World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(Research Article)

Check for updates

The impact of artificial intelligence usage on learning outcomes: Evidence from students at the school of economics, Hanoi university of industry

Thuy Thi Nguyen [1,*], Minh Nguyen Hoang [2], Ngan Nguyen Thu [2], Ly Dinh Thi Khanh [2] and Huy Nguyen Quang [1]

[1] *School of Economics, Hanoi University of Industry.*
[2] *Student of School of Economics, Hanoi University of Industry.*

World Journal of Advanced Research and Reviews, 2026, 30(01), 1403-1410

Publication history: Received on 27 February 2026; revised on 10 April 2026; accepted on 13 April 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.30.1.0872

Abstract

This study examines the mechanism through which artificial intelligence (AI) usage influences students' learning outcomes. Survey data were collected from 342 students at the School of Economics, Hanoi University of Industry and analyzed using both measurement and structural models based on the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach. The results indicate that AI usage exerts a positive impact on learning outcomes through six mediating variables, including self-regulated learning, learning motivation, learning attitude, creativity, technology acceptance, and time management efficiency, among which time management efficiency emerges as the most significant mediating pathway. Notably, multi-group analysis (PLS-MGA), combined with mean value trend assessment, reveals a divergence between surface-level academic performance and actual competence among students with low academic integrity, providing empirical evidence for the phenomenon of "competence illusion." The study offers important implications for educational institutions in redesigning assessment methods and strengthening academic integrity management in the digital era.

Keywords: Artificial Intelligence (AI); Learning Outcomes; Students; Hanoi University of Industry

1. Introduction

1.1. Theoretical Foundations of Cognitive Interaction in Digital Learning Environments

The rapid advancement of artificial intelligence (AI) in higher education not only provides learning support tools but also has the potential to reshape how students access knowledge, develop motivation, and regulate their learning behaviors. To explain this mechanism, this study builds its theoretical foundation upon three dominant perspectives: Social Cognitive Theory (SCT), the Post-Adoption Model (PAM), and Self-Regulated Learning (SRL) theory. According to Social Cognitive Theory proposed by Bandura [1], human behavior is formed through the reciprocal interaction among environmental, personal, and behavioral factors. In the context of digital education, AI tools can be conceptualized as a novel learning environment in which students interact directly with knowledge-support systems. Rapid access to information and the analytical capabilities provided by AI can reduce cognitive barriers, thereby enhancing perceived self-efficacy and fostering learning motivation.

In addition, the Post-Adoption Model developed by Bhattacherjee [2] offers an important perspective for explaining the continued use of technology beyond the initial adoption stage. This model suggests that when users perceive that a technology delivers practical value and meets their initial expectations, expectation confirmation is established, which in turn leads to user satisfaction and sustained usage over time. In educational settings, this implies that when students perceive AI as saving time, supporting analytical tasks, or enabling personalized learning, they are more likely to integrate such tools into their regular learning processes. However, effective technology use depends not only on

* Corresponding author: Thuy Thi Nguyen

motivation but also on learners' self-regulatory capabilities. Self-Regulated Learning theory, as proposed by Zimmerman [3], conceptualizes learning as an active process involving goal setting, progress monitoring, and the adjustment of learning strategies. In a context where AI can automate various information-processing tasks, self-regulation becomes particularly critical to ensure that technology functions as a cognitive support tool rather than a substitute for learners' thinking processes. These three theoretical perspectives therefore complement one another in explaining how technological environments, usage motivation, and self-regulatory capacity jointly influence students' learning processes.

1.2. The Mechanism of AI's Impact on Learning Activities

Building upon the aforementioned theoretical foundations, a growing body of recent empirical studies has examined the role of artificial intelligence (AI) in students' learning activities. From a positive perspective, AI not only functions as an information provider but also contributes to the development of metacognitive capabilities [4], while simultaneously guiding cognitive processes through analytical suggestions, content synthesis, and conceptual explanations. Studies by Bai and Wang [5], as well as Hwang and Chang [6], indicate that interaction with large language models can help students overcome difficulties in accessing knowledge, thereby improving learning attitudes and fostering creative thinking. In the context of economics education in Vietnam, several studies have also reported that AI effectively supports students in searching for academic materials, synthesizing secondary data, and preparing learning content [7]. As a result, students can significantly reduce the time spent on technical tasks and allocate more cognitive resources to higher-order analytical and reasoning activities.

