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LINKING AI LITERACY, SELF-EFFICACY, ATTITUDES, AND ACHIEVEMENT: A MIXED-METHODS STUDY ON THE MODERATING ROLE OF AI USAGE AND STUDY YEAR

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ABSTRACT

Aim/Purpose	This study addresses a key gap in the AI in education literature by examining whether AI literacy, attitudes towards AI, and AI self-efficacy are related to academic achievement and whether their effects vary by duration of AI use and study year among undergraduates at an institution in Ho Chi Minh City, Vietnam.
Background	The rapid growth of AI in higher education presents both opportunities and risks for student learning; however, empirical evidence on AI competencies and achievement remains limited, particularly in emerging contexts such as Vietnam. Drawing on Control-Value Theory, this study focuses on how students' perceived control (skills, self-efficacy) and value (attitudes) in using AI tools relate to their academic outcomes.
Methodology	This study employed a mixed-methods design that combined a cross-sectional survey of 376 undergraduates in Ho Chi Minh City, Vietnam, with qualitative analysis of open-ended responses from eight students. Quantitative data were analyzed using Spearman correlations, ordinal logistic regression, and moderation tests, while qualitative data were examined through template analysis to explain how and why students use generative AI tools in their learning.

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Contribution	The study integrates Control-Value Theory with AI-use competencies and tests two under-examined moderators (duration of AI use, years of study). It complements statistical results with qualitative insights that explain when and why AI competencies translate into achievement.
Findings	AI self-efficacy was the only significant predictor of a higher GPA category. AI literacy showed small positive correlations with GPA, whereas attitudes toward AI were not directly related to achievement. Moderation analyses indicated diminishing returns, as the associations between AI literacy and AI self-efficacy were stronger for lighter users and first-year students, and weaker with heavier use and in later years. Qualitative themes highlighted AI as a scaffold for summarizing, idea generation, and drafting; key frictions were accuracy, Vietnamese expression quality, and prompting skills.
Recommendations for Practitioners	Prioritize building AI self-efficacy with low-stakes practice, explicit error-spotting, claim-checking, and revision routines. Use a phased approach: offer light support for beginners, and in advanced years, require records of prompts and sources, comparative prompting, and clear citation and verification to reduce automation bias.
Recommendations for Researchers	Pursue longitudinal or experimental designs to test causal effects of self-efficacy and verification training and compare domain-specific contexts where task complexity and error costs differ.
Impact on Society	Practical guidance on the competent and critical use of AI can support the equitable, ethical, and effective integration of AI in higher education, helping students turn access to AI into real learning gains.
Future Research	Future studies can expand the scope of this research by extending it to diverse institutions, majors, and incorporating interviews to deepen insight into when, how, and why AI use builds or undermines self-efficacy, as well as how this connects to students' attitudes and perceived learning.
Keywords	AI literacy, AI self-efficacy, attitudes toward AI, academic achievement, duration of AI usage, study year, Control-Value Theory

INTRODUCTION

As artificial intelligence (AI) continues to grow rapidly in everyday life, especially in educational settings, its impact on teaching and learning has become more noticeable (Miao et al., 2021; Qian et al., 2024). AI now supports instruction through automated assessments, access to learning resources, and even by acting as a teaching assistant or mentor (A. P. Singh et al., 2024; Xu et al., 2025). As a result, students interact with AI tools that shape their learning processes and academic performance (Bećirović et al., 2025; Chu et al., 2022). These effects are not limited to academics but also influence students' personal development, cognitive habits, and ethical thinking. Therefore, developing AI literacy and learning how to use AI tools responsibly and effectively has become essential for both academic achievement and future competitiveness in a digital society (Brew et al., 2023; D. T. K. Ng et al., 2024).

At the same time, attitudes toward AI also play an important role. Positive attitudes are associated with reduced anxiety about information technology (IT), increased confidence in problem-solving, and a deeper understanding of AI (S. W. Kim & Lee, 2020; Wagner & Sherwood, 1969). Also, AI can support positive emotional experiences by helping students feel more in control and see greater value in their learning tasks, while recognizing negative emotions that may interfere with learning (Guo &

Wang, 2025; Ruokamo et al., 2023). Self-efficacy, in turn, does not develop on its own but is influenced by both AI literacy and students' attitudes toward AI (Bewersdorff et al., 2025). These connections highlight the importance of exploring how cognitive (AI literacy), affective (attitudes toward AI), and motivational (AI self-efficacy) factors interact and influence student learning.

This present study adopts Control-Value Theory (CVT) as a guiding framework to explain how students' belief about control (their confidence in completing academic tasks) and value (the perceived usefulness, interest, or cost of tasks) influence their learning behaviors and academic performance (Pekrun, 2006; Pekrun et al., 2017). Within this framework, AI literacy contributes to students' sense of control by reducing uncertainty and building their competence in using AI effectively. At the same time, attitudes toward AI reflect students' evaluations of task value, including whether they find AI helpful or interesting. When both control and value are high, students are more likely to experience positive emotions and engage deeply in learning, which in turn enhances their academic outcomes (Honicke & Broadbent, 2016; Qi et al., 2024). CVT, therefore, provides a useful theoretical lens to link the variables examined in this study. It also supports the qualitative phase, which explores how students experience control and value when applying AI in their coursework.

Existing research on AI in higher education has also relied primarily on quantitative methods (Chun et al., 2025; Shi & Zhang, 2025; E. Singh et al., 2025), with relatively little qualitative inquiry to explain how and why observed patterns occur (Bond et al., 2024). While quantitative approaches are useful for identifying broad patterns, they may overlook the personal experiences and contextual factors that shape AI use in everyday academic life. To address this limitation, this study adopts a mixed-methods design that integrates statistical testing with open-ended responses to gain a deeper understanding of students' purposes, challenges, and reflections when using AI for learning.

Despite this emerging work, several theoretical and practical gaps remain. Practically, there is limited empirical evidence from Vietnamese higher education on how students use AI in their everyday coursework, how confident they feel when doing so, and under what conditions AI support is associated with better academic outcomes. Theoretically, most studies focus on general technology acceptance or digital skills (Davis, 1989; W. Ng, 2012; Venkatesh et al., 2003) and rarely examine AI literacy, attitudes toward AI, and AI self-efficacy together as components of perceived control and value within Control-Value Theory. The relationships between these AI-related competencies and academic achievement remain underexplored, and the potential moderating roles of the duration of AI use and year of study have received little attention. Testing these moderators helps identify for whom and under what conditions AI literacy, attitudes, and self-efficacy lead to academic success.

To address these gaps, the present study focuses on the Vietnamese higher education context. It examines how AI literacy, attitudes toward AI, and AI self-efficacy relate to academic achievement, as well as whether these relationships vary by the duration of AI use and the number of years of study. By combining quantitative analyses with qualitative insights into students' experiences with AI, the study aims to contribute both theoretically, by extending Control-Value Theory to AI-integrated learning, and practically, by informing the design of pedagogical strategies that foster competent and critical use of AI.

