MIER Journal of Educational Studies Trends & Practices
November 2026, Vol. 16, No. 2, pp. 697 - 736
DOI: 10.52634/mier/2026/v16/i2/3135
ISSN: 0976-8203 e-ISSN: 2319-1945

Student Perceptions of Artificial Intelligence in Higher Education Mathematics: A Structural Equation Modelling Approach in Assam, India

Munmi Saikia and Derhasad Basumatary

This study explores Artificial Intelligence (AI) integration in higher education mathematics among students from six universities in Assam, India, where pedagogical guidance and institutional frameworks for AI integration are still developing. Guided by the Technology Acceptance Model (TAM), Expectation-Confirmation Theory (ECT), and selected educational psychology (EP) constructs, the study examines mathematics students' general perceptions of AI-supported learning in higher education mathematics, focusing on perceived usefulness (PU), perceived ease of use (PEOU), engagement and motivation (EM), perceived academic performance (PAP), self-efficacy (SE), trust in AI outputs (TR), satisfaction with AI tools (SAT), and future use intention (FU), rather than mathematics-specific cognitive processes. Partial Least Squares Structural Equation Modelling (PLS-SEM) was employed to test fourteen hypothesised relationships using 105 valid survey responses collected from undergraduate, postgraduate, and research-level mathematics students. The quantitative findings were supplemented by an exploratory thematic analysis of open-ended responses. The results indicate that PEOU significantly influenced PU and SAT, while PU positively influenced EM and PAP. EM further positively influenced PAP, SE, and SAT. PAP significantly predicted SE, TR, SAT, and FU, whereas SAT demonstrated significant positive effects on TR and FU. The study as a whole highlights mathematics students' positive perceptions of AI-supported learning in higher education mathematics while emphasising the importance of pedagogically guided and responsible AI integration.

Munmi Saikia ✉
Assistant Professor, Department of Mathematics, Patharkandi College, Patharkandi, Assam, India
Email: munmi19saikia@gmail.com. ORCID: https://orcid.org/0009-0009-3105-7935

Derhasad Basumatary
Assistant Professor, Department of Physics, Patharkandi College, Patharkandi, Assam, India
Email: derhasadbasumatary@gmail.com. ORCID: https://orcid.org/0009-0005-9748-7701

This is an open access article distributed under the terms of the Creative Commons Attribution License (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

KEYWORDS: Artificial Intelligence, Mathematics Education, Higher Education, Student Perceptions, PLS-SEM, Technology Acceptance Model

Introduction

Mathematics is a foundational discipline in higher education, underpinning scientific advancement and technological innovation. University mathematics is cognitively demanding, requiring sustained problem-solving, abstract reasoning, and conceptual understanding. Differences in students' prior knowledge, learning pace, engagement, and motivation often challenge conventional instruction and contribute to uneven learning outcomes (Bandura, 1997; Fredricks et al., 2004).

Recent advances in AI have intensified interest in its potential to support higher education. AI-based tools increasingly provide personalised support, adaptive feedback, and expanded access to academic assistance (Baker & Siemens, 2014; Luckin et al., 2016). However, their educational value depends not only on technical capability but also on how learners perceive, trust, and engage with them. In mathematics, AI-supported systems may enhance conceptual understanding and independent learning.

AI integration in mathematics presents both opportunities and challenges. Because mathematics emphasises conceptual understanding, logical reasoning, procedural accuracy, and critical thinking, students may be particularly sensitive to the reliability of AI-generated explanations and solutions. Concerns regarding overdependence on AI, reduced independent reasoning, and the continuing importance of human instruction have also become increasingly relevant (Zawacki-Richter et al., 2019).

Within the Indian higher education context, particularly in Assam, AI adoption remains at an early stage. Institutions continue to face infrastructural, technological, and teaching-related challenges (Handique, 2023), while frameworks for responsible AI use continue to evolve. Subsequent national initiatives, including the All India Council for Technical Education's (2025) declaration of 2025 as the Year of Artificial Intelligence in Education, further highlight the increasing policy emphasis on AI integration in higher education. Mathematics presents distinct pedagogical challenges because it emphasises logical reasoning, procedural accuracy, and problem-solving. Consequently, AI may influence mathematics learning differently from many other disciplines. Although recent studies have examined AI in mathematics education, research focusing on higher education mathematics students' perceptions and experiences remains limited (Pepin et al., 2025; Rizos & Gkrekas, 2025).

