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Understanding dynamic learning profiles in AI-supported environments in Vietnam: Evidence from a three-wave latent transition analysis

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Abstract

Artificial intelligence has become increasingly integrated into higher education, transforming how students engage with academic tasks and regulate learning processes. This study examined how Vietnamese undergraduate students adapted to AI-supported learning through the interplay of AI self-efficacy, cognitive offloading, and metacognitive regulation across one academic semester. A three-wave longitudinal design was conducted with 725 students from a large public university in Vietnam. Latent profile analysis identified three distinct learning profiles: Optimal, Moderate, and Maladaptive. The Optimal profile was characterized by high AI self-efficacy, strong metacognitive regulation, and low cognitive offloading, whereas the Maladaptive profile demonstrated extensive delegation of cognitive processes accompanied by weak regulatory control. Latent transition analysis revealed substantial profile stability over time (entropy = .825), suggesting that patterns of AI-supported learning remained relatively stable throughout the semester. Students in the Optimal profile consistently achieved higher academic performance than those in the Moderate and Maladaptive profiles. Cognitive offloading was strongly and negatively associated with metacognitive regulation (r = − .596). Findings indicate that successful adaptation to AI-supported learning depends on maintaining regulatory control over cognitive processes rather than increasing reliance on AI systems.

1. Introduction

Artificial intelligence has moved from peripheral support to direct participation in students' academic work, altering how idea generation, explanation, and problem solving are carried out in higher education contexts. Students increasingly depend on generative AI systems to construct arguments, clarify complex concepts, and organize academic responses, which redistributes cognitive effort across human cognition and machine-generated outputs (Granda et al., 2024; Wang & Zhang, 2026). A critical issue emerges from this transformation because improved efficiency in completing academic tasks may coincide with reduced depth of cognitive engagement when learners transfer core meaning-making processes to AI systems. Research has demonstrated that heavy reliance on AI-generated responses can weaken higher-order thinking and limit opportunities for active knowledge construction when evaluation and integration processes are bypassed (Zhai et al., 2024).

Policy direction in Vietnam has explicitly mandated the integration of advanced technologies into higher education through Decision No. 131/QĐ-TTg (2022), which defines digital transformation in education as the systematic incorporation of digital technologies, including artificial intelligence, to improve teaching quality, expand access to learning resources, and foster learner autonomy. Decision No. 131/QĐ-TTg (2022) requires higher education institutions to redesign instructional practices, implement intelligent learning systems, and develop digital learning environments that support personalized and flexible learning pathways. The strategic importance of Decision No. 131/QĐ-TTg (2022) lies in its role as a national directive that links technological adoption with expected improvements in learning outcomes and educational quality. However, implementation has concentrated on infrastructure development,

digital platforms, and tool accessibility, while mechanisms explaining how students regulate learning under AI-supported conditions remain insufficiently examined.

Research on artificial intelligence in education has examined constructs such as self-efficacy, engagement, and academic achievement, yet dominant analytical approaches estimate average relationships and assume uniform effects across learners (Chen et al., 2025). Such analytical approaches cannot capture how students combine confidence in AI use, delegation of cognitive processes, and regulation of learning into distinct patterns of engagement. Learning outcomes in AI-supported environments depend on how AI self-efficacy, cognitive offloading, and metacognitive regulation operate together during task execution rather than on isolated effects of single constructs. Students who report similar levels of AI use may demonstrate different learning behaviors when strong regulatory control constrains cognitive offloading or when weak regulation allows extensive delegation of cognitive processes. A direct focus on configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation becomes necessary for explaining how learning operates in technology-rich environments.

A second problem concerns the absence of temporal analysis in explaining how learning behaviors develop during sustained interaction with artificial intelligence. Interaction with AI systems unfold across repeated learning episodes, during which learners adjust strategies, refine levels of cognitive delegation, and stabilize patterns of engagement across a semester (Achuthan, 2025). Cross-sectional designs provide only static representations of learner behavior and cannot capture movement between different configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation. Movement across configurations reflects an adaptive process through which learners either strengthen regulatory control or increase reliance on AI for core cognitive operations. Understanding AI-supported learning requires examination of how configurations evolve across time and how changes in configurations influence academic performance outcomes.

This study addresses the identified problems by conceptualizing AI-supported learning as a dynamic system of cognitive regulation in which AI self-efficacy, cognitive offloading, and metacognitive regulation jointly structure patterns of engagement across time. This study employs a three-wave longitudinal design to identify distinct learning profiles, examine transitions between profiles, and evaluate associations between profile membership, profile transitions, and academic performance. This study provides a theoretically grounded and empirically rigorous explanation of how students adapt to AI-supported learning environments and how different configurations of cognitive processes influence academic outcomes within the context of ongoing digital transformation in higher education.

2. Literature Review

2.1 AI Self-Efficacy in AI-supported learning as a system of cognitive regulation

The rapid integration of artificial intelligence into higher education has fundamentally reshaped how students engage with academic tasks and manage cognitive demands during learning processes (George & Wooden, 2023). In contemporary classrooms, generative AI systems increasingly participate in idea generation, explanation construction, information organization, and problem-solving sequences that were traditionally performed through internal cognitive effort (Granda et al., 2024). Academic activity no longer resides solely within individual cognition but unfolds across an interactive system involving the learner, the task, and AI-mediated outputs (Dovhaniuk et al., 2025). This redistribution of cognitive processing introduces a new form of co-regulated learning, in which students continuously negotiate control over thinking processes while interacting with intelligent systems. Meanwhile, variation emerges in how students allocate cognitive responsibility between internal reasoning and AI-supported assistance, creating meaningful differences in engagement patterns across individuals (Chen et al., 2025). A system-level perspective becomes necessary because isolated examination of single variables cannot adequately represent the complexity of AI-supported learning environments or the dynamic allocation of cognitive effort within those environments (Fartusnic et a., 2025).