LITERATURE REVIEW

AI LITERACY

AI literacy refers to the set of essential skills and knowledge that allow individuals to interact competently with artificial intelligence technologies, including understanding fundamental AI concepts, engaging in critical evaluation, and using AI tools ethically across various contexts (Kandlhofer et al., 2016; Long & Magerko, 2020). D. T. K. Ng et al. (2021) identified four foundational components of AI literacy: knowledge and understanding, application and use, evaluation and creation, and ethical awareness. Further elaborating on this framework, Zhao et al. (2022) emphasized that foundational knowledge of AI is the most critical component in shaping how educators perceive and respond to AI.

With the rise of Generative artificial intelligence (GenAI) technologies such as ChatGPT, Gemini, and Claude, AI literacy has become increasingly important for equipping users with the skills needed to interact with systems capable of autonomously generating texts, images, and other forms of media (Y. Jin et al., 2025; Yan et al., 2024). Notably, those with higher levels of AI literacy tend to exhibit more positive perceptions and attitudes toward AI (Edwards et al., 2018; Yi-No Kang et al., 2023), as well as improved learning outcomes (Chun et al., 2025; E. Singh et al., 2025). However, despite the educational potential of GenAI, Zawacki-Richter et al. (2019) argued that teachers and students frequently misunderstand AI's capabilities and limitations, leading to either overreliance or distrust. That is also why it is essential to emphasize the importance of AI literacy, and it is crucial for people to learn how to effectively use AI systems (Almatrafi et al., 2024).

Taking Control-Value Theory as a framework, this study views AI literacy as a factor that supports perceived control. Students with higher AI literacy are more able to understand what AI can and cannot do, check the quality of AI outputs, and use AI appropriately in their coursework (Hornberger et al., 2023). These skills can increase their sense of control when working with AI (Bewersdorff et al., 2025; Pan & Zhang, 2025). In this way, AI literacy helps build control in AI-rich learning environments.

Numerous studies have reported positive associations between AI literacy and academic achievement (Chun et al., 2025; E. Singh et al., 2025). However, the strength of this relationship varies across contexts. For example, a study in the Philippines (Asio, 2024) reported a very weak correlation, whereas E. Singh et al. (2025) found a very significant one in India. To address this gap, this study examines whether AI literacy is associated with academic performance in the Vietnamese context.

AI Self-Efficacy

According to Asio and Suero (2024), AI self-efficacy refers to an individual's confidence in their ability to use AI tools and systems effectively. This concept emphasizes the ability to leverage AI technologies effectively, and it serves as the operational definition adopted in this study. Within the Control-Value Theory, AI self-efficacy is interpreted as a component of perceived control over tasks supported by AI. People who believe they can use AI effectively are more likely to feel that they can manage the demands in their tasks (Collie et al., 2024), which in turn is expected to be associated with their academic achievement.

Furthermore, Khan (2024) and Kwak et al. (2022) revealed that attitudes toward AI had a significant influence on AI self-efficacy, which in turn had a relevant effect on individuals' intent to adopt AI-based decisions. In addition, recent advancements in AI have improved students' access to relevant learning resources, thereby boosting their confidence and reducing the likelihood of plagiarism in academic work (Kabir et al., 2025; Kurniawan et al., 2024). B. J. Kim et al. (2024) emphasized that belief in one's AI self-efficacy exerts a positive effect, suggesting that individuals with higher confidence in their ability to use AI tend to experience lower levels of job stress when facing work overload.

At the same time, AI self-efficacy has been shown to reduce anxiety related to AI use and foster learners' attitudes toward both AI technologies and their real-world applications (Chen et al., 2024; Lin & Chen, 2024). In line with this, Morales-García et al. (2025) and Zhang et al. (2023) argue that enhancing individuals' AI self-efficacy facilitates greater acceptance and more effective use of AI. However, excessive reliance on AI may increase vulnerability to technological failures, which not only undermines their trust in AI but also diminishes their self-confidence (Chong et al., 2022; Wang et al., 2022). Overall, current research indicates that AI self-efficacy is a promising yet complex predictor of learning. However, evidence is still limited on how it relates to academic achievement when examined together with AI literacy, attitudes toward AI, and factors such as duration of AI use and study year. This study aims to address this gap.

While most research on AI literacy typically focuses on academic factors such as academic performance, studies on AI self-efficacy often emphasize non-academic outcomes such as resilience, attitude, or self-regulated learning, and report a positive association (Chen et al., 2024; S.-H. Jin et al., 2023; Shi & Zhang, 2025). However, few studies directly test the link between AI self-efficacy and academic achievement.

ATTITUDES TOWARD AI

Attitude is defined as a person's liking or disliking of another person, a specific object, or a particular behavior (Ajzen & Fishbein, 2000; Kemp et al., 2019). Beyond the emotional dimension, such as the degree of fondness, attitudes also include cognitive components that reflect one's beliefs and thought processes (Metsärinne & Kallio, 2016; Petty & Briñol, 2014). Therefore, attitude toward artificial intelligence is understood as the set of beliefs, viewpoints, and feelings that individuals hold about AI (Dwivedi & Kochhar, 2023; Morales-García et al., 2025). Building on the Control-Value Theory, the present study treats attitudes toward AI as an indicator of perceived task value. It reflects the extent to which students see AI-supported learning as useful, interesting, or beneficial versus risky or problematic. According to CVT, such value judgments, together with perceived control, are expected to influence students' achievement.

GenAI tools have made it easier for users to interact directly with AI technologies, thereby enhancing accessibility and engagement (S. Singh & Paiva, 2025; Z. Yu et al., 2025). Such direct interaction plays a critical role in shaping an individual's attitudes toward technology (Emon & Khan, 2025; Theotokis et al., 2008). When users engage with AI systems, their perceptions of the system's competence become especially important, which makes people more likely to develop positive attitudes toward technologies (Cheng et al., 2022).

However, AI is often perceived as non-human, which can raise concerns related to privacy and generate feelings of discomfort or distrust (W. Kim et al., 2024; S. Yu et al., 2023). These perceptions are often driven by fear about AI's integration into everyday life and its impact on human interaction, which may contribute to the development of negative attitudes toward AI. In line with these concerns, the present study also explores how students' experiences with AI shape their attitudes through qualitative analysis.

Most research on attitudes toward AI has focused on non-academic outcomes, whereas many studies have indicated a positive relationship between attitudes and non-academic outcomes (Óturai et al., 2023; Özönder, 2015), but evidence on attitudes toward AI specifically and their direct link to learning outcomes remains limited. Therefore, our study aims to investigate how attitudes towards AI affect academic performance, thereby strengthening the theoretical base for future work.

