

The influence of AI-based learning perceptions on learning outcomes in calculus: The mediating role of cognitive and emotional responses using a PLS-SEM approach

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Abstract

This research evaluates how students' perceptions of artificial intelligence (AI)-based learning tools affect calculus education by examining the middle factors between cognitive and emotional student responses. Research built upon cognitive load theory and social cognitive theory evaluates how students perceive AI adaptability, feedback accuracy, trust, and pedagogical value because these perceptions alter their learning processes as well as their academic outcomes. University professors from nine Rajamangala Universities of Technology in Thailand provided data through structured questionnaires to the research study. The researchers used partial least squares structural equation modeling (PLS-SEM) to evaluate their proposed theoretical connections. Results show that student perceptions regarding AI-based learning directly affect cognitive-emotional responses, and these responses powerfully determine academic achievements. The predictive model detects 75.7% of learning outcome variance in student performance ($R^2 = 0.757$), which demonstrates robust model specification and documentation. Research revealed that emotional and cognitive outcomes serve to bridge AI-based learning perceptions and educational outcomes, thereby demonstrating their importance in the learning achievement process. The research emphasizes the need to build AI learning platforms that enhance students' engagement alongside their resilience and confidence because these elements drive academic achievement in calculus and STEM subjects.

Keywords: AI-based learning, cognitive load, emotional engagement, learning outcomes, PLS-SEM

INTRODUCTION

Traditional education now relies on artificial intelligence (AI) to create personalized learning solutions that use data analytics for adaptive teaching techniques, according to Baker and Inventado (2016) and Luckin and Holmes (2016). Luckin and Holmes (2016) argued that AI has the potential to transform education by enabling personalized and data-driven learning experiences. Their work emphasizes that AI can support teachers in understanding students' learning needs and provide adaptive feedback that promotes autonomy and deeper understanding. Several AI-driven learning

resources provide mathematics students with dynamic feedback along with system-generated problem help and customized educational sequences (Holmes et al., 2019). STEM students find calculus to be fundamental and challenging because this subject presents conceptual challenges as well as cognitive stress, according to research by Tall (2013). STEM students find calculus to be both fundamental and challenging because this subject imposes substantial conceptual demands and cognitive stress. Cognitive stress arises when learners' working memory is overloaded by complex symbolic reasoning, abstract concepts, and multi-step procedures inherent in calculus (Sweller, 2011). The necessity to

Contribution to the literature

- In order to explain the effects of AI-based learning in calculus education, this study combines cognitive and emotional theories.
- According to empirical data, perceptions and results of AI learning in Thai universities are mediated by cognitive and emotional factors.
- A four-dimension AI perception model that has been validated improves learning success measurement and prediction.

integrate algebraic manipulation with conceptual understanding often exceeds students' cognitive capacity, leading to anxiety, confusion, and reduced problem-solving efficiency (Holmes et al., 2019; Tall, 2013). AI-based learning systems work to minimize barriers toward learning through targeted instruction yet need additional empirical research to prove their effectiveness in boosting student engagement and math concept retention and self-efficacy (Zawacki-Richter et al., 2019).

More teachers are implementing AI educational technologies, yet several essential research questions need answers. Previous studies examined AI effects on learning efficiency along with problem-solving competencies, yet they provide minimal evidence regarding the influence of student-held AI tool perceptions on calculus learning, cognitive engagement, and emotional responses (Chen et al., 2020). Cognitive load theory (CLT) demonstrates that students are prone to diminished learning results when they expend excess cognitive effort, yet researchers understand little about how AI tools affect these difficulties in calculus education (Sweller, 2011). The effectiveness of AI enhancements for short-term results is established, yet researchers are still investigating its impact on long-term retention along with the transferability of STEM problem-solving abilities (Nye et al., 2014; VanLehn, 2011). A deep evaluation involving structural equation modeling (SEM) must analyze AI adaptability and feedback accuracy and student engagement alongside learning outcome indicators to repair gaps in current understanding. The research investigates AI effects on calculus learning through direct pathways along with indirect mechanisms, which will expand existing knowledge about AI in mathematics education.