However, alongside these potential benefits, the use of AI also presents several challenges for the learning process. When learners become overly reliant on the system's ability to retrieve and synthesize information, they may reduce the cognitive effort required for knowledge processing [8]. Lin and Chen [9] further suggest that the convenience of AI systems may lead learners to overestimate their level of understanding, thereby giving rise to the phenomenon of "illusion of competence." In such cases, learners' confidence may increase without a corresponding improvement in their actual analytical and critical thinking abilities.

Despite the increasing number of studies on AI in education, existing empirical research has not yet reached consensus regarding appropriate approaches to evaluating its impact. Several quantitative studies, such as those conducted by Nguyen Si Thieu and Nguyen Hai Yen [10], primarily focus on analyzing the direct relationship between the frequency of AI usage and academic performance indicators. While this approach provides initial evidence, it fails to adequately explain the underlying mechanisms mediated by psychological and behavioral factors. In particular, the application of the Post-Adoption Model (PAM) [2] to assess AI integration in the post-experience stage, as well as the Self-Regulated Learning (SRL) framework [3] to quantify learners' self-regulatory capacity, remains limited. Moreover, many studies tend to treat the sample as relatively homogeneous, whereas actual learning outcomes may be influenced by diverse individual characteristics. Factors such as academic integrity norms and technological proficiency may play a critical role in shaping how students utilize AI in their learning processes [11].

In addition, the conceptualization of "AI usage in learning" in existing studies raises certain measurement concerns. Most research operationalizes AI usage through aggregated indicators such as frequency or level of use. Although this approach reflects the prevalence of AI in learning environments, it may not fully capture the nature of the interaction between learners and AI systems. In practice, students engage with AI in multiple ways, including information retrieval and processing, academic content development, and interactive exchanges for idea generation and evaluation. Studies on AI in education also suggest that such interactions involve diverse cognitive and learning activities rather than merely the extent of technology use [12], [13]. Taken together, the current literature reveals several limitations, including the fragmented examination of psychological and behavioral factors, insufficient clarification of indirect mechanisms in the post-adoption context, and overly generalized measurement approaches. Accordingly, this study adopts a multidimensional perspective on AI usage and develops a research model to examine the mediating roles of psychological-attitudinal and skill-behavioral factors in the relationship between AI usage and learning outcomes, thereby contributing additional empirical evidence to the field.

