influence of student interaction with generative artificial intelligence (GAI) on their performance due to self-efficacy as well as cognitive engagement. Due to the instant use and individualized character of generative artificial intelligence, it was assumed that interactions between students and GAI had an effect on the achievements. The authors conducted a survey among 389 persons and tested the proposed assumptions. The findings indicate that the authors proved that the relationship between student interaction with GAI and the performance of learners is positive. Moreover, the data obtained showed that self-efficacy plays a role of a mediator in the relationship between interaction of students with GAI and their achievements because of mediation 0.015. Cognitive engagement is another mediator which is even more effective than self-efficacy because its mediation is equal to 0.046. At the same time, both self-efficacy and cognitive engagement serve as sequential mediators in the direct link between the interaction of students with GAI and the performance. In addition, propensity score matching (PSM) method was used in the study to avoid self-selection bias.

Silitubun (2023) suggest that connection of self-confidence, AI-assisted learning, and academic success, covering aspects of motivation and learning. The aim was to find out the impact of the AI technology used in education on self-confidence of students and its influence on academic performance. The research was conducted through quantitative methods including the use of questionnaires among 120 students from several universities such as STPK St. Yohanes Rasul Jayapura, Thomas Aquinas College of Agriculture, and Papua International University. The research revealed that both self-confidence and AI support are important factors contributing positively to academic results. The AI technology used in education makes learning contents accessible and helps students develop their self-confidence and learning capacities. The results of the research indicate that implementation of AI and related technologies in education can improve students' educational achievements and thus, educational institutions should utilize it in teaching students in order to help them acquire self-confidence and study successfully.

Chou et al (2022) examine the cantered on how effective university students are at learning applications of artificial intelligence and at discovering what influences such effectiveness. It aims to offer some help in planning and

implementing artificial intelligence in the field of information and communication technologies education. The data were obtained from 1,552 university students, examining how the self-efficacy in the field of information and communication technologies influences learning effectiveness of the applications of artificial intelligence and how human-computer experience has an indirect effect on learning effectiveness of the applications of artificial intelligence. In addition to that, it shows that the model of impact is stable enough to prove that variables of self-efficacy in the field of information and communication technologies influences by itself directly learning effectiveness of the applications of artificial intelligence technology and that human-computer interaction experience somehow influences learning effectiveness indirectly. Hence, the findings suggest that the educational system in the Republic of China (Taiwan) should create better learning environment for learning artificial intelligence and appropriate platforms for developing and utilizing educational technologies.

III. PROBLEM STATEMENT

The rapid adoption of Generative Artificial Intelligence (GenAI) in higher education has transformed students' learning practices by providing instant, personalized, and interactive academic support; however, increasing dependence on these technologies also raises concerns regarding their influence on students' actual learning outcomes and cognitive development. Existing studies have reported positive associations between AI interaction, self-efficacy, cognitive engagement, and academic achievement, while other evidence suggests that excessive AI dependency may encourage cognitive outsourcing and weaken independent learning. Despite growing research in this area, there remains insufficient empirical understanding of how AI dependency influences student learning outcomes and the mechanisms through which cognitive engagement and self-efficacy shape this relationship. Therefore, the problem is to systematically examine the relationship between AI dependency and student learning outcomes, with particular emphasis on the mediating roles of cognitive engagement and self-efficacy, in order to provide a stronger empirical basis for understanding responsible and effective GenAI-assisted learning in higher education.

IV. RESEARCH METHODOLOGY

4.1 Research Design

The research design implemented in this investigation is quantitative, and it employs a survey that is cross-sectional in nature to study the effects of AI dependency on student learning outcomes through the mediating variables of cognitive engagement and self-efficacy. The research adopts a positivist approach wherein causal relationships among hidden constructs are tested with the help of robust measurement scales and statistical inference.

4.2 Population and Sampling Technique

The study population consisted of undergraduate and postgraduate students from institutions of higher education who have utilized generative AI tools (such as ChatGPT, Gemini, and Copilot) in an academic context during the academic year in question. There was the use of stratified random sampling to guarantee a proportional representation in terms of academic level, discipline, and gender, thus reducing selection bias and enhancing the results' generalizability.

4.3 Sample Size Determination

Krejcie and Morgan (1970) and the '10-times rule' commonly used in PLS-SEM (minimum sample = 10 × the largest structural paths that point towards the same construct) were used to calculate needed sample size. In this case, five paths pointed to the dependent construct, so the minimum number of needed responses was 50. Yet, to enhance the reliability and generalizability of the results, questionnaires were distributed to 480 students. In total, 438 responses (91.3%) were received out of which 412 were considered valid after screening the data which results in a valid response rate of 85.8%, which is above the required one.