LITERATURE REVIEW

AI in Mathematics Education

Research focuses on AI applications in education due to their positive effects on student performance, particularly when used to deliver customized learning experiences combined with immediate performance feedback (Zawacki-Richter et al., 2019). Adaptive learning tools powered by AI technology enable students to learn independently at variable speeds through personalized guidance tailored to each learner's

unique profile. However, the idea of supporting autonomous learning predates the widespread adoption of AI. Earlier technologies such as intelligent tutoring systems (ITS) (VanLehn, 2011), adaptive hypermedia, and computer-assisted instruction (Luckin & Holmes, 2016) had already been developed to promote self-regulated learning by providing feedback and scaffolding aligned with individual progress. What distinguishes modern AI-based tools is their capacity to analyze learner data in real time, predict performance patterns, and continuously refine instructional strategies, thereby enhancing personalization and autonomy in calculus learning. The tools generate adaptive feedback and provide intelligent recommendations with interactive visualizations, which makes them ideal for calculus education (Holmes et al., 2019; Sweller, 2011). According to VanLehn (2011), AI-based tutoring systems enhance learning efficiency through continuous adaptation of instructional content toward students' cognitive needs and progress. The AI-driven learning platforms actively facilitate self-directed learning so students can independently investigate calculus concepts under guidance that emulates personalized tutoring experiences (Chen et al., 2020; Luckin & Holmes, 2016). AI technologies toward enhanced learning outcomes enable both cognitive growth and decrease math-related stress when combined with purposefully designed instruction (Dweck, 2006; Nye et al., 2014).

The abstract essence and complex algorithms, as well as intricate problem-solving approaches in calculus, create major learning difficulties for students, according to Tall (2013). Students face multiple barriers in mathematics, particularly in calculus, where they often experience excessive cognitive load, mathematics anxiety, and difficulty connecting symbolic procedures with conceptual understanding. The abstract and sequential nature of calculus requires learners to integrate algebraic reasoning, visualization, and multi-step problem-solving, which can easily overload working memory and lead to cognitive stress (Sweller, 2011; Tall, 2013). Modern AI tools, including ITS integrated with automated assessment platforms, help mitigate these barriers by providing step-by-step feedback, personalized assignments, and real-time error detection (Chen et al., 2020). Modern AI tools, including ITS systems coupled with automated platforms and AI

evaluation systems, combine step-by-step explanations with personalized assignments while enabling real-time error recognition (Chen et al., 2020). The system enables students to construct a stronger conceptual grasp of the material because it lets them examine their incorrect responses and improve their problem-solving approaches. The long-term effects of AI on student retention of concepts and independent reasoning abilities and general STEM discipline knowledge transfer need additional experimental research studies designed to address this issue (Nye et al., 2014). AI-assisted learning tools succeed in developing higher-order thinking abilities and extended mathematical proficiency through effective tool design, which maintains deep understanding and metacognitive activities and sustains mathematical thinking after initial assistance.

Students' Perceptions of AI-Assisted Learning

Students' evaluations of AI-assisted learning guide the efficiency of AI educational tools for calculus education because they need understandable lessons and organized guidance with adaptive support—that is, instructional assistance that dynamically adjusts to individual learners' needs. In calculus learning, adaptive support may involve providing step-by-step scaffolding when students struggle with differentiation or integration, adjusting task difficulty according to performance, and offering conceptual visualizations to reduce cognitive overload and enhance understanding (Holmes et al., 2019; Sweller, 2011). Students outline their understanding of AI-assisted education through four primary influences that combine their individual learning pattern capabilities with AI feedback accuracy, AI explanation reliability, and the teaching capabilities of tutors (Chen et al., 2020; Holmes et al., 2019). The perception of AI systems as flexible and responsive technologies leads students to become more involved with AI-driven educational platforms, thus enhancing motivation levels and persistence and developing better conceptual knowledge (Luckin & Holmes, 2016).

Trust in AI-based educational tools may decrease according to students who worry about system dependability while questioning human-free instruction and possible wrong information (Baker & Inventado, 2014). The belief that AI-generated responses provide superficial understanding of material or poorly understand student requirements or provide insufficient guidance will cause students to avoid AI learning and revert to traditional methods. Student experiences using AI technology create differences in their readiness to use AI during learning because technology-literate students show stronger engagement when compared to students who lack experience with AI-driven education (Zawacki-Richter et al., 2019). Students from diverse educational backgrounds and cultural backgrounds form specific expectations of AI learning tools that

determine how they accept AI suggestions and automated feedback. The successful implementation of AI-based learning environments depends on grasping these student perceptions, which ensures AI tools will improve student independence alongside meaningful feedback delivery and self-learning promotion for creating beneficial educational experiences with lasting academic impact.