Furthermore, the effectiveness of AI-supported learning depends less on the presence of AI tools and more on how learners regulate the distribution of cognitive processes during task execution and knowledge construction (He, 2025). Students who maintain active control over interpretation, evaluation, and integration processes are more likely to preserve deep learning engagement, whereas excessive delegation of thinking processes to AI can reduce opportunities for meaningful cognitive processing (Sabri et al., 2024). At the same time, confidence in interacting with AI systems influences willingness to engage, yet confidence alone does not guarantee effective learning outcomes when regulatory processes remain insufficient. A conceptualization of AI-supported learning as a system of cognitive regulation thus highlights three interrelated dimensions that structure student behavior: perceived capability to use AI, degree of cognitive delegation to AI, and capacity to regulate ongoing learning processes (Kim et al., 2025).

Moreover, the redistribution of cognitive processing in AI-supported learning introduces a critical tension between cognitive support and cognitive substitution, which directly influences the depth and quality of learning engagement (Hong & Guo, 2025). When AI systems are used to assist idea generation or clarify complex concepts, learners may benefit from reduced cognitive load and increased access to information, allowing greater focus on higher-order reasoning processes (Du et al., 2025). However, when learners begin to rely on AI to perform core meaning-making activities, including explanation construction and problem-solving, cognitive engagement may gradually diminish as internal processing is replaced by externally generated outputs (Burns & Burns, 2025). This shift raises important concerns regarding the sustainability of deep learning, since meaningful knowledge construction requires active involvement in organizing, integrating, and evaluating information (Burns & Burns, 2025). The role of metacognitive regulation becomes increasingly central, as learners must continuously monitor the extent to which cognitive processes are delegated to AI and determine whether such delegation supports or undermines learning objectives (Romdhoni et al., 2025). At the same time, perceived capability to use AI systems may encourage more frequent engagement, yet greater engagement does

not necessarily translate into more effective learning when regulatory processes fail to maintain cognitive control.

2.2. Interplay of AI self-efficacy, cognitive offloading, and metacognitive regulation

AI self-efficacy, cognitive offloading, and metacognitive regulation collectively structure how learners engage with AI-supported academic tasks and distribute cognitive effort across different stages of learning processes (Iqbal et al., 2025). AI self-efficacy reflects perceived capability to use AI systems effectively, which shapes initial engagement and determines whether learners approach AI as a supportive partner or a primary source of answers (Xu et al., 2025). Cognitive offloading captures the extent to which learners transfer idea generation, explanation, and problem-solving processes to AI, thereby modifying the internal demands of academic work (Wang & Zhang, 2026). Metacognitive regulation refers to the capacity to plan, monitor, and evaluate ongoing learning processes, ensuring that cognitive activity remains aligned with learning objectives despite external support (Achuthan, 2025). However, each dimension operates within a broader system of interaction, because perceived capability, delegated processing, and regulatory control continuously influence one another during AI-mediated learning (Gkanatsiou et al., 2025). A systemic perspective becomes essential for understanding how learners maintain or lose control over cognitive engagement when interacting with AI technologies.

The relationship among AI self-efficacy, cognitive offloading, and metacognitive regulation does not follow a simple linear pattern, since similar levels of one dimension may lead to different outcomes depending on the configuration of the remaining dimensions (Hidayat-ur-Rehman, 2024). High AI self-efficacy can increase the frequency and sophistication of AI use, yet learning quality depends on whether cognitive offloading remains strategically constrained through active monitoring and evaluation processes (Gkintoni et al., 2025). Cognitive offloading, when guided by strong metacognitive regulation, may reduce unnecessary cognitive load while preserving meaningful engagement with content (Surbakti et al., 2024). In contrast, elevated levels of cognitive offloading combined with limited regulatory oversight can result in superficial processing, as learners rely on AI outputs without critically examining underlying reasoning. The effectiveness of AI-supported learning depends on how AI self-efficacy, cognitive offloading, and metacognitive regulation interact to shape the distribution of cognitive responsibility between human cognition and AI-generated support (Hooper, 2025).

The distinct configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation give rise to qualitatively different learning patterns that extend beyond the explanatory capacity of variable-centered approaches (Mariani et al., 2025). Some learners demonstrate high self-efficacy alongside controlled delegation and strong regulation, reflecting an adaptive pattern that integrates AI without undermining cognitive engagement (Wu et al., 2025). Other learners exhibit high levels of cognitive offloading coupled with weak regulatory capacity, indicating a maladaptive pattern characterized by overreliance on AI for core cognitive processes (Zhai et al., 2024). Meanwhile, other learners would display moderate levels of AI self-efficacy, cognitive offloading, and metacognitive regulation, suggesting

a transitional state in which learners have not yet stabilized effective strategies for integrating AI into academic work. There is a need to examine AI self-efficacy, cognitive offloading, and metacognitive regulation as integrated configurations to understand how combined patterns influence learners' learning trajectories. A configuration-based perspective will provide a more precise framework for capturing the diversity of AI-supported learning behaviors and for explaining variations in academic performance.

Furthermore, the interaction among AI self-efficacy, cognitive offloading, and metacognitive regulation can be better understood through a regulatory mechanism in which learners continuously adjust the allocation of cognitive effort during AI-mediated tasks. AI self-efficacy may increase learners' willingness to engage with AI systems and explore diverse strategies for completing academic work, thereby expanding the range of available cognitive resources (Alqurni, 2026; Xu et al., 2025). However, increased engagement with AI tools often leads to greater cognitive offloading, as learners begin to rely on AI-generated outputs for idea development, explanation, and problem-solving processes (Iqbal et al., 2025; Hooper, 2025). Without sufficient metacognitive regulation, this shift in cognitive responsibility may reduce opportunities for active processing, limiting the depth of understanding and weakening knowledge construction over time (Zhai et al., 2024; Surbakti et al., 2024). In contrast, strong metacognitive regulation enables learners to monitor the accuracy and relevance of AI outputs, evaluate alternative interpretations, and maintain control over learning processes despite extensive AI support (Achuthan, 2025; Wu et al., 2025). Learning effectiveness depends on how AI self-efficacy, cognitive offloading, and metacognitive regulation jointly structure the regulation of cognitive effort, rather than on the independent influence of each construct.