4.4 Research Instrument

Information was gathered via a self-administered, structured questionnaire with two parts. In Section A, data on the respondents' demographics (such as gender, age, year of study, and field of study) was acquired. Section B consists of 22 questions that

assess the four variables, which were measured on a five-point Likert scale that goes from 1 (Strongly Disagree) to 5 (Strongly Agree).

Table 1 summarizes the operationalization of the study variables.

Construct	Code	Items	Sample Item	Source
AI Dependency (AID)	AID1–AID6	6	"I rely on AI tools to complete most of my academic tasks."	Adapted from Fang et al. (2026)
Cognitive Engagement (CE)	CE1–CE5	5	"I put effort into understanding course material even when it is difficult."	Adapted from Liang et al. (2023)
Self-Efficacy (SE)	SE1–SE5	5	"I am confident I can perform well academically even without AI assistance."	Adapted from Jia et al. (2025)
Learning Outcomes (LO)	LO1–LO6	6	"My academic performance has improved this semester."	Adapted from Yassine et al. (2026)

4.5 Data Collection Procedure

The questionnaire was conducted online through a reliable survey platform over six weeks. An introductory letter accompanying the survey explains the aim of the research, guarantees anonymity and confidentiality to the respondents, and makes it clear that the participation is voluntary. Before the full distribution of the questionnaire, it was pre-tested with 40 students in order to determine its clarity and reliability. The wording was changed slightly as a result of the pre-testing stage.

4.6 Data Analysis Technique

Data analysis proceeded in two stages. Stage 1 involved descriptive and preliminary analysis (frequency distribution, normality checks, and common method bias assessment) conducted in SPSS (version 27). Stage 2 employed Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS (version 4) to assess the measurement model (convergent and discriminant validity) and the structural model (path coefficients, R^2, Q^2, and effect sizes). A bootstrapping procedure with 5,000 resamples was used to test the significance of direct, indirect, and serial mediation effects, consistent with the approach used in related studies.

4.7 Reliability and Validity

The questionnaire was conducted online through a reliable survey platform over six weeks. An introductory letter accompanying the survey explains the aim of the research, guarantees anonymity and confidentiality to the respondents, and makes it clear that the participation is voluntary. Before the full distribution of the questionnaire, it was pre-tested with 40 students in order to determine its clarity and reliability. The wording was changed slightly as a result of the pre-testing stage.

4.8 Ethical Considerations

- Ethical approval was granted by the Institutional Research/Ethics Committee before collecting data.
- Participation was completely voluntary, and all respondents gave their informed consent.
- Respondents' anonymity and confidentiality of data were protected during the study.
- Respondents could withdraw their participation at any time without facing penalties.
- Data were solely used for academic research purposes and stored on a secure device with password protection.

V. RESULTS AND DISCUSSION

5.1 Response Rate and Data Screening

In terms of the questionnaires, out of the total administered 480 questionnaires, only 438 of them were duly filled and returned by the respondents. After discarding the 26 incomplete and linearly responded questionnaires, only 412 were valid and usable (usable response rate = 85.8%). Only 5% of responses had any missing data, while Little's MCAR test indicated no presence of tail questions (χ^2 = 112.4, df = 98, p = .152)—this indicates that data was

random in nature. Harman's single factor test showed that there was only 31.4% of variance with only one factor, which is lesser than the required threshold of 50%, thus indicating that common method bias is not a major issue.

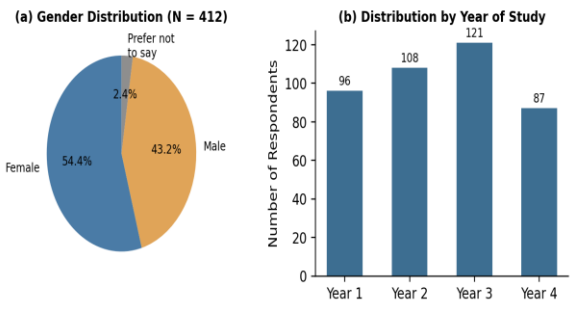
5.2 Demographic Profile of Respondents

According to Table 2, which displays the demographic characteristics of the 412 participants, the sample was quite balanced in terms of gender, and also equally represented in terms of the academic year of study. However, representation from science disciplines was slightly higher.