Cognitive Load and Emotional Responses in AI Learning

Cognitive load and emotional responses serve as major factors in AI-assisted learning, and they significantly impact the understanding of abstract calculus concepts due to their complex procedural nature. Learning becomes most effective under CLT principles when cognitive resources are efficiently managed. However, student performance declines when learners experience cognitive overload or excessive mental stress that interferes with working memory processes (Sweller, 2011). Prior studies in calculus learning have reported similar findings: for example, Tall (2013) found that the abstract nature of calculus concepts often overwhelms students' cognitive capacity, while Holmes et al. (2019) demonstrated that excessive cognitive demands during symbolic manipulation tasks significantly reduce problem-solving accuracy and retention. AI teaching tools simplify education through streamlined guidance systems, but their effectiveness depends on the clarity of explanations and consistency of feedback in addition to proper scaffolding methods (Chen et al., 2020).

The relationship between students and AI-based learning is substantially influenced by emotional factors beyond cognitive requirements. Students with high growth mindsets along with frustration tolerance respond well to AI-generated explanations and problem-solving suggestions. Students who possess a growth mindset, which conveys that learning intelligence and abilities through effort brings benefits, tend to stay focused despite challenges and use AI for educational purposes while remaining motivated (Dweck, 2006). The inability of students to handle frustration tolerantly causes them to separate from AI-based learning when the AI-generated responses fail to match their expectations, which in turn creates elevated anxiety levels and reduces confidence alongside decreased reliance on AI support (Zawacki-Richter et al., 2019). The combination of relying too heavily on AI with insufficient active engagement or metacognitive strategies produces shallow understanding instead of deep semantic mastery. According to research, it is crucial to maintain proper cognitive challenges alongside developing positive emotions when using AI-assisted learning tools because this approach optimizes learning benefits by strengthening students'

understanding and self-assurance and enabling long-term academic success in mathematics.

AI and Student Learning Outcomes

The application of AI assists students in achieving better educational outcomes in calculus by providing adaptive feedback, visual representations, and step-by-step problem-solving guidance for complex concepts that often hinder understanding. However, AI-generated solutions are not always accurate and may occasionally produce incorrect or oversimplified explanations. Therefore, students must engage in critical verification and reflection when using AI tools to ensure conceptual accuracy and deep understanding (Holmes et al., 2019). The main strength of AI-driven education includes boosting student self-efficacy because students with immediate adaptive feedback and guided problem-solving assistance develop stronger mathematical self-assurance (Chen et al., 2020). AI demonstrates features for recognizing gaps in learning while providing detailed breakdowns of steps and individualized practice so students can receive specific help that decreases their frustration and leads to better learning success. The implementation of AI-based learning shows positive associations with concept retention over time because its personalized pathways with spaced repetition techniques combined with interactive problem-solving activities enhance long-term memory retention (VanLehn, 2011). The capability of AI-based tools lies in their ability to modify difficulty settings automatically so students move forward with optimal speed beyond cognitive overload limits.

Experts have discovered that AI-driven education creates transferable skills that students can use to solve problems in physics, engineering, and computer science (Holmes et al., 2019). Students find the cross-disciplinary application especially useful because they need to unite mathematical principles across various fields when solving real-world problems. AI tools generate math anxiety for students who encounter stress and feelings of uncertainty while working with AI systems, particularly when these students do not understand AI technology or feel overwhelmed by automated feedback systems (Luckin & Holmes, 2016). AI's benefits for STEM education stem from its ability to provide cognitive support and foster engagement and problem-solving proficiency but require optimal alignment between cognitive help systems and emotional engagement and individualized learning approaches to generate successful academic results and build enduring STEM skills.