2.3. Person-centred approaches to AI-supported learning

Research on AI-supported learning has predominantly relied on variable-centered approaches that estimate relationships among constructs using regression-based or structural equation modeling techniques (Bencsik et al, 2026). Analytical strategies of this type assume that associations between AI self-efficacy, cognitive offloading, and metacognitive regulation remain consistent across all learners, thereby overlooking meaningful heterogeneity in how students engage with AI systems during academic tasks (Jiang & Yu, 2025). However, AI-supported learning environments inherently generate diverse patterns of interaction because learners differ in confidence, delegation strategies, and regulatory capacity when navigating AI-mediated tasks (Lee & Lee, 2025). The identical levels of a single construct may produce divergent learning outcomes depending on how remaining constructs operate in combination within individual learners (Li et al., 2022). A person-centered perspective is essential for capturing variation that cannot be explained through average effects, allowing researchers to identify distinct subgroups characterized by unique configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation.

Moreover, heterogeneity in AI-supported learning reflects systematic differences in how learners coordinate AI self-efficacy, cognitive offloading, and metacognitive regulation during academic engagement rather than random variation across individuals. Learners enter AI-mediated environments

with distinct prior experiences, beliefs about AI capability, and levels of regulatory capacity, which shape how cognitive effort is distributed between internal processing and AI-supported assistance across learning tasks (Li et al., 2022; Chen et al., 2025). As a result, similar observable behaviors, including frequency of AI use or comparable academic outcomes, may emerge from fundamentally different underlying configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation. Variable-centered approaches cannot adequately capture this structural diversity because variable-centered approaches estimate average relationships that obscure meaningful differences in how learners organize cognitive processes.

In contrast, a person-centered perspective allows direct identification of coherent patterns that represent how AI self-efficacy, cognitive offloading, and metacognitive regulation operate jointly within individual learners across academic contexts. A person-centered perspective aligns with contemporary views of self-regulated learning, which conceptualize learning as an emergent process shaped through continuous interaction among cognitive, motivational, and regulatory processes rather than isolated influences (Achuthan, 2025; Kim et al., 2025). Different configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation can produce distinct pathways of engagement, ranging from sustained cognitive control to increasing reliance on AI for core processing activities. Recognition of structured variation across learners provides a theoretical basis for identifying meaningful subgroups and for examining how different configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation contribute to variation in academic performance.

2.4. Temporal dynamics and academic outcomes: the need for latent transition analysis

Learning in AI-supported environments unfolds through a cumulative process in which repeated interaction with AI systems gradually reshapes how learners allocate cognitive effort and regulate academic engagement across time (Jallali et al., 2026; Lima et al., 2026). Initial exposure to AI often involves experimentation, during which learners test how AI can support idea generation, explanation, and problem solving under varying academic demands (Changkui, 2025; Wang & Zhang, 2026). Continued interaction produces iterative feedback loops that reinforce configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation, allowing certain patterns of engagement to become increasingly dominant as learning progresses (Achuthan, 2025; Romdhoni et al., 2025). Repeated reliance on AI-generated outputs without sufficient monitoring may gradually strengthen habitual delegation of cognitive processes, whereas sustained regulatory control may support stable strategies that integrate AI assistance without weakening internal processing (Zhai et al., 2024; Wu et al., 2025). A cumulative mechanism explains how learning patterns emerge, stabilize, and shape the quality of academic engagement across a semester.

A developmental perspective further clarifies that evolving configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation cannot be adequately captured through cross-sectional research designs, since cross-sectional research designs represent only static observations of learner

behavior at a single moment (Achuthan et al., 2025). Academic engagement under AI-supported conditions involves continuous adjustment as learners respond to increasing task complexity, shifting performance expectations, and accumulated experience across a semester. Movement across configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation reflects an adaptive process in which learners either strengthen regulatory control or progressively rely on AI for core cognitive operations. Distinct trajectories of learning behavior may emerge, reflecting differences in how learners balance internal cognition with AI-assisted processing across time. A temporal analytical approach becomes necessary to capture how configurations evolve and to examine how changes in learning patterns relate to academic performance outcomes.

Latent transition analysis extends person-centered approaches by modeling probabilities of movement between profiles across multiple time points, thereby capturing the dynamic nature of learning adaptation in AI-mediated contexts (Yang & Du, 2025). Through this approach, researchers can identify whether learners maintain stable patterns or transition between adaptive and maladaptive configurations as academic demands increase. Furthermore, linking profile membership and transitions to academic performance outcomes, such as semester grade point average, allows evaluation of the practical consequences of different learning trajectories (Fu et al., 2022). Changes in AI self-efficacy, cognitive offloading, and metacognitive regulation across time have not been examined in relation to academic outcomes, leaving the longitudinal impact of AI-supported learning insufficiently understood. A longitudinal person-centered framework provides a rigorous basis for examining how learning behaviors evolve and how adaptive configurations contribute to improved academic performance (Alqurni, 2026). Studies on AI in education predominantly rely on variable-centered techniques, which constrain theoretical development regarding how combinations of cognitive and motivational factors jointly shape learning behaviour. A shift toward person-centered analysis is necessary to gain a more nuanced understanding of learner diversity and establishes a foundation for examining how different configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation relate to academic performance outcomes (Joo et al., 2026).

3. Research Methods

3.1 Research design and procedure

This study employed a three-wave longitudinal design to examine how undergraduate students adapted to AI-supported learning environments across one academic semester in Vietnamese higher education. Data were collected from September to December 2025, corresponding to the second semester of the 2025 academic year. The research context was a large public university in Vietnam with established digital learning infrastructure and regular student exposure to AI-supported academic tools. A longitudinal design was considered appropriate because learning adaptation in AI-supported environments develops progressively through repeated interaction with intelligent systems rather than through isolated learning episodes (Yeh et al., 2016).

The three measurement occasions reflected different phases of learning adaptation. The first wave was administered during the first two weeks of the semester to capture baseline levels of AI self-efficacy, cognitive offloading to AI, and metacognitive regulation before sustained engagement with semester-based coursework. The second wave was conducted during weeks seven to eight, when students experienced increased workload intensity and more frequent use of AI-supported tools for academic tasks. The third wave was administered during weeks thirteen to fourteen, when patterns of AI-supported learning behavior had become more stable and semester academic outcomes could be assessed. The temporal spacing was designed to capture short-term adjustment, mid-semester consolidation, and end-of-semester stabilization in cognitive engagement.