ACADEMIC ACHIEVEMENT

Academic achievement is a core indicator of educational success that reflects students' understanding, retention of knowledge, and ability to apply skills (Lemberger et al., 2012). It describes the extent to which a student has reached their learning goals. Academic achievement can be assessed using various indicators, such as course grades, rubric-based evaluations, surveys, and tests (Dong et al., 2025). In this study, academic achievement is measured using students' GPA categories. It serves as the primary learning outcome for examining associations with AI literacy, attitudes toward AI, and AI self-efficacy. Focusing on GPA as the main achievement indicator enables the study to examine how these AI-related competencies and beliefs relate to formal academic performance, rather than just to self-reported outcomes such as perceived learning or satisfaction.

Within Control-Value Theory, academic achievement is viewed as an outcome of students' perceived control over learning tasks and the value they assign to those tasks, which together shape their emotions and engagement in learning. In AI learning environments, academic achievement reflects the extent to which students are able to turn access to AI tools into real performance gains, rather than using AI in ways that leave their underlying understanding unchanged.

Duration of AI Use and Study Year as Moderators

To extend the scope of this study, we examine two moderating variables: (a) duration of AI use, and (b) study year. Prior work suggests that greater technology experience and more frequent AI use are associated with stronger information and communication technologies (ICT) self-efficacy and higher AI literacy (Li et al., 2022; Toker Gokce et al., 2025). In addition, senior students are often more familiar with digital tools and tend to have more positive attitudes toward AI than they did in earlier years (Mehak & Jafree, 2025).

However, greater experience does not always lead to consistent gains. Research on the expertise reversal effect (Nievelstein et al., 2013) indicates that instructional support and tools designed to help beginners can become less effective, or even harmful, for more advanced learners if they create redundancy or encourage over-reliance. In AI-supported learning, students who have used AI extensively may be more likely to depend on AI-generated content or to reduce their efforts to verify information (Abubakar et al., 2025). Examining duration of AI use and year of study as moderators, therefore, helps identify for whom, and under what conditions, AI literacy, attitudes toward AI, and AI self-efficacy are most strongly linked to academic achievement

Conceptual Summary and Research Model

Taken together, prior research suggests that AI literacy, attitudes toward AI, and AI self-efficacy are directly or indirectly linked to engagement and performance in higher education (Asio, 2024; Bewersdorff et al., 2025; D. T. K. Ng et al., 2021; A. P. Singh et al., 2024). From a Control-Value Theory perspective (Pekrun, 2006; Pekrun et al., 2017), AI literacy and AI self-efficacy can be understood as parts of students' perceived control over AI-supported tasks, while attitudes toward AI reflect the value they attach to these tasks. These constructs are expected to shape students' achievement emotions and engagement, which, in turn, are associated with academic achievement. At the same time, the duration of AI use and the study year may influence these relationships by altering students' experience with AI tools and the extent to which they rely on AI in their coursework.

Based on this literature, the present study proposes a research model in which AI literacy, attitudes toward AI, and AI self-efficacy are associated with academic achievement, and these associations are moderated by the duration of AI use and the year of study. Figure 1 presents this model and provides the basis for the quantitative and qualitative research questions examined in the following sections.

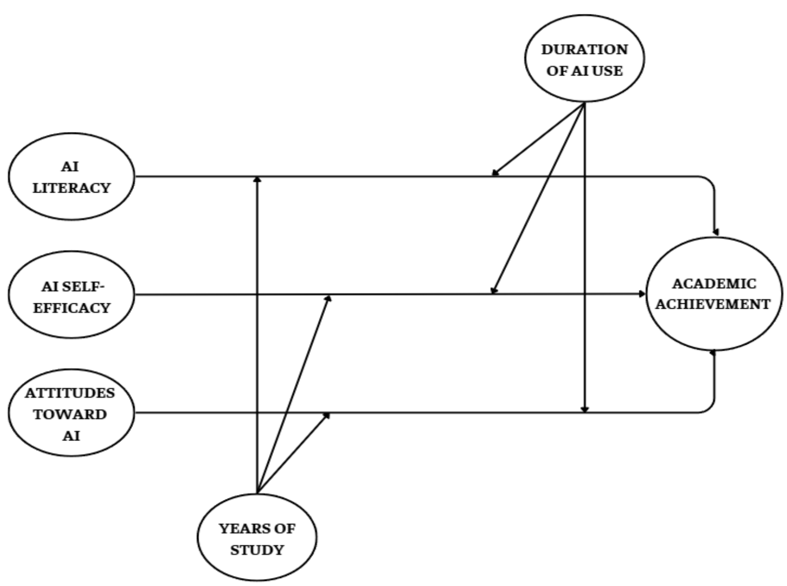

Figure 1. Research model

RQ1: How do AI competencies influence academic achievement among university students?
- **RQ1a:** How does AI literacy influence academic achievement among university students?
- **RQ1b:** How does AI self-efficacy influence academic achievement among university students?
- **RQ1c:** How do attitudes toward AI influence academic achievement among university students?

RQ2: Does the duration of AI use moderate the paths between AI literacy, attitudes toward AI, AI self-efficacy, and academic achievement?
RQ3: Does the study year of AI use moderate the paths between AI literacy, attitudes toward AI, AI self-efficacy, and academic achievement?
RQ4: How do students describe their purposes and frequency of AI use in coursework?
RQ5: What challenges do students face when using AI?
RQ6: In what ways do students perceive that their use of AI builds or undermines AI self-efficacy?
RQ7: How do these students perceive that experiences with AI relate to their attitudes and their perceived learning outcomes?

RQ1-RQ3 are examined with Spearman correlations, ordinal logistic regression, and moderation analysis; RQ4-RQ7 are addressed with template analysis of open-ended responses.

METHODOLOGY

SUBJECTS

Data were collected via an online questionnaire on Google Forms. Of 398 responses received, 22 were excluded due to missing data or patterns of straight-lining (selecting the same response option for all items). After data clearing, 376 valid questionnaires remained for analysis. In this study, academic achievement was measured based on students' grade point average (GPA). The demographic characteristics of the respondents are summarized in Table 1.

Table 1. Demographic of respondents

Participant characteristics		Frequency	%
Gender	Female	327	87.0
	Male	49	13.0
Years of Study	Year 1	201	53.5
	Year 2	104	27.7
	Year 3	59	15.7
	Year 4	12	3.2
Duration of AI Usage	Past 1 semester	225	59.8
	Past 2 semesters	82	21.8
	Past 3 semesters	41	10.9
	Past 4 semesters	21	5.6
	Other	7	1.9
Grade Point Average (GPA)	Poor (<5.0)	0	0
	Average (5.0-6.99)	15	4.0
	Good (7.0 - 7.99)	175	46.5
	Very Good (8.0 - 8.99)	175	46.5
	Excellent (≥ 9.0)	11	2.9

Academic achievement was measured using students' self-reported cumulative grade point average (GPA). To align with institutional grading practices and facilitate ordinal modeling, the GPA was converted into five ordered categories: Poor, Average, Good, Very Good, and Excellent. These categories reflect increasing levels of academic performance and were treated as an ordinal outcome in subsequent analyses. In this study, academic achievement therefore captures students' formal performance in higher education rather than perceived learning or satisfaction. Because the dependent variable is ordinal rather than continuous, this study employed ordinal logistic regression to investigate the relationship between AI literacy, attitudes toward AI, and AI self-efficacy and movement into higher GPA categories.