Table 2. Demographic Profile of Respondents (N = 412)

Category	Group	Frequency (n)	Percentage (%)
Gender	Female	224	54.4
	Male	178	43.2
	Prefer not to say	10	2.4
Age	18–20 years	187	45.4
	21–23 years	165	40.0
	24 years and above	60	14.6
Year of Study	Year 1	96	23.3
	Year 2	108	26.2
	Year 3	121	29.4
	Year 4	87	21.1
Academic Discipline	Sciences	152	36.9
	Social Sciences	130	31.6
	Humanities	74	18.0
	Others	56	13.5

Figure 2. Demographic Profile of Respondents



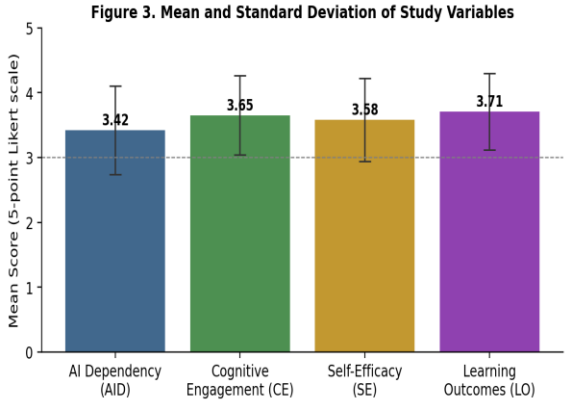
5.3 Descriptive Statistics of Study Variables

The average, standard deviation, skewness and kurtosis figures for those constructs appear in Table 3. The mean scores were all higher than the middle point of the 5-point scale (3.0), denoting positive attitudes. The skewness and kurtosis values were both in the range of ±1, thus confirming the normality assumption and applicability for the further multivariate analysis.

Table 3. Descriptive Statistics of Study Variables (N = 412)

Variable	No. of Items	Mean	SD	Skewness	Kurtosis
AI Dependency (AID)	6	3.42	0.68	−0.21	−0.34
Cognitive Engagement (CE)	5	3.65	0.61	−0.18	0.12
Self-Efficacy (SE)	5	3.58	0.64	−0.25	−0.09
Learning Outcomes (LO)	6	3.71	0.59	−0.31	0.21

Figure 3. Mean and Standard Deviation of Study Variables



5.4 Measurement Model Assessment

The measurement model was assessed for internal consistency reliability, convergent validity, and discriminant validity. As shown in Table 4, all constructs exceeded the recommended thresholds: Cronbach's alpha and composite reliability (CR)

values were above .70, and average variance extracted (AVE) values exceeded .50, confirming adequate reliability and convergent validity.

Table 4. Reliability and Convergent Validity

Construct	Items	Loading Range	Cronbach's α	CR	AVE
AI Dependency (AID)	6	.71–.84	.86	.89	.58
Cognitive Engagement (CE)	5	.74–.86	.88	.91	.63
Self-Efficacy (SE)	5	.70–.85	.85	.88	.60
Learning Outcomes (LO)	6	.73–.87	.89	.92	.61

Discriminant validity was confirmed using the Fornell–Larcker criterion (Table 5): the square root of the AVE for each construct (shown in bold on the diagonal) exceeded its correlations with all other constructs, and all HTMT ratios remained below the conservative threshold of .85.

Table 5. Discriminant Validity — Fornell–Larcker Criterion (diagonal values are √AVE)

Construct	AID	CE	SE	LO
AI Dependency (AID)	0.762			
Cognitive Engagement (CE)	0.512	0.794		
Self-Efficacy (SE)	0.487	0.601	0.775	
Learning Outcomes (LO)	0.398	0.583	0.612	0.781

5.5 Correlation Analysis

Pearson correlation analysis (Table 6) showed that all four constructs were positively and significantly correlated with one another ($p < .01$), providing preliminary support for the hypothesized relationships prior to structural model testing.

Table 6. Correlation Matrix of Study Variables (**$p < .01$, two-tailed)

Variable	1. AID	2. CE	3. SE	4. LO
1. AID	1			
2. CE	.512**	1		
3. SE	.487**	.601**	1	
4. LO	.398**	.583**	.612**	1

5.6 Structural Model and Hypothesis Testing

The structural model explained 48.7% of the variance in learning outcomes ($R^2 = .487$), 13.8% in cognitive engagement ($R^2 = .138$), and 11.6% in self-efficacy ($R^2 = .116$). The model demonstrated adequate predictive relevance ($Q^2 = .291$) and acceptable fit (SRMR = .058). Figure 4 presents the structural model with standardized path coefficients, and Table 7 summarizes the hypothesis-testing results based on 5,000 bootstrap resamples.