The Relationship Between AI Perceptions, Cognitive Load, and Learning Outcomes in Calculus Education

Students form their perception of AI-based learning tools, which determines how engaged they become and

how they handle cognitive load and manage their emotions, which affects their academic performance. Studies indicate that AI systems that dynamically modify content through individual learning needs analysis improve student motivation alongside their engagement and problem-solving abilities before decreasing cognitive mental stress (Holmes et al., 2019; Zawacki-Richter et al., 2019). Student trust in AI-assisted learning directly correlates to how accurate the feedback provided by AI technologies proves to be. Students develop trust in AI-driven instruction when the technology delivers exact and purposeful feedback and individualized responses, according to Chen et al. (2020). AI feedback that provides inaccurate or unspecific information produces negative results that include student frustration and disengagement while increasing their mental load until they start doubting the reliability of AI learning tools (Luckin & Holmes, 2016).

The manner in which students perceive AI affects both their mental processing capabilities and their emotional capability to handle challenges and their overall commitment to learning activities. The effective learning process happens when we minimize extraneous cognitive load because it gives students the opportunity to focus on solving core problems according to CLT (Sweller, 2011). AI systems, which offer detailed explanations together with adaptable learning routes, enable students to manage mental load better; therefore, they become more efficient at processing new information while actively participating in educational tasks (Chen et al., 2020). Students who maintain a growth mindset that allows them to grow abilities through effort succeed more persistently in their problem-solving work. Students who receive support from AI-assisted learning through structured instruction and adaptive difficulty levels typically succeed at overcoming obstacles and strengthen their mathematical skills (Dweck, 2006; Zawacki-Richter et al., 2019). Students who face difficulty tolerating annoyance find it challenging to work with AI-driven educational systems, which results in increased worry and reduced engagement and purposeful task-avoidance habits (Holmes et al., 2019).

AI perceptions along with cognitive engagement and emotional responses create a direct impact on student learning outcomes in calculus. Research proves that mathematics self-efficacy functions as a leading indicator of academic success because students who receive adaptive AI support with positive reinforcement tend to develop higher confidence and improved conceptual retention and problem-solving abilities (Chen et al., 2020; VanLehn, 2011). AI-assisted learning provides better transferability of skills which enables students to implement calculus concepts across physics engineering and computational sciences (Holmes et al., 2019). Students tend to develop math anxiety related to AI when they face challenges due to heavy cognitive

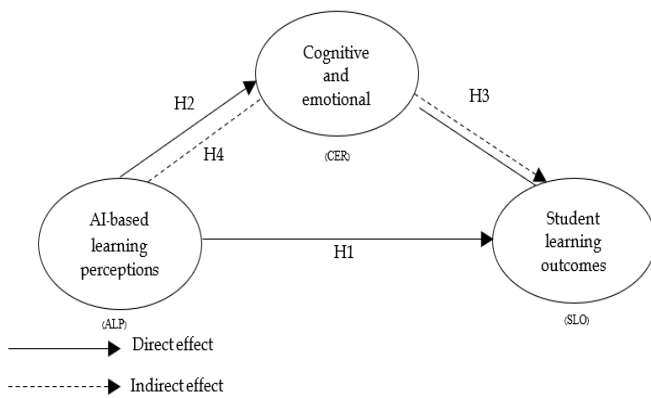


Figure 1. Conceptual framework (Source: Authors' own elaboration)

workload and do not trust the feedback produced by AI systems (Luckin & Holmes, 2016). Stressful mental work and poor tolerance for discomfort create anxiety which prevents effective retention and conceptual application of learned material (Sweller, 2011). Empirical findings show AI-based learning experiences become more effective when researchers decrease cognitive obstacles and develop positive emotions for students which results in improved active participation alongside enhanced comprehension together with sustainable achievement outcomes (Chen et al., 2020). AI instruction faces obstacles that can be resolved so it optimizes learning outcomes specifically for calculus subjects by boosting student confidence and lowering anxiety.

CONCEPTUAL FRAMEWORK

The research framework demonstrates how students' AI-based learning tool perceptions affect their academic results and shows cognitive and emotional responses function as intermediary variables. The positive assessment of AI features like adaptability, feedback accuracy, trust, and pedagogical value drives better student learning results, including improved self-efficacy and better retention and skill transfer to other STEM subjects (H1). The positive perceptions that students hold about AI technologies directly affect their cognitive processing along with emotional reactions, which include lighter cognitive burdens, elevated interest levels, increased tolerance for frustration, and stronger commitment toward development. Hypothesis 3 (H3) indicates that students develop enhanced confidence levels together with improved persistence abilities and deeper conceptual assimilation due to their internal responses. Hypothesis 4 (H4) establishes that cognitive along with emotional responses function as intermediaries linking student outcome performance to perceived experiences with AI technology. Learning outcomes from AI education depend on both computational abilities and learner perception of AI through CLT (Sweller, 2011) and social cognitive theory (SCT) (Bandura, 1997), as it determines their mental

response and emotional experience, as shown in **Figure 1**.