3.2 Participants

Participants consisted of undergraduate students enrolled in diverse academic programs at a large public university in Vietnam. The initial sample included 725 students at Time 1. The sample decreased to 670 students at Time 2 and to 600 students at Time 3, corresponding to cumulative attrition of 17.24% across the semester. Participants represented both STEAM and non-STEAM disciplines, allowing examination of disciplinary variation in AI-supported learning patterns.

Gender and field of study were included as covariates because previous research demonstrated that technology-supported learning behavior and self-regulated learning strategies can vary across learner characteristics and disciplinary contexts (Yeh & Chu, 2018). Attrition was examined prior to substantive analyses to determine whether dropout patterns were systematically associated with demographic or academic variables. Missing data were handled using full information maximum likelihood estimation.

3.3 Measures

All profile indicators were measured at Time 1, Time 2, and Time 3 using parallel item wording across the three waves. All items were rated on a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Higher scores indicated stronger endorsement of the corresponding construct.

AI Self-Efficacy

AI self-efficacy was measured using four items assessing students' perceived capability to use AI tools effectively for academic learning. The items captured confidence in using AI systems to generate ideas, solve academic problems, clarify difficult concepts, and support coursework completion. The scale was conceptually adapted from Bandura's (1997) self-efficacy theory and from prior technology-supported learning studies examining mastery experience and confidence in digital learning environments (Yeh et al., 2019). The measurement logic was also informed by the mastery-experience framework used in creativity digital game-based learning research, particularly the dimensions "ability to solve problems" and "confidence in solving problems" reported by Yeh et al. (2019). Item wording was contextualized specifically for AI-supported academic tasks.

Cognitive Offloading to AI

Cognitive offloading to AI was measured using four self-developed items assessing the extent to which students delegated core cognitive processes to AI systems during learning activities. The items focused on reliance on AI for idea generation, explanation construction, summarizing information, and problem-solving processes. The reviewed scale sources did not provide a validated instrument directly measuring cognitive offloading to AI. Therefore, the construct was operationalized as a context-specific measure grounded in theoretical distinctions between cognitive support and cognitive substitution in AI-mediated learning environments. The conceptual foundation was informed by studies examining redistribution of cognitive processing in technology-supported learning and dynamic interaction between human cognition and digital systems (Yeh et al., 2012; Yeh et al., 2016).

Metacognitive Regulation in AI-Supported Learning

Metacognitive regulation was measured using four items conceptually adapted from the Inventory of Self-Regulation in e-Learning developed by Yeh and Chu (2018). The original ISRE measured information retrieval and organization, strategy regulation and schedule monitoring, and time management efficiency in e-learning contexts (Yeh & Chu, 2018). For the present study, the item wording was contextualized for AI-supported learning environments. The adapted items assessed students' ability to monitor AI dependence, evaluate AI-generated responses, regulate learning strategies while using AI, and maintain control over learning goals during AI-supported academic work.

The construct was additionally informed by reflective learning and mindful learning literature emphasizing monitoring, self-awareness, and regulatory control during technology-supported learning processes (Yeh, 2004; Yeh et al., 2019). Higher scores indicated stronger regulatory control over AI-assisted learning behavior.

Academic performance and covariates

Prior academic performance was measured using cumulative grade point average on the ten-point grading scale commonly used in Vietnamese higher education. Semester GPA at the end of the semester served as the distal academic outcome. Gender and field of study were included as covariates predicting profile membership and transition probabilities.

3.4 Instrument adaptation and validation

The measurement development process followed a contextual adaptation approach rather than direct adoption of existing scales. AI self-efficacy items were adapted from self-efficacy and mastery-experience traditions in technology-supported learning research (Bandura, 1997; Yeh et al., 2019). Metacognitive regulation items were adapted from the Inventory of Self-Regulation in e-Learning and reflective learning frameworks (Yeh & Lin, 2015; Yeh & Chu, 2018). Cognitive offloading items were newly developed because existing reviewed instruments did not directly measure delegation of cognitive processing to artificial intelligence systems.

All adapted items were reviewed for conceptual clarity and contextual appropriateness in AI-supported higher education environments. Confirmatory factor analysis was conducted to examine construct validity across the three waves. Composite reliability, average variance extracted, and discriminant validity indices were evaluated prior to latent profile analysis.

3.5 Data analysis strategy

Data analysis followed a sequenced procedure implemented in Mplus. The first stage examined descriptive statistics, distributional properties, attrition patterns, and correlations among key variables. Robust maximum likelihood estimation was used to address potential deviations from normality.

The second stage evaluated the measurement model for AI self-efficacy, cognitive offloading, and metacognitive regulation across the three measurement occasions. Confirmatory factor analysis examined factor structure, convergent validity, and discriminant validity. Composite reliability and average variance extracted were calculated for each construct.

The third stage employed latent profile analysis separately at each wave to identify distinct configurations of AI-supported learning behavior. AI self-efficacy, cognitive offloading, and metacognitive regulation served as profile indicators. Model selection relied on information criteria, entropy, profile size, classification precision, and theoretical interpretability.

The fourth stage employed latent transition analysis to examine movement across profiles over time. Prior GPA, gender, and field of study were entered as covariates predicting profile membership and transition probabilities. Semester GPA was included as a distal outcome variable to evaluate academic consequences associated with different developmental trajectories of AI-supported learning behavior.

4. Research results

4.1 Data quality, descriptive statistics, and correlations

A three-wave longitudinal design resulted in progressive sample reduction across measurement occasions, which required explicit statistical examination before conducting substantive analyses. The dataset included 725 participants at Time 1, decreased to 670 participants at Time 2, and further declined to 600 participants at Time 3, corresponding to cumulative attrition of 17.24% across the semester. Attrition was evaluated using logistic regression models to determine whether missingness was associated with baseline characteristics. Missing data were handled using full information maximum likelihood estimation, allowing incomplete observations to contribute to parameter estimation without listwise deletion. Robust maximum likelihood estimation was applied to maintain stability of standard errors under potential deviations from normality, ensuring reliable estimation across all subsequent analyses. Table 1 presents descriptive statistics and distributional properties for all study variables.

Table 1.