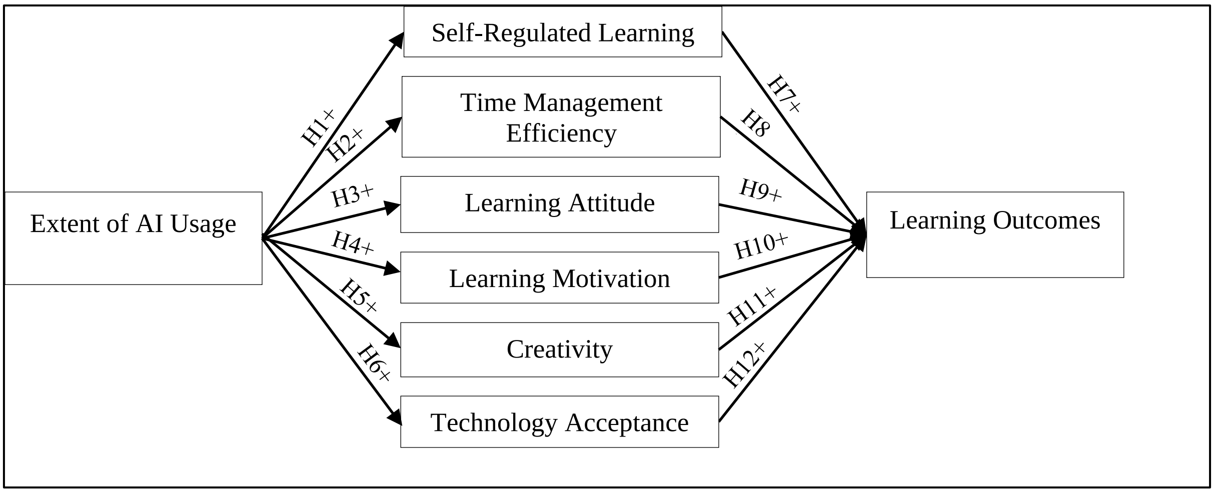
1.3. Research Hypotheses

- H1: Extent of AI Usage has a positive impact on self-regulated learning.
- H2: Extent of AI Usage has a positive impact on time management efficiency.
- H3: Extent of AI Usage has a positive impact on learning attitude.
- H4: Extent of AI Usage has a positive impact on learning motivation.
- H5: Extent of AI Usage has a positive impact on creativity.
- H6: Extent of AI Usage has a positive impact on technology acceptance.

- H7: Self-regulated learning has a positive impact on learning outcomes.
- H8: Time management efficiency has a positive impact on learning outcomes.
- H9: Learning attitude has a positive impact on learning outcomes.
- H10: Learning motivation has a positive impact on learning outcomes.
- H11: Creativity has a positive impact on learning outcomes.
- H12: Technology acceptance has a positive impact on learning outcomes.

1.4. Proposed Research Model

Based on prior studies on the application of artificial intelligence in learning contexts, combined with foundational theories including Social Cognitive Theory (SCT), the Post-Adoption Model (PAM), and Self-Regulated Learning (SRL) theory, the authors develop and propose the overall research model as follows:



(Source: Authors' own elaboration)

Figure 1 Proposed Research Model

2. Data and research methodology

The study employs a convenience sampling method, directly approaching students who use AI in their learning at the School of Economics, Hanoi University of Industry. The measurement scales are adapted from established studies and refined through expert consultation to ensure contextual relevance. Out of 355 online survey responses collected, after data screening, 342 valid observations were retained for analysis, fully satisfying the minimum sample size requirements for complex structural model testing.

Regarding the data analysis procedure, SPSS was utilized in the initial stage to assess reliability and conduct Exploratory Factor Analysis (EFA). Subsequently, given that the PLS-SEM approach, while strong in prediction, has limitations in providing traditional model fit indices [14], AMOS was incorporated to perform Confirmatory Factor Analysis (CFA) in order to obtain global model fit indices. Finally, the measurement and structural models were estimated using the PLS-SEM approach in SmartPLS, which was selected for its advantages in handling complex models and maximizing exploratory and predictive capabilities. The hypothesis testing procedure was conducted using 5,000 bootstrap resamples, combined with PLS-MGA and mean value trend analysis to compare differences in impact mechanisms across levels of academic integrity and digital technological competence among students. Specifically, the sample was divided into three groups: Group 1 (high academic integrity and high technological proficiency), Group 2 (high academic integrity and basic technological proficiency), and Group 3 (low academic integrity). Notably, in the trend analysis stage, the construct of learning outcomes was decomposed into surface-level academic performance and actual competence in order to identify the lag in knowledge transformation across different groups.

3. Results and discussion

Out of 342 valid responses collected from students at the School of Economics, Hanoi University of Industry, the sample exhibits a relatively representative distribution. In terms of gender, female respondents account for the highest proportion at 48.5%, followed by male respondents at 44.4%, while the remaining 7.1% identify as other genders.

Regarding academic year, most respondents are third-year students (35.4%) and second-year students (26.0%). Concerning current academic performance, the majority of students have a Grade Point Average (GPA) ranging from 2.5 to below 3.6 (Good to Very Good), accounting for 74.9% of the sample.

3.1. Measurement Model Assessment

The analysis results indicate that all outer loadings of the observed variables exceed the threshold of 0.708, thereby ensuring the reliability of each indicator. In addition, most Cronbach's Alpha coefficients are above 0.8, and the composite reliability (CR) values are largely above 0.9, indicating a high level of internal consistency of the measurement scales [14]. Specifically, the CR values range from 0.853 to 0.921, satisfying the recommended threshold of CR ≥ 0.7. The Average Variance Extracted (AVE) values for all constructs exceed 0.5, ranging from 0.538 to 0.684, thereby confirming the convergent validity of the scales (Table 1). Furthermore, discriminant validity assessed using the Heterotrait-Monotrait ratio (HTMT) shows that all values are below 0.85, confirming that the constructs achieve adequate discriminant validity [14].