Research Hypotheses

The study tested the following research hypothesis:

1. H1. AI-based learning perceptions has a direct effect on cognitive and emotional responses.
2. H2. AI-based learning perceptions has a direct effect on student learning outcomes.
3. H3. Cognitive and emotional responses has a direct positive effect on student learning outcomes.
4. H4. Cognitive and emotional responses mediate relationship between AI-based learning perceptions and student learning outcomes.

METHODOLOGY

Participants

The research received institutional review board approval to conduct the study while gathering participant consent before data collection started. The data protection process consisted of anonymous responses to preserve confidentiality. Surveys and structured interviews carried out online enabled professors to discuss AI implementation in higher education along with its pedagogical results and the obstacles they encounter from AI-assisted instruction.

Materials and Measures

A structured questionnaire served to evaluate essential concepts regarding AI-assisted learning in calculus education. Research on previous literature served as the foundation to design this instrument that suits higher education institutions in Thailand. The instrument contained three essential parts, which included

- (1) AI-based learning perceptions,
- (2) cognitive and emotional responses, and
- (3) student learning outcomes.

The survey used a 5-point Likert scale that ran from 1 ("strongly disagree") through to 5 ("strongly agree") for measuring all survey items.

AI-based learning perceptions (independent variables)

Participating students used this construct to evaluate their general attitudes toward AI-based learning tools. It included four sub-dimensions:

1. The first dimension is AI adaptability perception (AAP): Describes how learning tools powered by AI adjust their content based on how students perform (Yang et al., 2013; Zawacki-Richter et al., 2019).

2. Feedback calibration accuracy (FCA): Students benefit from dependable AI feedback, which boosts their intellectual comprehension of the material (Zapata et al., 2024).
3. AI learning trust (ALT): AI tools earn my trust for distributing reliable and effective explanations of calculus concepts to students (Pepin et al., 2025; Yang et al., 2020).
4. Perceived AI pedagogical value (PPV): Demonstrates that AI-assisted learning reaches equal effectiveness to human-led tutoring in teaching calculus (Serhan & Welcome, 2024).

Cognitive and emotional responses (mediating variables)

Psychological perceptions toward AI demonstrate how they affect both mental effort requirements and emotional involvement during this process. It included four sub-dimensions:

1. Cognitive load (CL): Student learning with AI assistance demands notable mental concentration for completing their assignments (Sajja et al., 2023; Sweller, 2011).
2. Growth mindset in calculus (GM): AI-supported practice together with persistent effort, students can develop their capabilities to solve calculus problems (Boaler, 2016; Dweck, 2006).
3. Engagement with AI (EAI): Students benefit when I advise them to manipulate calculus problems through the use of AI-based tools (Awang et al., 2025; Heung & Chiu, 2025).
4. Frustration tolerance (FT): Students are able to work through problems that prove difficult using AI-based feedback tools (Alsaiani et al., 2024).

Student learning outcomes (dependent variables)

AI-assisted learning effectiveness in calculus was assessed using four outcome indicators within this construct. It included four sub-dimensions:

1. Self-efficacy in calculus (SE): Students develop stronger calculus problem-solving self-efficacy through their experience with AI tools, according to SE (Jia & Tu, 2024).
2. AI-induced math anxiety (AIMA): Using AI tools for calculus problem-solving generates anxiety among certain students who need this assistance (Chen et al., 2025).
3. Delayed retention (DR): Students retain calculus concepts for delayed periods after utilizing AI-driven educational tools for learning (McLaren et al., 2015).
4. Transferability of skills (TS): The implementation of AI for calculus education leads to enhanced

competency for handling physics and engineering applications (Alvarez, 2024).