Figure 4. Structural Model with Standardized Path Coefficients

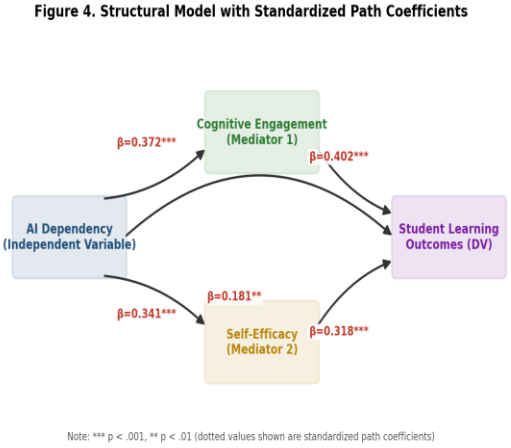


Table 7. Structural Path Coefficients and Hypothesis Testing

Hypothesis	Path	β	t-value	p-value	Decision
H1	AID → LO	0.181	3.42	.001	Supported
H2	AID → CE	0.372	6.87	<.001	Supported
H3	AID →	0.341	6.12	<.001	Supported

	SE				
H4	CE → LO	0.402	7.55	<.001	Supported
H5	SE → LO	0.318	5.89	<.001	Supported

5.7 Mediation Analysis

The average, standard deviation, skewness and kurtosis figures for those constructs appear in Table 3. The mean scores were all higher than the middle point of the 5-point scale (3.0), denoting positive attitudes. The skewness and kuttosis values were both in the range of ±1, thus confirming the normality assumption and applicability for the further multivariate analysis.

Table 8. Bootstrapped Mediation Analysis (Indirect Effects)

Hypothesis	Indirect Path	Effect	SE	95% CI (Boot)	Decision
H6	AID → CE → LO	0.150	0.028	[.098, .207]	Partial mediation
H7	AID → SE → LO	0.108	0.024	[.065, .159]	Partial mediation
H8	AID → CE → SE → LO (serial)	0.045	0.014	[.021, .076]	Significant

5.8 Discussion of Findings

The findings reveal that students' dependence on AI significantly influences their learning outcomes, both directly (H1) and indirectly through the mediating roles of cognitive engagement (H6) and self-efficacy (H7). This finding is consistent. Self-efficacy and cognitive engagement act as important mediators of the relationship between student-AI interactions and academic performance. Cognitive engagement was found to be the strongest predictor of learning outcomes (β = .402), which means that the extent to which students process and use information obtained through AI interaction is more important than the frequency of use of AI. This finding is also in line who found cognitive engagement to be one of the most important mediators in the very epoch when AI is effective.

Concurrently, the fact that the direct impact of AID on LO (β = .181) is relatively low in comparison with the mediated pathways suggests that AI reliance is not sufficient for learning success. Hints of this notion can be found in the ideas, who noted the appearance of an effect reminiscent of the Dunning-Kruger effect, according to which AI reliance causes people to believe they are more self-efficacious than they actually are. The argument made by Jia et al. indicates that it is advisable to be cautious when using AI: it may boost learning outcomes, but the absence of psychological engagement means that deep knowledge cannot be achieved.

The results, in terms of practical implications, show that educational institutions should not concentrate their efforts on restricting access to AI but rather concentrate on formulating educational strategies that utilize AI intentionally in a way that stimulates cognition, as in the case of utilizing reflective prompts, AI-generated formative feedback, and designing tasks that engage students in critical analysis of AI materials rather than passive acceptance of them. Educational institutions can further enhance self-efficacy by combining AI technologies with tasks that require independent problem-solving thus using AI as an aid to learning rather than as a replacement for it.

Despite numerous contributions of the study, it does have a number of limitations. The design used in this study limits causality conclusions and self-reported data can be affected by social desirability bias. As such, the future studies should apply the longitudinal or experimental design and take into account additional moderators such as perceived teacher's caring in order to understand the conditions when AI dependency contributes to student learning or vice versa.

VI. CONCLUSION

In conclusion, the study suggests that dependence on Generative AI has an impact on students' learning outcomes. It was shown that students' cognitive engagement has more predictive power in terms of learning outcomes, although self-efficacy plays an important role as well, while the important consecutive mediation process illustrates the joint

influence of students' cognitive and psychological states on effective learning with the help of AI. Hence, the authors argue that educational efficiency of GenAI should not be measured solely in regard to accessibility or use frequency; the benefits of AI depend on whether it stimulates students to think critically, solve problems independently, reflect on knowledge, and feel confident about their learning. Therefore, higher education institutions have to abandon conservative methods of evaluating the effectiveness of GenAI and develop pedagogical practices that see Generative AI as a learning assistant, rather than substitute for students' cognitive activity. Still, the researchers' choice of a cross-sectional research design and reliance on self-reported data makes it difficult to draw causal conclusions and understand the evolution of AI dependence and students' learning behavior. It is suggested that longitudinal and experimental designs be employed in future research to determine causal relationships, include objective performance measures and actual use of AI, and explore the various possible moderators that may be influencing the results, including teacher empathy, AI comprehension, academic discipline, learning context, and AI usage type and degree. It is also recommended to carry out comparative studies across institutions and disciplines in order to enhance the applicability of results.

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