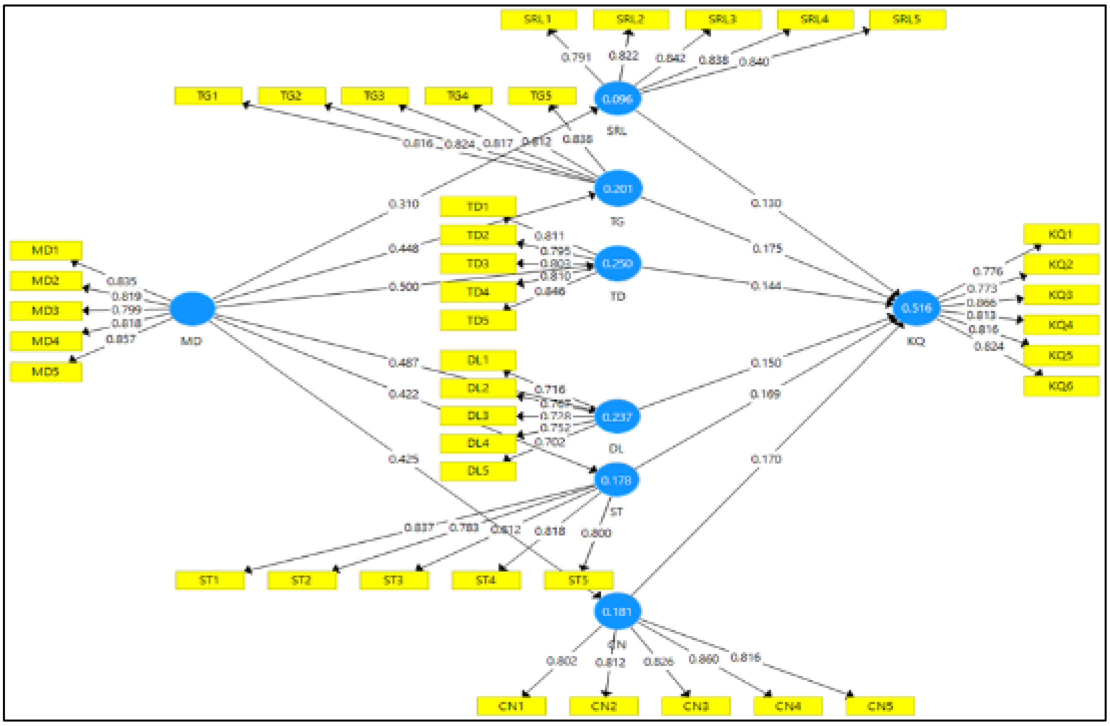
Table 1 Composite Reliability and Convergent Validity

Variable	Cronbach's Alpha	rho_A	CR	AVE
CN	0.881	0.881	0.913	0.678
DL	0.785	0.786	0.853	0.538
KQ	0.896	0.898	0.921	0.660
MD	0.884	0.887	0.915	0.682
SRL	0.884	0.886	0.915	0.684
ST	0.869	0.871	0.905	0.656
TD	0.872	0.875	0.907	0.661
TG	0.880	0.881	0.912	0.675

(Source: Authors' data analysis)

3.2. Structural Model Assessment

The results of the structural model assessment indicate that the Variance Inflation Factor (VIF) values of all endogenous constructs are below the threshold of 3.0, thereby satisfying the requirement for the absence of multicollinearity in the dataset [14]. In terms of explanatory power, the dependent variable Learning Outcomes achieves a coefficient of determination (R^2) of 0.516, indicating that the proposed model explains 51.6% of the variance in actual learning outcomes. For the mediating variables, the model also demonstrates an acceptable level of explanatory power for Self-Regulated Learning (R^2 = 0.096), Time Management Efficiency (R^2 = 0.201), Learning Attitude (R^2 = 0.250), Learning Motivation (R^2 = 0.237), Creativity (R^2 = 0.178), and Technology Acceptance (R^2 = 0.181). Furthermore, the Stone-Geisser (Q^2) value for Learning Outcomes reaches 0.331, while all mediating variables exhibit Q^2 values greater than 0, thereby meeting the criterion for the model's predictive relevance [14].