Expert reviewers validated the constructs for content validity before the researcher tested their reliability and consistency levels using Cronbach's alpha and composite reliability (CR). A prior confirmatory factor analysis validated construct validity before the structural model received its constructs.

Construct Reliability

A measurement model reliability assessment occurred through evaluation of Cronbach's alpha and CR. The measurement model performed acceptably with Cronbach's alpha levels crossing the threshold ≥ 0.70 as per Tavakol and Dennick (2011). The factor loadings and error variances were effectively analyzed by $CR \geq 0.70$ to validate the latent constructs' reliability (Hair et al., 2019). This research confirmed the statistical reliability of the instrument along with its consistency in measuring AI-based learning perceptions and cognitive-emotional responses and learning outcomes since all constructs surpassed the suggested standards.

Construct Validity

The researchers evaluated construct validity by performing tests for convergent and discriminant validity (Schumacker et al., 2019). The assessment of convergent validity showed favorable results using factor loadings ≥ 0.50 and average variance extracted (AVE) ≥ 0.50 and CR measuring ≥ 0.70 to prove indicators from the same construct displayed high interdependence (Hair et al., 2019). Each construct demonstrated discriminant validity based on the Fornell-Larcker criterion (Fornell & Larcker, 1981), where the AVE square root value exceeded all other construct correlations. The SEM analysis benefits from the reliable measurement model because its constructs demonstrate both statistical distinction and conceptual soundness.

Data Analysis

Each survey item underwent a reverse-notation transformation before analysis commenced. The authors employed partial least squares structural equation modeling (PLS-SEM), which Henseler et al. (2016) and Kock (2022) described as the multivariate statistical technique for testing their proposed research model after performing descriptive statistics examination. The complex relationship models explored in exploratory studies utilize PLS-SEM because of its effectiveness (Kock, 2022). Analysis was performed through PLS-SEM because the research needed flexibility and met minimum sample size demands (Hair & Alamer, 2022). Using smartPLS software (Ringle et al., 2015), the analysis was carried out in two stages: measurement model assessment and structural model evaluation. PLS-

Table 1. Convergent validity

Construct	Item	Loadings	Cronbach's alpha	CR	AVE
ALP	AAP	0.894	0.886	0.922	0.747
	FCA	0.889			
	ALT	0.888			
	PPV	0.843			
CER	CL	0.899	0.902	0.931	0.772
	GM	0.911			
	EAI	0.879			
	FT	0.836			
SLO	SE	0.890	0.904	0.933	0.777
	AIMA	0.882			
	DR	0.906			
	TS	0.773			

SEM allows researchers to examine direct and indirect causal paths through which AI-based learning perceptions interact with cognitive-emotional responsive outcomes to affect educational results (Kline, 2005). The research utilized 368 participants who followed the sufficient requirements set by the 10-times rule for PLS-SEM (Hair et al., 2011).

RESULTS

Measurement Model

The assessment of latent variable reliability and validity came prior to examining construct relationships in the model. Each construct requires validated measurement to function properly in PLS-SEM analysis. An analysis of indicator reliability and internal consistency reliability together with convergent and discriminant validity was performed during the assessment (Hair et al., 2019).

Marker reliability met our standards through standardized factor loadings that reached or exceeded 0.70. The research utilized Cronbach's alpha and CR to analyze internal consistency reliability through threshold values exceeding 0.70 (Hair et al., 2019; Tavakol & Dennick, 2011). The AVE test demonstrated convergent validity by showing that construct variables explained more than fifty percent of their indicator variances when AVE exceeded 0.50, as shown in **Table 1**.

The evaluation of discriminant validity utilized the Fornell-Larcker criterion. The measurement model demonstrates discriminant validity if each construct's AVE square root exceeds its relationship strength with other constructs (Fornell & Larcker, 1981). The measurement model proved valid and reliable because each construct exceeded the minimum standards set by Fornell and Larcker (1981). Structural model analysis received suitable instrumentation through validation processes, as shown in **Table 2**.

Table 2. Discriminant validity

Construct	ALP	CER	SLO
ALP	0.879		
CER	0.718	0.882	
SLO	0.719	0.857	0.865

Structural Model

PLS-SEM analysis showed that the structural model validated all proposed connections. The research results will now follow an analysis for each hypothesis.