Descriptive statistics of study variables

Variable	M	SD	Skewness	Kurtosis
Prior GPA	7.599	0.557	-0.082	-0.083
Gender	0.548	0.498	-0.191	-1.963
STEAM	0.508	0.500	-0.030	-1.999
Semester GPA	7.704	0.593	-0.143	-0.070
SE_T1	4.430	1.434	-0.309	-0.822
CO_T1	3.916	1.319	0.119	-0.622
MR_T1	4.254	1.289	-0.195	-0.576
SE_T2	4.433	1.329	-0.224	-0.648
CO_T2	3.875	1.269	0.162	-0.549
MR_T2	4.301	1.250	-0.054	-0.413
SE_T3	4.648	1.177	-0.101	-0.803
CO_T3	3.750	1.271	0.180	-0.409
MR_T3	4.424	1.234	0.084	-0.719

Distributional properties indicated acceptable ranges for skewness from −0.309 to 0.180 and kurtosis from −1.999 to −0.070, indicating no severe violations of normality assumptions. AI self-efficacy increased from 4.430 at Time 1 to 4.648 at Time 3, while cognitive offloading decreased from 3.916 to 3.750 and metacognitive regulation increased from 4.254 to 4.424, indicating gradual strengthening of regulatory engagement across the semester. Table 2 presents correlations among baseline learning constructs and academic performance outcomes.

Table 2.

Correlations among baseline constructs and academic performance

Variable	1	2	3	4	5
1. Prior GPA	1.000				
2. Semester GPA	0.957	1.000			
3. SE_T1	0.105	0.141	1.000		
4. CO_T1	-0.170	-0.232	-0.072	1.000	
5. MR_T1	0.179	0.232	0.278	-0.596	1.000

Prior GPA demonstrated a very strong positive association with semester GPA (r = 0.957), indicating substantial continuity in academic performance across the semester. AI self-efficacy demonstrated a positive association with metacognitive regulation (r = 0.278), indicating alignment between perceived capability and regulatory engagement. Cognitive offloading demonstrated a strong negative association with metacognitive regulation (r = −0.596), indicating that increased delegation of cognitive processes corresponded to reduced regulatory control during learning. The patterns provide empirical support for the proposed interaction among AI self-efficacy, cognitive offloading, and metacognitive regulation and establish a foundation for subsequent person-centered and longitudinal analyses.

4.2 Measurement model evaluation

Confirmatory factor analysis was conducted to evaluate the adequacy of the measurement model across three measurement occasions before estimating latent profiles and transition probabilities. Robust maximum likelihood estimation was applied to maintain stable parameter estimates under minor departures from normality and to preserve comparability across measurement occasions. Measurement model evaluation focused on global model fit, indicator loadings, composite reliability, average variance extracted, and discriminant validity, allowing a comprehensive assessment of whether AI self-efficacy, cognitive offloading, and metacognitive regulation were represented with sufficient precision for subsequent mixture modeling. Table 3 presents global fit indices for the measurement model.

Table 3.

Measurement model fit indices

Fit Index	Value	Recommended Threshold
χ^2 (df)	629.633 (522)	—
CFI	0.986	≥ 0.95
TLI	0.983	≥ 0.95
RMSEA	0.017	≤ 0.06
SRMR	0.029	≤ 0.08

Global fit indices indicated excellent correspondence between the hypothesized measurement structure and the observed data. Comparative fit index reached 0.986 and Tucker–Lewis index reached 0.983, both exceeding recommended thresholds for strong model fit. Root mean square error of approximation reached 0.017 and standardized root mean square residual reached 0.029, both far below commonly accepted cutoffs. Chi-square remained statistically significant, χ^2 (522) = 629.633, $p < .001$, although that pattern is expected under large samples and complex latent structures. Global fit evidence supports continued evaluation of the measurement model at the indicator and construct levels. Table 4 presents standardized factor loadings, composite reliability coefficients, and average variance extracted values for all constructs across measurement occasions.

Table 4.

Standardized factor loadings, composite reliability, and average variance extracted

Construct	Item	Loading	CR	AVE
AISE_T1	aise_t1_1	0.785	0.84	0.56
	aise_t1_2	0.762		
	aise_t1_3	0.769		
	aise_t1_4	0.690		
COFF_T1	coff_t1_1	0.820	0.83	0.55
	coff_t1_2	0.750		
	coff_t1_3	0.722		
	coff_t1_4	0.696		
MREG_T1	mreg_t1_1	0.755	0.81	0.52
	mreg_t1_2	0.736		
	mreg_t1_3	0.709		
	mreg_t1_4	0.680		
AISE_T2	aise_t2_1	0.808	0.85	0.58
	aise_t2_2	0.770		
	aise_t2_3	0.740		
	aise_t2_4	0.662		
COFF_T2	coff_t2_1	0.677	0.82	0.53
	coff_t2_2	0.734		
	coff_t2_3	0.747		
	coff_t2_4	0.653		
MREG_T2	mreg_t2_1	0.729	0.82	0.54
	mreg_t2_2	0.700		
	mreg_t2_3	0.692		
	mreg_t2_4	0.708		
AISE_T3	aise_t3_1	0.759	0.83	0.55
	aise_t3_2	0.708		
	aise_t3_3	0.701		
	aise_t3_4	0.583		

COFF_T3	coff_t3_1	0.734	0.83	0.55
	coff_t3_2	0.747		
	coff_t3_3	0.781		
	coff_t3_4	0.702		
MREG_T3	mreg_t3_1	0.697	0.81	0.51
	mreg_t3_2	0.632		
	mreg_t3_3	0.668		
	mreg_t3_4	0.536		

Standardized factor loadings ranged from 0.536 to 0.820 across all indicators, indicating acceptable to strong associations between observed items and latent constructs. Higher loadings appeared for aise_t2_1 at 0.808 and coff_t1_1 at 0.820, whereas lower loadings appeared for aise_t3_4 at 0.583 and mreg_t3_4 at 0.536.

Composite reliability values ranged from 0.81 to 0.85, indicating satisfactory internal consistency across constructs and measurement occasions, while average variance extracted values ranged from 0.51 to 0.58, exceeding the threshold of 0.50 and supporting convergent validity. Measurement precision remained stable across time, although slightly lower loadings at Time 3 suggested modest attenuation in item strength during later stages of the semester. Table 5 presents discriminant validity based on the Fornell Larcker criterion.