(Source: Authors' data analysis)

Figure 2 Structural Model Results

3.2.1. Hypothesis Testing

The bootstrapping results (5,000 resamples) indicate that all 12 direct hypotheses (H1-H12) are supported at the statistical significance level of $p < 0.05$. Specifically, on the antecedent side, Extent of AI Usage (MD) exerts the strongest effects on Learning Attitude (TD) (β = 0.500) and Learning Motivation (DL) (β = 0.487). It also positively influences Time Management Efficiency (TG) (β = 0.448), Technology Acceptance (CN) (β = 0.425), Creativity (ST) (β = 0.422), and Self-Regulated Learning (SRL) (β = 0.310). On the outcome side, Learning Outcomes (KQ) are most strongly affected by Time Management Efficiency (TG) (β = 0.175) and Technology Acceptance (CN) (β = 0.170), followed by the positive effects of Creativity (ST) (β = 0.169), Learning Motivation (DL) (β = 0.150), Learning Attitude (TD) (β = 0.144), and Self-Regulated Learning (SRL) (β = 0.130).

3.2.2. Indirect Effects Testing

Table 2 Results of Indirect Effects Testing

	Coefficient B	T Statistics	P Values	CI (2.5%)	CI (97.5%)
MD -> SRL -> KQ	0.040	2.352	0.019	0.009	0.077
MD -> TG -> KQ	0.079	2.772	0.006	0.023	0.132
MD -> TD -> KQ	0.072	2.237	0.025	0.014	0.142
MD -> DL -> KQ	0.073	2.415	0.016	0.018	0.136
MD -> ST -> KQ	0.071	2.742	0.006	0.024	0.125
MD -> CN -> KQ	0.072	2.663	0.008	0.023	0.129

(Source: Authors' data analysis)

Regarding the indirect effects mechanism, the results indicate that all six mediating pathways from Extent of AI Usage (MD) to Learning Outcomes (KQ) are statistically significant at the 95% confidence level ($p < 0.05$), with confidence intervals that do not include 0. Among these, Time Management Efficiency (TG) represents the strongest mediating mechanism (β = 0.079), followed closely by Learning Motivation (DL) (β = 0.073), Learning Attitude (TD) (β = 0.072), Technology Acceptance (CN) (β = 0.072), and Creativity (ST) (β = 0.071). The lowest coefficient is observed for Self-

Regulated Learning (SRL) (β = 0.040), suggesting that while AI may serve as an effective time-saving tool, its translation into actual learning outcomes remains dependent on learners' internal efforts.

3.2.3. Multi-Group Analysis

Differences in Mediation Mechanisms (PLS-MGA)

Table 3 Differences in Mediation Mechanisms

	Group 1 & 2		Group 1 & 3		Group 2 & 3	
	Diff	P-Value	Diff	P-Value	Diff	P-Value
MD -> CN -> KQ	0.055	0.287	-0.014	0.856	-0.069	0.315
MD -> DL -> KQ	0.001	0.970	-0.206	0.007	-0.207	0.045
MD -> SRL -> KQ	-0.110	0.065	0.015	0.721	0.124	0.061
MD -> ST -> KQ	0.008	0.889	-0.129	0.052	-0.137	0.083
MD -> TD -> KQ	-0.002	0.989	-0.059	0.392	-0.057	0.629
MD -> TG -> KQ	-0.149	0.105	-0.055	0.304	0.094	0.421

(Source: Authors' data analysis)

The PLS-MGA results indicate that the structural model demonstrates stability across groups. Specifically, pairwise comparisons (Group 1-2, 1-3, and 2-3) across five mediation pathways via Technology Acceptance (CN), Self-Regulated Learning (SRL), Creativity (ST), Learning Attitude (TD), and Time Management Efficiency (TG) reveal no statistically significant differences, with p-values ranging from 0.052 to 0.989 ($p > 0.05$). An exception is observed in the pathway via Learning Motivation (DL), where the differences between Group 3 and Groups 1 and 2 are -0.206 and -0.207, respectively ($p < 0.05$). Apart from this localized variation, the remaining mediation mechanisms appear to be largely invariant, suggesting that they are minimally influenced by differences in integrity levels or technological competence.