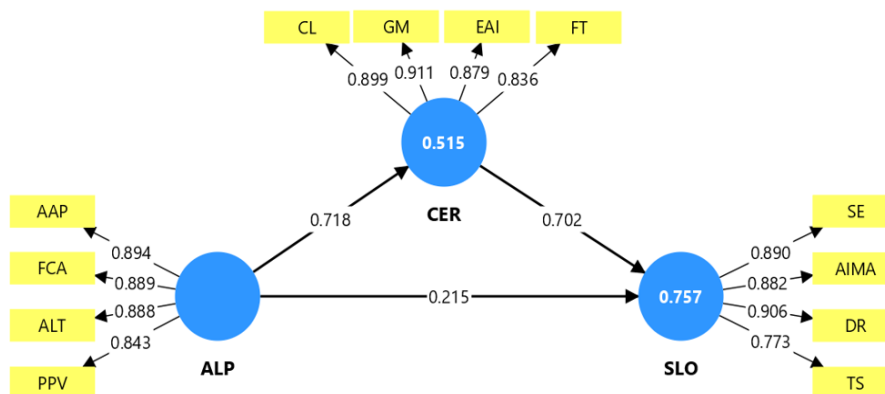
Results from data analysis indicate AI-based learning perceptions result in strong positive influences on cognitive and emotional aspects ($\beta = 0.718$, $t = 25.245$, $p < 0.001$). Teachers who believe AI tools are adaptive, trustworthy, and pedagogically valuable demonstrate higher levels of engagement and enable students to develop growth mindset capabilities and tolerate frustration better. The study findings mirror similar results obtained in Chen et al. (2020) and Zawacki-Richter et al. According to Zawacki-Richter et al. (2019), AI perception develops emotional resilience together with motivational factors. The outcome of β demonstrates users think perception plays an essential role in their internal processing of AI-based learning experiences.

The latest study findings support the conclusions of this research. Students received improved emotional feedback through AI systems, according to Alsaiani et al. (2024), which enhanced their engagement in classes. Positive student sentiments about AI tools directly impacted their ability to manage challenges and motivated their learning process, according to Yao and Liu (2025). Student performance improves when AI technology provides them programming assistance through higher intrinsic motivation and better emotional control, according to research by Fan et al. (2025). The real-time assessment of student engagement operates through an AI-powered learning analytics system developed by Sajja et al. (2023) to deliver customized educational programs. The research findings establish how students' understanding of AI tools creates internal psychological frameworks that deepen their educational success.

Research data showed that student learning outcomes maintain a strong correlation with AI-based learning perceptions, with $\beta = 0.215$, t value = 4.261, and a $p < 0.001$. Progressive student perceptions of AI constitute a moderate yet significant factor that enhances both confidence and memorization abilities and skill transfer in calculus courses. The research of Holmes et al. (2019), along with VanLehn (2011), shows how students' perception of AI effectiveness leads to academic success. Similarly, a study by Heung and Chiu (2025) showed that students experienced greater engagement when using ChatGPT during educational activities.

Table 3. Hypothesis testing

Hypothesis	Path	Path coefficient (β)	T statistics	p-value	Result
H1	ALP $\rightarrow$ CER	0.718	25.245	0.000	Supported
H2	ALP $\rightarrow$ SLO	0.215	4.261	0.000	Supported
H3	CER $\rightarrow$ SLO	0.702	11.994	0.000	Supported
H4	ALP $\rightarrow$ CER $\rightarrow$ SLO	0.504	13.084	0.000	Supported

**Figure 2.** Structural model developed using SmartPLS (Source: Authors' own elaboration)

Furthermore, a study by Zouhaier (2023) conducted a study that demonstrated AI can benefit students' cognitive abilities through increased critical thinking abilities together with more effective learning results, especially for students who actively approach their education. The study conducted by Blahopoulou and Ortiz-Bonnin (2025) analyzed students' interactions with AI tools in higher education by revealing improved productivity, but students also expressed concerns about excessive dependence and academic integrity violations.