The duration of AI usage was measured using a single ordered item that asked students how long they had been using generative AI tools for learning purposes. Response options differentiated between shorter and longer periods of engagement with AI (for example, less than one semester, one to two semesters, and more than two semesters). This variable was treated as an ordinal moderator representing accumulated exposure to AI in academic contexts rather than frequency or intensity of use. In the analyses, the duration of AI usage served two functions. First, it was included descriptively to characterize the distribution of AI experience within the sample. Second, it was incorporated as a moderator in PROCESS moderation models to test whether the associations between AI literacy, attitudes toward AI, AI self-efficacy, and academic achievement varied according to students' length of experience with AI in coursework. This approach allowed for the examination of whether the strength or direction of these relationships differed for students with relatively brief versus more extensive histories of AI use.

INSTRUMENTS

The instruments employed in the present study were adapted from various sources and translated into Vietnamese to facilitate participants' comprehension and ease of response (Appendix A). Expert evaluations were conducted on all translated versions to ensure and enhance their semantic clarity and validity.

First, the AI Literacy Scale (Carolus et al., 2023) comprised 18 items across four dimensions: Understanding AI, Apply AI, Detect AI, and AI Ethics, rated from 1 (strongly disagree) to 5 (strongly agree). Higher mean scores indicate greater AI knowledge. Second, the AI Self-Efficacy Scale (Carolus et al., 2023) included six items divided into problem-solving with AI and AI learning capability. Third, the AI Attitude Scale (Suh & Ahn, 2022) consisted of 14 items that measured cognitive attitude and affective attitude toward AI, both rated on a 1-5 scale, with higher means indicating more positive attitudes.

Based on the results of reliability and exploratory factor analyses (EFA), the measurement model demonstrated good internal consistency and construct validity for all three scales. After removing invalid items (UA5, UA6, DA3, AC7, AC8, AC9, AC10), Cronbach's α values were 0.838 for the AI Literacy scale, 0.808 for the AI Self-Efficacy scale, and 0.863 for the Student Attitudes toward AI scale, exceeding the recommended threshold of 0.70 (Nunnally, 1978) and confirming satisfactory reliability.

The Kaiser-Meyer-Olkin measure indicated sampling adequacy, and Bartlett's test of sphericity was significant, $p < 0.001$ (Bartlett, 1950; Kaiser, 1974), supporting the suitability of the data for factor analysis. EFA results revealed that the AI Literacy construct comprised four factors explaining 68.998% of the variance (factor loadings ranged from 0.619 to 0.873), the AI Self-Efficacy construct comprised two factors explaining 72.785% of the variance (loadings = 0.688-0.870), and the Attitudes toward AI construct comprised two factors explaining 62.692% of the variance (loadings = 0.644-0.837) (Table 2).

Table 2. Measurement items description

Variable	Construct items		Source
AI literacy	Indicate the level of agreement (1 - Strongly disagree, 5 - Strongly agree)		Adapted from Carolus et al. (2023)
	Understand AI (UA)	UA1: I know the most important concepts of the topic "artificial intelligence"	
		UA2: I know definitions of artificial intelligence	
		UA3: I can assess what the limitations and opportunities of using an AI are	
		UA4: I can assess what advantages and disadvantages the use of artificial intelligence entails	
	Apply AI (AA)	AA1: I can operate AI applications in everyday life	
		AA2: I can use AI applications to make my everyday life easier	
		AA3: I can use artificial intelligence meaningfully to achieve my everyday goals	
		AA4: In everyday life, I can interact with AI in a way that makes my tasks easier	
		AA5: In everyday life, I can work together gainfully with an artificial intelligence	
		AA6: I can communicate gainfully with artificial intelligence in everyday life	
	Detect AI (DA)	DA1: I can tell if I am dealing with an application based on artificial intelligence	
		DA2: I can distinguish devices that use AI from devices that do not	
	AI Ethics (AE)	AE1: I can weigh the consequences of using AI for society	
		AE2: I can incorporate ethical considerations when deciding whether to use data provided by an AI	
		AE3: I can analyze AI-based applications for their ethical implication	
AI self-efficacy	Indicate the level of agreement (1 - Strongly disagree, 5 - Strongly agree)		Adapted from Carolus et al. (2023)
	AI Problem solving (APS)	APS1: I can rely on my skills in difficult situations when using AI	
		APS 2: I can handle most problems in dealing with artificial intelligence well on my own	
		APS3: I can also usually solve strenuous and complicated tasks when working with artificial intelligence well	
	Learning (LE)	LE1: I can keep up with the latest innovations in AI applications	
		LE2: Despite the rapid changes in the field of artificial intelligence, I can always keep up to date	
		LE3: Although there are often new AI applications, I manage to always be "up-to date"	

Variable	Construct items		Source
Attitudes towards AI	Indicate the level of agreement (1 - Strongly disagree, 5 - Strongly agree)		Adapted from Suh and Ahn (2022)
	Cognitive components (CC)	CC1: It is essential to learn about AI in school	
		CC2: AI class is important	
		CC3: Lessons about AI should be taught in school	
		CC4: Every student should learn about AI in school	
	Affective Component (AC)	AC1: AI is essential for developing society	
		AC2: AI makes people's lives more convenient	
		AC3: AI is related to my life. I will use	
		AC4: AI helps me solve problems in real life	
		AC5: I will need AI in my life in the future	
		AC6: AI helps me solve problems in real life	

Data Analysis

Quantitative data were analyzed using SPSS. Initially, raw data were coded and cleaned to remove invalid entries and statistical outliers. The internal consistency of each measurement scale was then assessed using Cronbach's alpha. Exploratory Factor Analysis (EFA) was conducted to examine the underlying factor structure of the instruments. Following this, tests for data normality were performed to ensure the appropriateness of subsequent statistical techniques. Descriptive statistics, including means, standard deviations, and frequency distributions, were calculated to provide an overview of the sample characteristics. Given that academic performance was measured on an ordinal scale (Poor, Average, Good, Very Good, Excellent), relationships between constructs were analyzed using Spearman's rank-order correlation, which is suitable for ordinal-level data. After that, ordinal logistic regression was conducted to examine the predictive relationships among the variables. In addition, moderation analysis was performed using the PROCESS macro in SPSS.

For the qualitative data, thematic analysis was conducted following the Template Analyses approach by King et al. (2018). This method was chosen for its flexibility in allowing researchers to structure themes based on both theory and data, making it appropriate for a focused sample and context-specific exploration. An initial coding template was developed deductively based on literature on AI Literacy, AI Self-Efficacy, Attitudes toward AI, and Control-Value Theory. It was then refined inductively through close reading of the responses. The first researcher revised the template and recorded the data to ensure that codes and themes accurately reflected participants' accounts.