Trend Analysis Based on Mean Values

Table 4 Trend Analysis Based on Mean Values

GROUP	MD	SRL	TG	TD	DL	ST	CN	KQ_1	KQ_2	KQ
1	4.248	4.004	4.213	4.199	4.120	4.226	4.221	4.126	4.241	4.203
2	3.840	3.870	4.050	3.997	3.827	4.147	3.817	3.850	4.038	3.975
3	3.300	3.664	3.727	3.793	3.698	3.802	3.839	3.926	3.872	3.890

(Source: Authors' data analysis)

Although the PLS-MGA results indicate stability in the mediation mechanisms across groups, the mean-based analysis reveals clear differences in performance levels among the groups. Group 1 (High Integrity/High Technology) consistently achieves the highest levels across Extent of AI Usage (MD) as well as the system of psychological and skill-related constructs, thereby optimizing both surface performance (KQ_1 = 4.126) and substantive capability (KQ_2 = 4.241). Group 2 (High Integrity/Basic Technology), despite recording the lowest KQ_1 score (3.850), maintains relatively strong levels across the system of psychological and skill-related constructs, as well as substantive capability (KQ_2 = 4.038). Notably, Group 3 (Low Integrity/Any Level of Technological Proficiency) provides evidence of an "illusion of competence." While this group demonstrates multidimensional Extent of AI Usage (MD), both the system of mediating constructs and substantive capability (KQ_2 = 3.872) remain at the lowest levels. However, its surface performance (KQ_1 = 3.926) is self-reported to be higher than that of the high-integrity group with limited technological capability. This discrepancy suggests that AI usage lacking academic integrity may enhance nominal performance while potentially undermining core competencies.

4. Conclusion

The study elucidates the multidimensional mechanisms through which artificial intelligence (AI) influences learning outcomes via six mediating factors, among which Time Management Efficiency (TG) and Technology Acceptance (CN) serve as the primary transmission pathways. From the perspectives of the Post-Acceptance Model (PAM) [2] and Social Cognitive Theory (SCT) [1], these findings reinforce the view that AI enables learners to reallocate cognitive resources to enhance learning performance [7], while also confirming its role as a flexible supportive environment that fosters learning motivation and positive learning attitudes [5, 9].

Notably, the study not only corroborates relationships identified in prior research but also extends the literature by demonstrating that the impact of AI operates through the interaction between two clusters of factors: psychological-attitudinal and skill-behavioral. In doing so, it repositions Technology Acceptance (CN) in the post-adoption context as a mediating mechanism rather than merely a prerequisite condition.

However, Self-Regulated Learning (SRL) exhibits the lowest level of mediation, reflecting its inherent dependence on intrinsic motivation and metacognitive capabilities-factors that are not easily substituted by AI systems [3], [4]. This finding also provides empirical support for the risk of “learning automation” [8], whereby AI may enhance surface-level performance while potentially diminishing higher-order cognitive processes if employed as a substitute for independent thinking.

Furthermore, the mean-based trend analysis reveals the phenomenon of an “illusion of competence,” in which students with low academic integrity report improved nominal performance but exhibit reduced substantive capability. This finding highlights a divergence between observable outcomes and the internalization of knowledge. It also underscores the delicate boundary between leveraging technology as a tool for cognitive augmentation [6] and relying on it as a mechanism for cognitive offloading.

Overall, these findings contribute to the theoretical understanding of digital learning behavior and emphasize the need to balance the effective utilization of AI with the preservation of independent thinking capacity and academic integrity among learners.

4.1. Implications and Recommendations

Based on the research findings, several key managerial implications are proposed to optimize the application of artificial intelligence (AI) in academic environments.

For universities: Establishing clear institutional guidelines governing AI usage in academic contexts should be prioritized, with explicit definitions of acceptable applications and principles of source transparency. In addition, universities should integrate digital competence and responsible technology use into compulsory curricula to strengthen students’ self-directed learning capabilities. Assessment practices may also require strategic adjustments toward process-oriented evaluation, increasing the proportion of oral examinations, presentations, or tasks that require students to justify their use of AI in completing academic work.