The study showed that academic achievement directly links to student cognitive-emotional responses with $\beta = 0.702$ and $t = 11.994$, respectively, at $p < 0.001$. Academic achievement is heavily dependent on psychological internal processes, which the study shows are fundamental elements. CLT (Sweller, 2011) and SCT (Bandura, 1997) show that students and instructors achieve better results when they have reduced cognitive pressure and improved emotional adaptability. The research data supports recent experimental investigations. Students who learn physics with AI-supported data analysis show improved academic outcomes and decreased stress while maintaining higher motivation, according to Henze et al. (2024). Emotionally enriched AI feedback, according to Lin and Chen (2024) studied how AI-integrated educational applications modify the creative abilities and academic feelings of college students to reveal major learning experience changes. The relationship between AI-based learning perceptions and student learning outcomes maintains its strength through cognitive and emotional mediation responses ($\beta = 0.504$, $t = 13.084$, $p < 0.001$). The data demonstrates that perception does not lead to direct outcomes because it requires participants to process information internally prior to producing outcomes.

Support systems and content delivery must harmonize in AI tools based on the insights of Dweck (2006) and Chen et al. (2020). For instance, Saxena and Doleck (2023) created a structural model to examine students' continued utilization of ChatGPT through their study, which proved perceived usefulness along with satisfaction as strong predictors of ongoing utilization by emphasizing cognitive and emotional student needs alignment with AI tools. Additionally, Jeilani and Abubakar (2025) established perceived institutional support as a strong determinant of how students view AI-supported learning, while perceived learning outcomes acted as a partial mediator, showing AI integration works best in supportive settings, as shown in Table 3 and Figure 2.

CONCLUSIONS

The study utilized PLS-SEM for analyzing how student perceptions of AI-based learning and cognitive and emotional responses link to calculus education learning outcomes. Perceptions of AI tools that emphasize adaptability and deliver accurate feedback while building trust and pedagogical value demonstrate strong effects on academic outcomes while improving internal learning processes. AI-based learning perceptions produced strong emotional and cognitive responses yet directly impacted student outcomes to a moderate extent. Direct cognitive-emotional responses from students produced student success indicators by decreasing mental task burden and boosting student interest and psychological development towards learning. Studies demonstrated that students' responses to AI-based learning experiences work as the bridge between their perception of AI and their academic achievements.

Research indicates that well-designed AI tools should be implemented as educational enhancements in higher education STEM fields, specifically calculus courses. This research builds academic understanding about optimizing AI learning systems to customize mathematics content delivery with cognitive effectiveness and emotional engagement for students. Research delivers essential knowledge about refining AI technology tools to deliver personalized mathematics instruction, which simultaneously decreases mental burden and builds strong audience engagement.

Recommendations

This study recommends AI-assisted learning instruments for deployment in calculus education to build positive perceptions among students and teachers. Learning institutions must educate their users about the AI's range of capabilities together with its accuracy levels and educational merits to build trust between users and improve their involvement with AI systems (Zawacki-Richter et al., 2019). The role of AI developers should involve creating usable systems that support students through information management and immediate feedback delivery to help maintain student motivation throughout tasks (Chen et al., 2020). The integration of human educators becomes crucial because AI exists solely to assist developers in creating educational programs that students can utilize independently. A variety of scholarly timescales are needed to investigate AI's impact on student performance outcomes along with competency levels, according to Zawacki-Richter et al. (2019). Institutions partaking in higher education can achieve effective and lasting AI implementations by adopting appropriate recommendations (Sanusi et al., 2023).

Limitations

Scientific understanding from this research needs to recognize its several known limitations. The cross-sectional research design prevents researchers from demonstrating the cause-and-effect relationships between AI perception and cognitive-emotional reactions as well as learning outcomes (Garcia et al., 2025). Future research needs to use longitudinal design approaches to monitor modifications that develop across time (Chen et al., 2020). The self-reported questionnaire used for data collection risks two weaknesses that stem from social desirability bias together with personal interpretations of items (Podsakoff et al., 2003). Research limitations arise from collecting data only from professors at nine Rajamangala Universities of Technology in Thailand, resulting in restricted applicability for other academic environments and student groups. PLS-SEM serves as a suitable tool for exploratory research of complex models yet requires researchers to interpret distribution assumptions with freedom during analysis (Hair et al., 2019). This

investigation concentrated on AI applications in calculus and STEM-related classes, leading to results that might not directly impact non-STEM subjects or AI-free educational frameworks. The researchers emphasize the requirement for future studies that will include diverse methodologies and examine additional educational contexts.

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