Results

Descriptive Statistics

Descriptive statistics indicated that students reported high levels of AI Literacy (M = 3.61, SD = 0.48), with subscales including Understand AI (M = 3.67), Apply AI (M = 3.57), and Detect AI (M = 3.50). AI Ethics (M = 3.67) also rated high. AI Self-Efficacy was moderate (M = 3.15, SD = 0.61), including Problem Solving (M = 3.18) and Learning (M = 3.11). Student Attitudes toward AI were high overall (M = 3.74, SD = 0.58), with cognitive (M = 3.69) and affective (M = 3.78) components both scoring above the midpoint. All skewness and kurtosis values were within ±2, indicating approximately normal distributions (Field, 2013) (Table 3).

Table 3. Descriptive statistics

Constructs	Mean	Level	SD	Skewness	Kurtosis
1. AI Literacy	**3.61**	**High**	**0.48**	**0.150**	**0.134**
1.1 Understand AI	3.67	High	0.62	0.108	0.118
1.2 Apply AI	3.57	High	0.73	-0.055	-0.019
1.3 Detect AI	3.5	High	0.86	-0.125	0.091
1.4 AI Ethics	3.67	High	0.75	0.011	-0.653
2. AI Self-efficacy	**3.15**	**Average**	**0.61**	**0.140**	**0.284**
2.1 AI Problem Solving	3.18	Average	0.76	0.018	0.440
2.2 Learning	3.11	Average	0.68	0.019	0.112
3. Attitudes towards AI	**3.74**	**High**	**0.58**	**0.159**	**-0.586**
3.1 Cognitive Components	3.69	High	0.65	0.107	-0.755
3.2 Affective Component	3.78	High	0.73	0.090	-0.446

Note: 1.00-1.79: very low; 1.80-2.59: low; 2.60-3.39: medium; 3.40-4.19: high; 4.20-5.00: very high.

SPEARMAN'S RANK CORRELATION COEFFICIENT

Results indicated a small but significant positive correlation between overall AI Literacy and GPA ($r = 0.140$, $p < 0.01$). Among subdimensions, Understand AI ($r = 0.113$, $p < 0.05$), Apply AI ($r = 0.069$, $p < 0.05$), Detect AI ($r = 0.121$, $p < 0.05$), and AI Ethics ($r = 0.094$, $p < 0.05$) were all weakly but positively correlated with GPA (Table 4).

Table 4. Correlation between AI literacy and academic achievement

Constructs	(1)	(2)	(3)	(4)	(5)	(6)
(1) Understand AI	1					
(2) Apply AI	0.249**	1				
(3) Detect AI	0.261**	0.184**	1			
(4) AI Ethics	0.351**	0.106*	0.282**	1		
(5) AI Literacy	0.626**	0.561**	0.702**	0.656**	1	
(6) Academic Achievement (GPA)	0.113*	0.069*	0.121*	0.094*	0.140**	1

Note: **$p < 0.01$, *$p < 0.05$

Similarly, AI self-efficacy was positively associated with GPA ($r = 0.173$, $p < 0.01$), with both AI problem solving ($r = 0.138$, $p < 0.01$) and AI learning ($r = 0.176$, $p < 0.01$) showing small but statistically significant correlations (Table 5). These results are consistent with prior findings that self-efficacy beliefs are modest predictors of academic performance.

In contrast, attitudes toward AI, including both cognitive ($r = 0.076$, $p > 0.05$) and affective components ($r = 0.094$, $p > 0.05$), did not significantly correlate with GPA (Table 6). This suggests that while students may value or appreciate AI, their attitudes alone are not directly associated with academic achievement.

Table 5. Correlation between AI self-efficacy and academic achievement

Constructs	(1)	(2)	(3)	(4)
(1) AI Problem Solving	1			
(2) Learning	0.417**	1		
(3) AI Self-Efficacy	0.799**	0.854**	1	
(4) Academic Achievement (GPA)	0.138**	0.176**	0.173**	1

Note: **p < 0.01

Table 6. Correlation between attitudes towards AI and academic achievement

Constructs	(1)	(2)	(3)	(4)
(1) Cognitive Component	1			
(2) Affective Component	0.442**	1		
(3) Attitudes Towards AI	0.861**	0.822**	1	
(4) Academic Achievement (GPA)	0.076	0.094	0.072	1

Note: **p < 0.01

In sum, AI literacy is positively related to academic performance ($r = 0.140$, $p < 0.01$), and AI self-efficacy likewise ($r = 0.173$, $p < 0.01$). In contrast, students' attitudes towards AI have a small, non-significant association with performance. These results are illustrated in Figure 2.

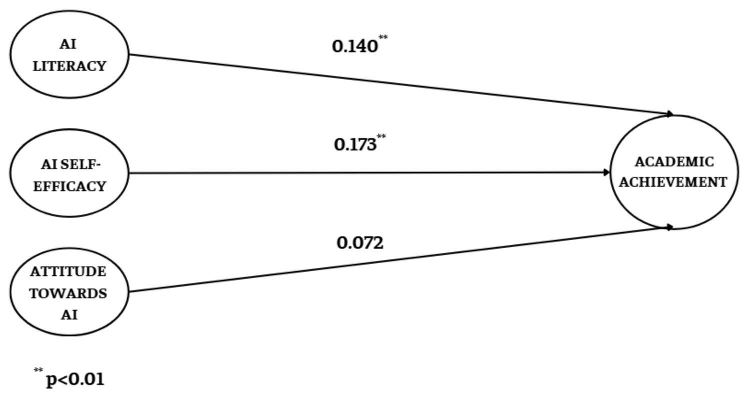

Figure 2. Spearman's rank correlation model of AI literacy, AI self-efficacy, attitudes toward AI, and academic performance

Ordinal Regression

Because academic achievement was measured on an ordinal GPA scale (poor, average, good, very good, excellent), we estimated an ordinal logistic regression model. Before estimating, we verified that multicollinearity among predictors: VIFs were 1.442 (AI literacy), 1.217 (AI self-efficacy), and 1.233 (attitudes toward AI), all well below commonly used investigation thresholds (≈4) and far from values that signal serious multicollinearity (≈10) (O'Brien, 2007). This satisfies the stability condition for coefficient estimation.

A cumulative logit proportional-odds model was then fit to the ordinal GPA outcome (Agresti, 2010). The predictor-augmented model improved fit over the intercept-only model $\chi^2 = 16.285$, $p = 0.001$ (Table 7). Pearson ($\chi^2 = 1072.912$, $p = 0.700$) and Deviance ($\chi^2 = 682.272$, $p = 1.000$) tests were non-significant (Table 8), indicating adequate model fit when using goodness-of-fit statistics appropriate for ordinal logistic models (Pulkstenis & Robinson, 2004). The Test of Parallel Lines was non-significant, $\chi^2 = 11.945$, $p = 0.063$ (Table 9), supporting the proportional odds assumption.