Table 5.

Discriminant validity (Fornell–Larcker criterion)

Construct	AISE	COFF	MREG
AISE	**0.748**		
COFF	-0.305	**0.742**	
MREG	0.487	-0.717	**0.714**

Square roots of average variance extracted exceeded inter construct correlations for comparisons involving AI self efficacy and cognitive offloading, supporting discriminant validity at the construct level. The correlation between cognitive offloading and metacognitive regulation reached −0.717, indicating a strong inverse relationship between delegation of cognitive processes and active regulatory engagement, while the square root of average variance extracted for metacognitive regulation reached 0.714, representing a borderline comparison. Additional evaluation using the heterotrait monotrait ratio supported conceptual separation across constructs, with the highest value reaching 0.79 for the cognitive offloading and metacognitive regulation pair, remaining below the conservative threshold of

0.85. Overall measurement model evaluation indicated that the latent structure demonstrated sufficient reliability and validity for subsequent latent profile analysis and latent transition analysis.

4.3 Latent Profile Analysis

Latent profile analysis was conducted at three measurement occasions to identify distinct configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation across students. Models ranging from one profile to five profiles were estimated separately at each time point, and model selection was guided by information criteria, entropy, likelihood ratio tests, and theoretical interpretability. Evaluation emphasized parsimony and conceptual clarity rather than purely statistical improvement, given that additional profiles may artificially improve fit without contributing meaningful distinctions. Table 6 presents model fit indices across profile solutions for all three time points.

Table 6.

Model fit indices for latent profile solutions

Wave	Profiles	AIC	BIC	Entropy	LMRT p
T1	2	7170.632	7216.494	0.678	0.000
T1	3	7039.919	7104.126	0.721	0.020
T1	4	6849.678	6932.229	0.823	0.000
T2	2	6446.418	6491.491	0.715	0.000
T2	3	6287.300	6350.402	0.801	0.000
T2	4	6184.794	6265.925	0.822	0.000
T3	2	5532.940	5576.910	0.797	0.000
T3	3	5389.567	5451.124	0.825	0.000
T3	4	5352.296	5431.441	0.770	0.001

Information criteria decreased as the number of profiles increased across all time points, indicating improved statistical fit with more complex solutions. AIC values declined from 7170.632 to 6849.678 at Time 1 and from 5532.940 to 5352.296 at Time 3, reflecting progressive improvement in model fit. Entropy provided clearer guidance for classification precision, increasing from 0.678 to 0.721 and then to 0.823 at Time 1, while reaching 0.825 at the three-profile solution at Time 3 before decreasing to 0.770.

Likelihood ratio tests supported model selection, as the transition from two profiles to three profiles remained statistically significant across all time points with LMRT p values below 0.05. Additional profiles did not enhance interpretability, since higher order solutions mainly subdivided existing patterns without introducing meaningful distinctions.

The three-profile solution demonstrated consistent structure across measurement occasions, combining acceptable fit, strong classification quality, and theoretical clarity. Figure 1 illustrates latent profile patterns across the three indicators.

Three distinct profiles emerged across all time points, reflecting different configurations of cognitive engagement in AI supported learning environments. The Optimal profile demonstrated high AI self efficacy ranging from 5.455 to 5.712, low cognitive offloading ranging from 2.564 to 2.576, and high metacognitive regulation ranging from 5.545 to 5.705, indicating strong regulatory control with selective use of artificial intelligence. The Moderate profile showed intermediate levels, with AI self efficacy ranging from 3.670 to 3.969, cognitive offloading ranging from 3.778 to 4.057, and metacognitive regulation ranging from 3.939 to 4.413, reflecting a transitional configuration of learning behavior. The Maladaptive profile combined high cognitive offloading ranging from 5.271 to 5.766 with lower metacognitive regulation ranging from 2.770 to 3.260, indicating extensive delegation of cognitive processes with limited regulatory control.

Replication of the three-profile structure across all measurement occasions indicated strong temporal consistency in learning configurations. Mean cognitive offloading decreased from 3.916 at Time 1 to 3.750 at Time 3, while metacognitive regulation increased from 4.254 at Time 1 to 4.424 at Time 3, indicating gradual improvement in regulatory engagement. Structural stability suggested that profiles reflected relatively stable orientations toward AI supported learning rather than short term behavioral fluctuation.

4.4 Latent transitions, covariates, and academic outcomes

Interpretation of longitudinal latent profiles required integration of attrition processes, covariate effects, and academic outcomes within a unified analytical framework. Attrition showed systematic associations with baseline learning characteristics, indicating non-random dropout that influenced later wave estimates.

Logistic regression results showed that prior GPA reduced attrition at Time 2 ($\beta = -2.656$, OR = 0.070, $p < .001$) and Time 3 ($\beta = -0.856$, OR = 0.425, $p < .001$), while AI self efficacy also lowered attrition probability at Time 2 ($\beta = -0.854$, OR = 0.426, $p < .001$) and Time 3 ($\beta = -0.496$, OR = 0.609, $p < .001$). In contrast, cognitive offloading increased attrition at Time 2 ($\beta = 1.008$, OR = 2.740, $p < .001$) and Time 3 ($\beta = 0.553$, OR = 1.738, $p < .001$), whereas metacognitive regulation reduced attrition risk at Time 2 ($\beta = -0.803$, OR = 0.448, $p < .001$) and Time 3 ($\beta = -0.371$, OR = 0.690, $p = .001$).

The observed pattern supported a Missing at Random assumption conditional on included predictors, although selective dropout associated with maladaptive learning tendencies suggested that later wave estimates may underestimate less adaptive profiles. Table 7 reports logistic regression results predicting attrition across measurement occasions.

Table 7.

Logistic regression predicting attrition

Predictor	T2 β	T2 OR	T2 p	T3 β	T3 OR	T3 p
Prior GPA	-2.656	0.070	< .001	-0.856	0.425	< .001
AI self-efficacy (T1)	-0.854	0.426	< .001	-0.496	0.609	< .001
Cognitive offloading (T1)	1.008	2.740	< .001	0.553	1.738	< .001
Metacognitive regulation (T1)	-0.803	0.448	< .001	-0.371	0.690	0.001
Gender	n.s.	—	> .05	n.s.	—	> .05
STEAM	n.s.	—	> .05	n.s.	—	> .05

Covariate effects on latent profile membership were examined to determine whether profiles reflected stable academic or demographic differences. Prior GPA did not consistently differentiate profiles across measurement occasions, while gender did not demonstrate statistically significant effects.