For academic staff: Pedagogical approaches should be refined through the design of learning tasks that emphasize critical thinking. Instructors may require students to evaluate the strengths and limitations of AI-generated outputs rather than focusing solely on final results. Leveraging machine learning systems to automate repetitive tasks may enable instructors to optimize their time allocation and concentrate on in-depth academic mentoring. Assessment criteria should also be recalibrated to prioritize logical problem-solving processes and the application of knowledge in practical contexts.

For students: Learners are encouraged to establish a controlled approach to technology usage, adhering to the principle of “independent thinking first, AI assistance second.” The use of critical prompting strategies to identify logical inconsistencies may enhance cognitive depth. Additionally, maintaining an AI audit log to document interaction histories may help demonstrate the added value of independent reasoning. These practices should be systematically integrated into the self-regulated learning process, from planning to self-evaluation and strategic adjustment.

For technology firms: Developing an “Academic Mode” is recommended to enhance the transparency of information sources. Platforms may incorporate mechanisms that introduce cognitive delay, providing guided prompts before delivering complete solutions, along with features that warn against over-reliance. Collaborative development of domain-specific AI tutors between technology firms and universities may contribute to the establishment of a comprehensive digital education ecosystem.

Despite providing valuable findings with a relatively strong explanatory power, the model may not fully capture all relevant contextual variables. Furthermore, the cross-sectional design, reliance on self-reported data, and the use of a convenience sample within the economics discipline may limit generalizability. Future research should consider expanding to multidisciplinary samples, employing longitudinal designs, and adopting mixed-method approaches. The incorporation of objective measures, such as GPA scores or Learning Management System (LMS) data, is expected to enable triangulation and provide clearer distinctions between supportive AI usage and cognitive substitution.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Bandura, A., 1986. Social foundations of thought and action: A social cognitive theory. Prentice-Hall, Englewood Cliffs, NJ.

[2] Bhattacherjee, A., 2001. Understanding information systems continuance: An expectation-confirmation model. MIS Quarterly, 25(3), 351-370.

[3] Zimmerman, B. J., 2000. Attaining self-regulation: A social cognitive perspective. Handbook of self-regulation, Academic Press, San Diego, 13-39.

[4] Li, L., và cộng sự, 2024. A systematic review of AI-supported self-regulated learning. Journal of Educational Technology.

[5] Bai, Y., Wang, S., 2025. AI interaction quality, academic self-efficacy, and learning performance: An empirical study. Scientific Reports, 15.

[6] Hwang, G. J., Chang, C. Y., 2024. Artificial intelligence-supported scaffolding in higher education: A Vygotskian perspective. Educational Technology & Society, 27(1), 15-28.

[7] Ly, N. N., Nguyen, N. L., Tran, H. A., Ngo, T. H., Ngo, Q. T., Nguyen, D. H., 2025. The impact of artificial intelligence applications on the learning capacity of economics students in Vietnam. Journal of Economics and Forecasting. Accessed on November 10, 2025.

[8] Bui, T. T., Nguyen, M. T., 2024. The impact of artificial intelligence in education on students' learning activities. Journal of Education, 24(10), 6-11.

[9] Lin, H., Chen, Q., 2024. Artificial intelligence (AI)-integrated educational applications and college students' creativity and academic emotions: Students and teachers' perceptions and attitudes. BMC Psychology, 12, 487.

[10] Nguyen, S. T., Nguyen, H. Y., 2024. The impact of artificial intelligence on learning outcomes: Evidence from the Academy of Policy and Development. Journal of Science and Training, 01, 116-128.

[11] Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., Siemens, G., 2024. A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. International Journal of Educational Technology in Higher Education, 21, 4.

[12] OECD, 2023. OECD Digital Education Outlook 2023: Towards an effective digital education ecosystem. OECD Publishing, Paris. Accessed on November 10, 2025. https://doi.org/10.1787/c74f03de-en.

[13] Holmes, W., Bialik, M., Fadel, C., 2019. Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign, Boston, MA.

[14] Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., 2021. A primer on partial least squares structural equation modeling (PLS-SEM). 3rd edition, SAGE Publications, Thousand Oaks, CA.