Table 7. Model fit

Model fitting information	-2 log likelihood	χ^2	df	Sig.
Intercept only	702.230			
Final	685.945	16.285	3	0.001

Table 8. Goodness-of-fit

Goodness-of-fit	χ^2	df	Sig.
Pearson	1072.912	1098	0.700
Deviance	682.272	1098	1.000

Table 9. Test of parallel lines

Model	-2 log likelihood	χ^2	df	Sig.
Null Hypothesis	685.945			
General	674.000	11.945	6	0.063

Parameter estimates are reported in Table 10. AI Self-Efficacy is the only statistically significant positive association with GPA category (B = 0.495, SE = 0.187, Wald = 6.972, p = 0.008). Substantively, a one-unit increase in AI Self-Efficacy corresponded to 64% higher odds of being in a higher GPA category (OR = 1.64, 95% CI [1.14, 2.37]). AI Literacy (B = 0.286, p = 0.260; OR = 1.33, 95% CI [0.81, 2.19]) and Attitudes toward AI (B = 0.154, p = 0.427; OR = 1.17, 95% CI [0.80, 1.71]) were positive but not statistically significant. As Pseudo-R^2 values are modest in logistic/ordinal models (Nagelkerke = 0.050; McFadden = 0.023; see Table 11), they will be interpreted as a descriptive indicator of model fit rather than explained variance. Overall, these results indicate that AI self-efficacy was more closely related to GPA category than AI literacy or attitudes toward AI.

Table 10. Ordinal regression (cumulative logit) parameter estimates

	B	SE	Wald	df	Sig.	95% CI		OR = e^B	95% CI (OR)
						Lower	Upper		
Threshold									
[GPA = 2]	-0.093	0.904	0.011	1	0.918	-1.866	1.679		
[GPA = 3]	3.181	0.896	12.612	1	<.001	1.426	4.937		
[GPA = 4]	6.747	0.970	48.431	1	<.001	4.847	8.648		
Location									
AI Literacy	0.286	0.253	1.271	1	0.260	-0.211	0.782	1.33	0.81- 2.19
AI Self-Efficacy	0.495	0.187	6.972	1	0.008	0.128	0.862	1.64	1.14-2.37
Attitudes toward AI	0.154	0.194	0.632	1	0.427	-0.227	0.536	1.17	0.80-1.71

Note: CI is Confidence Interval, OR is Odds Ratio, thresholds are cumulative cut-points (not category-specific intercepts), e is Euler's constant (e ≈ 2.71828)

Table 11. Pseudo-R^2

Pseudo R-Square	Value
Cox & Snell	0.042
Nagelkerke	0.050
McFadden	0.023

MODERATION ANALYSIS

This research tested whether duration of AI usage and study year moderated the associations of AI literacy, AI self-efficacy, and attitudes toward AI with GPA using the PROCESS macro with mean-centering of continuous predictors. For the duration of AI usage, interactions were significant for AI literacy ($B = -0.2565$, $SE = 0.0676$, $p = 0.0002$; $\Delta R^2 = 0.0363$) and AI self-efficacy ($B = -0.1174$, $SE = 0.0522$, $p = 0.0250$; $\Delta R^2 = 0.0129$), but not for attitudes toward AI ($p = 0.0691$).

For the study year, interactions were significant for AI literacy ($B = -0.1989$, $SE = 0.0775$, $p = .0106$; $\Delta R^2 = .0170$) and AI self-efficacy ($B = -0.2004$, $SE = 0.0633$, $p = .0017$; $\Delta R^2 = .0253$). In contrast, the interaction between years of study and attitudes toward AI was non-significant ($p = .495$). Taken together, these results indicate that attitudes toward AI did not show significant moderation effects. In contrast, both AI literacy and AI self-efficacy demonstrated significant moderation effects by duration of AI usage and years of study (Table 12).

Table 12. Interaction effects

Interaction (X × Moderator)	B	SE	t	p	95% CI	ΔR^2
AI literacy × Duration of AI usage	-0.2565	0.0676	-3.795	0.0002	[-0.389, -0.124]	0.0363
Attitudes toward AI × Duration of AI usage	-0.0938	0.0514	-1.823	0.0691	[-0.195, 0.007]	0.0087
AI literacy × Study year	-0.1989	0.0775	-2.568	0.0106	[-0.351, 0.047]	0.0170
AI self-efficacy × Study year	-0.2004	0.0633	-3.167	0.0017	[-0.325, -0.076]	0.0253
Attitudes toward AI × Study year	-0.0459	0.0673	-0.683	0.4950	[-0.178, 0.086]	0.0012

Simple-slope tests showed that the positive associations between AI literacy and GPA, and between AI self-efficacy and GPA, were strongest at low levels of AI usage and became weaker and non-significant at high levels of usage (Table 13). Conditional effects indicated that AI literacy and AI self-efficacy were positively associated with GPA in Year 1 and at the mean year of study, with these associations shrinking and becoming non-significant at High Year (Table 14).

Table 13. Simple-slope tests (effect of AI Literacy and AI self-efficacy on GPA at the duration of AI usage)

Predictor	Duration level	Effect (SE)	t	p	95% CI
AI literacy	Low (1.0000)	0.3641 (0.0795)	4.581	0.0000	[0.208, 0.520]
	Mean (1.6782)	0.1902 (0.0651)	2.922	0.0037	[0.062, 0.318]
	High (2.6769)	−0.0660 (0.0939)	0.703	0.4830	[−0.251, 0.119]
AI self-efficacy	Low (1.0000)	0.2712 (0.0630)	4.305	0.0000	[0.147, 0.395]
	Mean (1.6782)	0.1915 (0.0519)	3.690	0.0003	[0.089, 0.294]
	High (2.6769)	0.0742 (0.0734)	1.012	0.3120	[−0.070, 0.219]

Table 14. Simple-slope test (effect of AI Literacy and AI self-efficacy on GPA at the study year)

Predictor	Duration level	Effect (SE)	t	p	95% CI
AI literacy	Year (1.0000)	0.3347 (0.0848)	3.947	0.0001	[0.168, 0.501]
	Mean year (1.6862)	0.1982 (0.0656)	3.018	0.0027	[0.069, 0.327]
	High year (2.5362)	0.0291 (0.0926)	0.314	0.7540	[-0.153, 0.211]
AI self-efficacy	Year (1.0000)	0.3267 (0.0668)	4.892	0.0000	[0.195, 0.458]
	Mean year (1.6862)	0.1892 (0.0516)	3.664	0.0003	[0.088, 0.291]
	High year (2.5362)	0.0189 (0.0753)	0.251	0.020	[-0.129, 0.167]

Collectively, these findings suggest that AI literacy and AI self-efficacy are more strongly related to GPA among students with shorter experience using AI and those in earlier years of study. For students with longer AI experience and in later years, the relationships between AI literacy, AI self-efficacy, and GPA were weaker.

Thematic Analysis

Open-ended responses from eight undergraduates across diverse faculties were analyzed using the Template Analyses approach by King et al. (2018). An initial coding template was developed from a priori concepts (AI literacy, AI self-efficacy, attitudes, and challenges, guided by Control-Value Theory) to capture themes and codes.