Field of study showed a selective effect at Time 2, with STEAM students less likely to belong to the Maladaptive profile relative to the Moderate profile (β = −0.605, OR = 0.546, p = 0.030). Statistical significance did not appear at Time 1 (p = 0.075) or Time 3 (p = 0.644), indicating that disciplinary differences were temporary rather than structurally embedded. The latent profiles reflected dynamic learning configurations rather than fixed background characteristics. Table 8 reports covariate effects across measurement occasions.

Table 8.

Effects of field of study on profile membership

Time	Contrast	β	OR	p
T1	Maladaptive vs Moderate	-0.395	0.674	0.075
T2	Maladaptive vs Moderate	-0.605	0.546	0.030
T3	Maladaptive vs Moderate	-0.094	0.910	0.644

Academic outcomes were examined using both unadjusted estimates and mixture regression models controlling for prior GPA, gender, and field of study. Unadjusted results indicated significant differences across profiles at all time points, with $\chi^2 = 39.890$ at Time 1, $\chi^2 = 18.292$ at Time 2, and $\chi^2 = 27.267$ at Time 3, all reaching $p < .001$. Adjusted models indicated that prior GPA exerted a dominant influence on semester GPA, with coefficients of $\beta = 0.996$ at Time 1, $\beta = 1.004$ at Time 2, and $\beta = 1.002$ at Time 3, all reaching $p < .001$, indicating that prior academic performance explained a substantial proportion of

outcome variance. Table 9 presents both unadjusted and adjusted academic outcomes across latent profiles.

Table 9.

Semester GPA across latent profiles

Time	Profile	SE	CO	MR	BCH Mean GPA	Adjusted GPA	p
T1	Optimal	5.482	2.576	5.705	7.960	0.188	0.061
T1	Moderate	3.969	3.778	4.413	7.696	0.112	0.250
T1	Maladaptive	4.351	5.271	2.770	7.502	0.038	0.692
T2	Optimal	5.455	2.572	5.545	7.916	0.151	0.115
T2	Moderate	3.670	4.057	3.939	7.718	0.020	0.829
T2	Maladaptive	5.453	5.766	3.260	7.615	-0.028	0.767
T3	Optimal	5.712	2.564	5.672	7.957	0.198	0.029
T3	Moderate	3.853	3.941	3.990	7.735	0.040	0.652
T3	Maladaptive	5.373	5.593	3.375	7.612	-0.090	0.308

Academic performance showed a stable ordering across measurement occasions, with the Optimal profile achieving the highest GPA, followed by the Moderate profile, while the Maladaptive profile consistently recorded the lowest values. At Time 3, the Optimal profile reached a mean GPA of 7.957 and demonstrated a statistically significant adjusted estimate ($\beta = 0.198$, $p = 0.029$), whereas Moderate and Maladaptive profiles did not reach statistical significance.

Differences across profiles increased over time, indicating a cumulative process through which repeated patterns of engagement with artificial intelligence progressively shaped academic outcomes. Profile composition clarified this pattern, as the Optimal profile combined high metacognitive regulation with low cognitive offloading, whereas the Maladaptive profile reflected the opposite configuration. Academic performance aligned more closely with regulatory capacity than with perceived ability to use artificial intelligence, indicating that sustained cognitive control played a central role in academic success relative to reliance on external computational support.

5. Discussions

The conceptualization of AI-supported learning as a system of cognitive regulation reflects a growing body of work examining how artificial intelligence reshapes cognitive processes in academic contexts. Granda et al. (2024) and Burns and Burns (2025) emphasized that artificial intelligence can function simultaneously as a cognitive support mechanism and as a substitute for internal reasoning, creating

tension between efficiency and depth of processing during academic work. Zhai et al. (2024) demonstrated that extensive reliance on AI systems can weaken higher-order thinking when learners bypass internal meaning-making processes. This study extends this line of inquiry through the integration of AI self-efficacy, cognitive offloading, and metacognitive regulation within a single analytical framework that captures redistribution of cognitive effort during learning. A key distinction lies in the focus on configurations instead of isolated relationships, which allows explanation of why comparable levels of AI use may produce divergent academic outcomes.

The interaction among AI self-efficacy, cognitive offloading, and metacognitive regulation has been explored within research on self-regulated learning and artificial intelligence, yet existing approaches have often assumed linear relationships among constructs. Achuthan (2025) emphasized the importance of metacognitive regulation in maintaining learner autonomy under conditions of AI mediation, while Iqbal et al. (2025) demonstrated that cognitive offloading can enhance learning outcomes when supported through coordinated regulation. Wu et al. (2025) further highlighted that effective AI use requires sustained monitoring and evaluation of cognitive processes during task execution. This study advances current understanding through the identification of structured configurations that differentiate adaptive, transitional, and maladaptive patterns of engagement. An important insight emerges in the finding that high AI self-efficacy does not guarantee effective learning when regulatory processes remain insufficient to constrain cognitive delegation. A second insight concerns the dual role of AI engagement, which expands available cognitive resources while simultaneously increasing the likelihood of over-delegation when regulation weakens.

Methodological development within AI-supported learning research has increasingly emphasized the need to move beyond variable-centered approaches that estimate average effects across heterogeneous learners. Bencsik et al. (2026) and Jiang and Yu (2025) relied on analytical strategies that assume uniform relationships among constructs, which limits the ability to capture meaningful variation in learning behavior. Yang and Du (2025) argued for integrating person-centered approaches with dynamic modeling to represent evolving patterns of engagement, while Fu et al. (2022) demonstrated the value of trajectory-based analysis for understanding academic development across time. This study demonstrates that learning behavior represents an evolving system shaped through continuous interaction with artificial intelligence, providing a more precise explanation of adaptation in technology-rich educational environments.