Students reported that AI was primarily used for practical academic purposes, including summarizing lectures, retrieving study materials, brainstorming ideas, and drafting outlines. As one student explained, "I frequently use AI to suggest creative ideas so I can develop content more quickly and effectively." Another noted, "I often rely on AI tools to help answer my academic questions." Patterns of frequency varied; some integrated AI regularly into their assignments, while others turned to it mainly under time pressure, and a smaller group used AI only when they felt stuck or lacked resources.

Despite these benefits, students highlighted three common challenges. Accuracy was a recurring concern: "The biggest difficulty is that some of the answers are vague, which can easily lead to misunderstanding." Expression quality in Vietnamese also required heavy editing. Prompting skills were described as difficult to master: "The hardest part for me is creating prompts that help AI really understand my question." At the same time, students observed that rephrasing prompts could improve outcomes: "After adjusting the way I described the problem, AI suggested many more creative ideas."

Experiences of AI use shaped students' confidence and attitudes in nuanced ways. Several reported strong self-efficacy for straightforward tasks, "I feel quite confident when using AI for my learning," but lower confidence for complex or analytical assignments. At the same time, students positioned AI as a scaffold, not a substitute, emphasizing its role as a reference: "I once used AI for language learning, and it provided a very detailed and easy-to-understand explanation."

Attitudes toward AI reflected both enthusiasm and caution. Enthusiasm centered on personalization and efficiency: "What excites me most is the ability to personalize my learning process." Yet this was tempered by concerns about over-reliance: "I worry that people will become dependent on AI." These ambivalent attitudes also shaped perceptions of learning outcomes. Students highlighted that AI improved comprehension and supported creativity, but they warned that uncritical reliance risked undermining genuine understanding. As one respondent summarized: "AI will be a powerful support tool, but teachers still play the central role."

Overall, students viewed AI as a practical tool for enhancing efficiency, comprehension, and idea generation; however, they remained cautious due to concerns about accuracy, language quality, and prompt formulation. These mixed experiences explain why AI self-efficacy and AI literacy mattered most for lower-usage and earlier-year students in the quantitative findings, while benefits diminished with greater experience. Consistent with Control-Value Theory, students engaged most productively when they felt both control over AI outputs and value in its contributions, positioning AI as a scaffold rather than a substitute for learning. Table 15 summarizes all themes and codes that emerged from the thematic analysis.

Table 15. Thematic analysis

Theme	Code
1. Purposes of AI use in coursework	1.1 Summarizing lectures
	1.2 Finding academic materials
	1.3 Brainstorming ideas
	1.4 Drafting essays/outlines
2. Frequency and situational triggers	2.1 Regular use for assignments
	2.2 Deadline-driven use
	2.3 Occasional use when students feel stuck
3. Challenges in AI use	3.1 Accuracy issues
	3.2 Vietnamese expression quality
	3.3 Prompting skill
4. Confidence based on task complexity	4.1 High confidence in simple tasks
	4.2 Low confidence in complex tasks
5. AI as scaffold, not replacement	5.1 Use as a reference tool
	5.2 Verification and editing of outputs
	5.3 Integration with students' own knowledge
6. Attitude towards AI shaped by experience	6.1 Enthusiasm for efficiency & personalization
	6.2 Caution due to inaccuracy & language limits
7. Perceived learning outcomes	7.1 Faster comprehension
	7.2 Idea generation support
	7.3 Risk of shallow learning if over-relied on

DISCUSSION

This mixed-methods study investigated how AI literacy, attitudes toward AI, and AI self-efficacy relate to academic achievement, and how these links vary by duration of AI use and year of study. It also examined how students describe their purposes, frequency, and challenges when using AI in coursework, and how such experiences shape self-efficacy, attitudes, and perceived learning.

RQ1: How do AI competencies influence academic achievement among university students?

AI Self-efficacy emerged as the only significant indicator of academic achievement, whereas AI literacy had only small associations with GPA, and attitudes toward AI were non-significant. This pattern is consistent with meta-analytic evidence that academic self-efficacy has a direct, moderate link with performance and often outperforms attitudinal variables once cognitive and behavioral factors are considered (Honicke & Broadbent, 2016).

Within AI-learning contexts, AI self-efficacy also tends to be the proximal driver of actual use and effective engagement, with attitudes tending to have weaker or indirect effects (Chen et al., 2024). Taken together, RQ1 is answered in favor of AI self-efficacy: students who feel capable of verifying, editing, and productively editing AI outputs translate access into achievement, whereas simply liking AI or possessing baseline literacy is insufficient without felt control.

RQ2: Does the duration of AI use moderate the paths between AI literacy, attitudes toward AI, AI self-efficacy, and academic achievement?

RQ3: Does the study year of AI use moderate the paths between AI literacy, attitudes toward AI, AI self-efficacy, and academic achievement?

The negative interactions for duration of AI use (with both AI literacy and AI self-efficacy) and for study year (with AI literacy) indicate a pattern of diminishing returns: the benefits are strongest for lighter users and earlier-year students but gradually reduce as usage intensifies, and academic tasks become more complex. This pattern reflects the expertise reversal effect, which suggests that scaffolding tools that benefit novices may become redundant or even counterproductive as learners acquire more knowledge and are required to solve complex problems (Nievelstein et al., 2013).

At high levels of AI exposure, additional risks such as over-reliance and automation bias also grow, which can potentially weaken students' critical evaluation skills and learning to poorer outcomes when AI-generated advice is accepted uncritically (Al-Zahrani, 2024; Klingbeil et al., 2024). These findings offer clear answers to RQ2 and RQ3: both duration of AI use and study year tend to weaken the relationships between AI literacy and AI self-efficacy with academic achievement. This suggests that guidance should shift from getting started skills to advanced verification and domain-specific prompting as students progress.

RQ4: How do students describe their purposes and frequency of AI use in coursework?
RQ5: What challenges do students face when using AI?

Qualitative findings provide insight into RQ4 by illustrating how students incorporate AI into their academic workflow. Students primarily used AI to summarize readings, brainstorm ideas, draft outlines, and localize resources when stuck or near deadlines. For RQ5, students reported experiencing friction when prompts were imprecise, outputs were inaccurate, or Vietnamese phrasing felt unnatural, leading them to blend AI with their own notes and editing. These patterns align with broader studies in higher education, in which students value AI for efficiency, ideation, and personalization but remain cautious of its limits and biases (Al-Zahrani, 2024; Lin & Chen, 2024).

RQ6: In what ways do students perceive that their use of AI builds or undermines AI self-efficacy?

For RQ6, qualitative findings indicate that competent, purpose-aligned use can build situational self-efficacy, which is confidence in verifying and refining outputs, especially on well-structured tasks. In contrast, complex or open-ended tasks can undermine confidence if students cannot diagnose hallucinations or adapt prompts. These patterns suggest that AI self-efficacy is strengthened when learners experience controllability and receive timely feedback and weakened by excessive behavior that suppresses critical judgment.

RQ7: How do these students perceive that experiences with AI relate to their attitudes and their perceived learning outcomes?