6. Conclusions

Patterns identified across three measurement occasions revealed that AI-supported learning does not operate as a uniform process but instead emerges through distinct configurations of AI self-efficacy, cognitive offloading, and metacognitive regulation that shape how learners engage with academic tasks. This study demonstrated that the Optimal profile, characterized by high metacognitive regulation and constrained cognitive offloading, consistently achieved the highest academic performance, whereas the Maladaptive profile, defined by extensive delegation of cognitive processes combined with limited

regulatory control, exhibited the lowest outcomes. Transitional movement between profiles followed gradual pathways, with improvement occurring primarily through shifts from Moderate to Optimal configurations rather than direct movement from Maladaptive patterns. Longitudinal evidence further indicated that cognitive offloading decreased while metacognitive regulation increased across the semester, suggesting that effective learning involved progressive rebalancing of cognitive responsibility toward internal control. Academic performance differences across profiles became more pronounced over time, indicating that repeated patterns of engagement with artificial intelligence accumulated into measurable differences in achievement.

A central contribution of this study lies in demonstrating that artificial intelligence reshapes learning not only through access to information but through reorganization of cognitive effort across interacting processes that evolve across time. AI self-efficacy alone did not produce higher academic outcomes unless accompanied by sustained regulatory engagement, highlighting that perceived capability must be supported through active monitoring and evaluation of learning processes. Cognitive offloading functioned as a double-edged mechanism, enabling efficient task completion while increasing the risk of reduced cognitive depth when not constrained through metacognitive regulation. Integration of latent profile analysis and latent transition analysis provided evidence that learning behaviors represent dynamic configurations rather than isolated variables, offering a more precise explanation of how students adapt to artificial intelligence within a semester. Findings from this study indicate that effective AI-supported learning requires deliberate maintenance of cognitive control, suggesting that educational design should prioritize development of regulatory capacity alongside technological proficiency to ensure that artificial intelligence enhances rather than diminishes meaningful learning processes.

Declarations

Competing interests

The authors declare that they have no competing financial, professional, or personal interests that could have influenced the conduct, analysis, interpretation, or reporting of this research.

Ethics approval

Ethical approval for this study was granted by the Science and Training Council of the VNU University of Education, Vietnam National University, Hanoi. The research was conducted as part of the approved Vietnam National University, Hanoi Science and Technology Project QG.24.87 under Decision No. 3073/QĐ-ĐHQGHN dated 28 June 2024. All research procedures involving human participants were performed in accordance with the ethical requirements of VNU University of Education, Vietnam National University, Hanoi, applicable regulations governing research involving human participants, and the ethical principles of the Declaration of Helsinki.

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Data availability

The dataset supporting the findings of this study is publicly available through Zenodo:

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Ethics approval

Ethical review and approval for this study were provided in accordance with institutional research governance procedures of Vietnam National University, Hanoi, as part of an approved science and technology research project under Decision No. 3073/QĐ-ĐHQGHN dated 28 June 2024.

Consent to participate

Informed consent was obtained from all participants prior to data collection.

Consent to publish

Not applicable.

Competing interests

The authors declare no competing interests.

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Figures

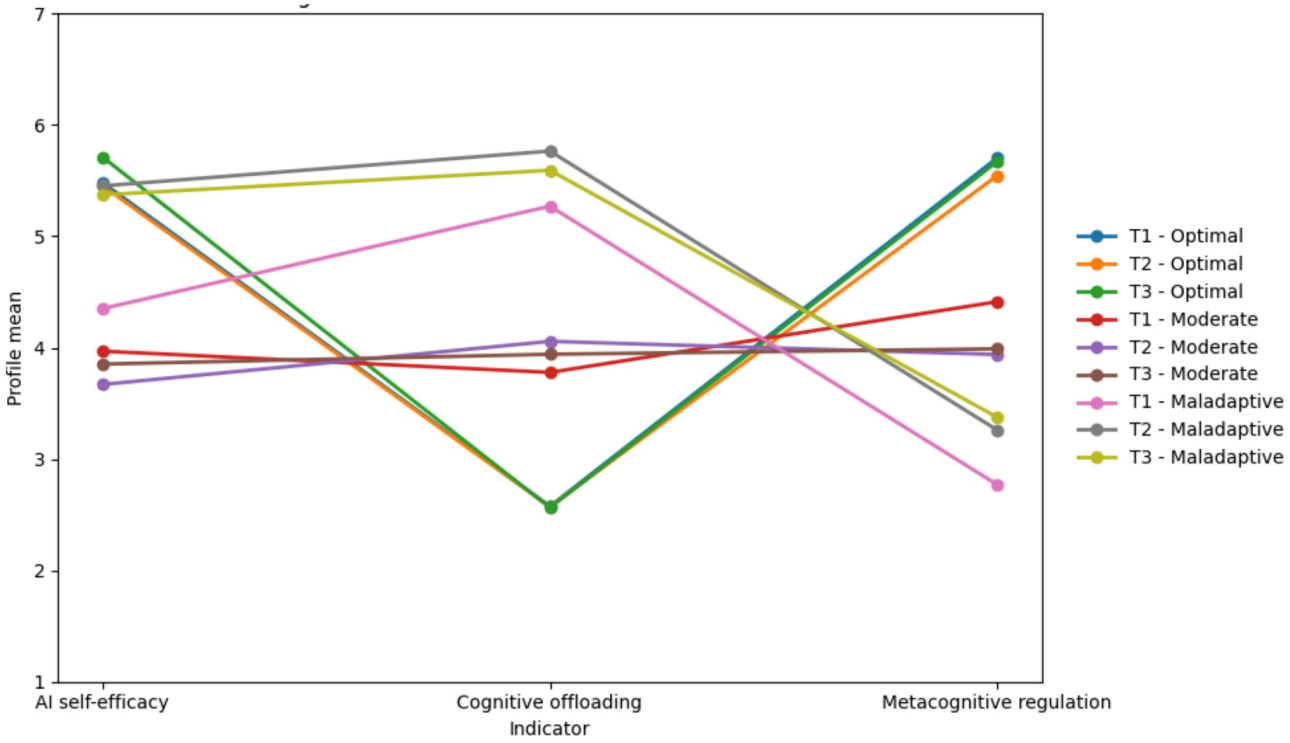


Figure 1

Latent profile patterns across indicators