Regarding RQ7, students' attitudes and perceived learning outcomes were mixed. They appreciated the efficiency and personalization that AI offers and felt it supported comprehension and idea generation, yet they also worried about over-dependence and shallow learning if AI outputs were accepted uncritically. These accounts map closely onto Control-Value Theory, in which students engage most productively when they perceive both control over AI outputs and value in AI-supported tasks, while still seeing AI as a scaffold rather than a replacement for their own thinking.

Theoretically, this study contributes in three ways. First, it treats AI literacy and AI self-efficacy as forms of perceived control, and attitudes toward AI as a form of perceived value. In doing so, it applies Control-Value Theory in the higher education context and shows that perceived control variables are more closely linked with formal academic achievement than perceived value attitudes. Second, by including duration of AI use and study year as moderators, the study illustrates that the links between control beliefs and achievement are not the same for all students but differ depending on how long they have used AI and how far they are in their degree. Third, by combining quantitative and qualitative findings, the study clarifies how students' everyday ways of using AI, the challenges they encounter, and their reflections on AI can either support or weaken their sense of control and task value, helping to interpret the statistical patterns observed in the analyses.

Moreover, this research has two practical implications. First, teaching should focus on building AI self-efficacy rather than trying to change attitudes. In practice, courses should teach students how to spot errors, check claims, and revise AI outputs, including low-stakes practice with feedback and gradually raising the expected level of evidence and reasoning as students progress. Studies in higher education indicate that these skills will predict productive AI use (Knoth et al., 2024). Second, because benefits decline with heavier use and in later years, programs should take a stepwise approach to AI: offer light support for beginners, and in advanced years require students to keep a clear record of their steps and sources, ask the AI to compare alternatives, and provide clear citations to reduce automation bias (Gonsalves, 2025; Sutton et al., 2023)

This study also has limitations. The cross-sectional design and self-reported, ordinal GPA constrain causal claims. Moreover, the convenience sampling and an imbalanced gender distribution limit generalizability. Also, some measures were adapted and shortened after EFA. The qualitative data relied on open-ended survey responses (not interviews), which favors breadth over depth (Appendix B). Future work should (a) use longitudinal or experimental designs to test whether targeted AI self-efficacy and verification training causally improve academic achievement, (b) examine domain differences, such as programming problem sets, writing-intensive courses where task complexity and the risks of mistakes differ.

CONCLUSION

In sum, learners get the most benefit from AI when its use is competent, purposeful, and accompanied by critical verification. The findings suggest that AI self-efficacy, rather than general attitudes, is the most robust correlate of academic achievement. However, these benefits tend to diminish with increased usage and academic seniority, likely due to escalating task complexity and ongoing technical or cognitive frictions. From a Control-Value Theory perspective, enhancing students' perceived control (skills to evaluate and edit AI outputs) alongside task-specific value (alignment between AI use and learning objectives) appears to be the most effective pathway for translating access to AI into meaningful academic gains.

Theoretically, the study extends Control-Value Theory by treating AI literacy and AI self-efficacy as indicators of control, and attitudes toward AI as an indicator of value. It also demonstrates that control-related constructs are more closely linked with academic achievement than value-related attitudes in a higher education context. It also highlights that these associations differ according to students' AI experience and academic seniority. Practically, the findings point to the importance of building students' competence and confidence in using AI through activities that practice checking, comparing, and revising AI outputs rather than focusing on positive attitudes alone. At the same time, several limitations should be acknowledged: the cross-sectional, self-report design and convenience sampling limit causal inference and generalizability, and broad categories for duration of AI use and brief open-ended responses constrain measurement precision. Future work using longitudinal or experimental designs, richer indicators of AI use quality, and more diverse samples could further test and refine these patterns and inform the design of AI pedagogy in higher education.

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APPENDIX A: INSTRUMENTS

Instruments		Source
AI Literacy	**Understand AI (UA)**	Carolus et al. (2023)
	UA1: I know the most important concepts of the topic "artificial intelligence".	
	UA2: I know definitions of artificial intelligence.	
	UA3: I can assess what the limitations and opportunities of using an AI are.	
	UA4: I can assess what advantages and disadvantages the use of an artificial intelligence entails.	
	UA5: I can think of new uses for AI.	
	UA6: I can imagine possible future uses of AI.	
	Apply AI (AA)	
	AA1: I can operate AI applications in everyday life.	
	AA2: I can use AI applications to make my everyday life easier.	
	AA3: I can use artificial intelligence meaningfully to achieve my everyday goals.	
	AA4: In everyday life, I can interact with AI in a way that makes my tasks easier.	
	AA5: In everyday life, I can work together gainfully with artificial intelligence.	
	AA6: I can communicate gainfully with artificial intelligence in everyday life.	
	Detect AI (DA)	
	DA1: I can tell if I am dealing with an application based on artificial intelligence.	
	DA2: I can distinguish devices that use AI from devices that do not.	
	DA3: I can distinguish if I interact with an AI or a "real human".	
	AI Ethics (AE)	
	AE1: I can weigh the consequences of using AI for society.	
	AE2: I can incorporate ethical considerations when deciding whether to use data provided by an AI.	
	AE3: I can analyze AI-based applications for their ethical implication	
AI Self-efficacy	**AI Problem Solving (APS)**	Carolus et al. (2023)
	APS1: I can rely on my skills in difficult situations when using AI.	
	APS2: I can handle most problems in dealing with artificial intelligence well on my own.	
	APS3: I can also usually solve strenuous and complicated tasks when working with artificial intelligence well.	
	Learning (LE)	
	LE1: I can keep up with the latest innovations in AI applications.	

Instruments		Source
	LE 2: Despite the rapid changes in the field of artificial intelligence, I can always keep up to date.	
	LE 3: Although there are often new AI applications, I manage to always be "up-to date".	
Attitudes towards AI	**Cognitive Components**	Suh and Ahn (2022)
	CC1: It is essential to learn about AI in school.	
	CC2: AI class is important.	
	CC3: Lessons about AI should be taught in school.	
	CC4: Every student should learn about AI in school.	
	Affective Component	
	AC1: AI is essential for developing society.	
	AC2: AI makes people's lives more convenient	
	AC3: AI is related to my life I will use	
	AC4: AI to solve problems in daily life.	
	AC5: I will need AI in my life in the future.	
	AC6: AI helps me solve problems in real life.	
	AC7: AI is necessary for everyone.	
	AC8: AI produces more good than bad.	
	AC9: AI is worth studying.	
	AC10: Most jobs in the future will require knowledge related to AI	

APPENDIX B: OPEN-ENDED SURVEY

1. How often do you use AI tools or applications? In what ways do they support your learning or coursework?
2. What are the main challenges or difficulties you encounter when learning about and using AI?
3. Do you feel confident when using AI tools for learning or coursework? Why?
4. Have you successfully solved a problem using AI? Please describe that experience.
5. What aspects of using AI in learning make you feel excited, and what aspects make you concerned?
6. Do you think AI could replace the role of teachers in the future? Why or why not?

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