Addressing these gaps, this study investigates mathematics students' perceptions of AI-supported learning among students from six universities in Assam, India. Although the study focuses on mathematics students, the proposed model examines their general perceptions of AI-supported learning rather than mathematics-specific processes such as proof verification, symbolic accuracy, or formal reasoning. Guided by the Technology Acceptance Model (TAM), Expectation-Confirmation Theory (ECT), and selected educational psychology (EP) constructs, it examines relationships among perceived usefulness (PU), perceived ease of use (PEOU), engagement and motivation (EM), Perceived Academic Performance (PAP), self-efficacy (SE), trust in AI outputs (TR), satisfaction with AI tools (SAT), and future use intention (FU). Qualitative responses additionally provide contextual insight into students' experiences regarding AI-supported mathematics learning.

This study aims to address the following objectives:

1. Examine higher education mathematics students' general perceptions of AI-supported mathematics learning.
2. Investigate the relationships among the study constructs.
3. Analyse students' experiences regarding AI-supported mathematics learning.
4. Provide context-sensitive insights into the pedagogical implications of AI integration in higher education mathematics within a regional setting.

The rest of the paper presents the theoretical foundation, research hypotheses, methodology, results, discussion, implications, limitations, and conclusion.

Theoretical Foundation

The study is grounded primarily in TAM and ECT and is further informed by EP. These perspectives explain students' perceptions of AI-supported mathematics learning in higher education.

TAM, proposed by Davis (1989), identifies PU and PEOU as key determinants of technology acceptance. In educational settings, technologies perceived as useful and easy to use are more likely to promote EM and positive learning experiences. In AI-supported mathematics learning, students may perceive AI tools as useful when they are perceived to support conceptual understanding and problem-solving, while PEOU may encourage engagement with these systems (Alhumaid et al., 2023; Davis, 1989).

The framework also draws on ECT (Bhattacherjee, 2001), which explains post-adoption satisfaction and continued technology use. Satisfaction develops when users perceive that their experiences meet or exceed prior expectations. Although ECT primarily explains continuance through satisfaction, the present study extends this perspective by additionally examining whether students' perceived academic performance is associated with future use intention.

Selected concepts from EP further support the framework. EM contributes to academic achievement and learning effectiveness (Fredricks et al., 2004; Liu et al., 2024). AI-supported learning environments may be perceived as strengthening both through adaptive feedback, personalised assistance, and increased learning support, contributing to students' perceived academic performance and satisfaction.

The framework additionally incorporates SE and TR. SE, derived from Bandura's social cognitive theory (1997), refers to learners' confidence in performing academic tasks successfully. In mathematics, positive perceived academic experiences may strengthen confidence in mathematical abilities.

TR is important because students evaluate the reliability of AI-generated explanations and solutions. In mathematics education, where procedural correctness is critical, positive perceived academic experiences may strengthen trust in AI-generated outputs.

Together, these perspectives provide a framework for examining mathematics students' perceptions of AI-supported mathematics learning and its behavioural outcomes.

Literature Review

AI in education and mathematics learning

Research on AI in education has expanded rapidly, highlighting its potential to support adaptive learning, personalised feedback, and intelligent tutoring (Baker & Siemens, 2014; Luckin et al., 2016). In higher education, AI-supported systems increasingly improve learning efficiency, conceptual understanding, and problem-solving. In mathematics, AI tools may be perceived as supporting conceptual understanding and procedural skill development. However, because mathematics emphasises logical reasoning and procedural accuracy, students may critically evaluate the reliability and accuracy of AI-generated explanations.

Despite growing interest in AI-supported learning, research focusing specifically on higher education mathematics remains limited, with many studies emphasising technology adoption.

Technology acceptance and AI-supported learning

Technology acceptance research identifies PU and PEOU as key determinants of technology adoption (Davis, 1989). In educational settings, technologies perceived as useful and easy to use are more likely to be adopted. Previous studies suggest that AI tools perceived as useful positively influence students' engagement, satisfaction, and future use intention (Alhumaid et al., 2023; Malik et al., 2023).

PEOU is also important because AI tools that are easier to operate may encourage active learning participation. In mathematics, ease of use may support sustained EM in AI-supported learning. However, this relationship should be interpreted within the distinctive context of mathematics pedagogy.

Engagement and motivation, perceived academic performance, and self-efficacy

EM contributes positively to learning effectiveness and academic achievement (Fredricks et al., 2004; Liu et al., 2024). AI-supported learning environments may be perceived as strengthening these outcomes through adaptive support, immediate feedback, and opportunities for independent learning. Previous studies similarly suggest that EM contributes positively to students' learning outcomes (Fredricks et al., 2004; Liu et al., 2024). In the present study, these learning outcomes are operationalised as perceived academic performance.

SE is particularly relevant in mathematics, where students often experience low confidence when solving complex problems. AI-supported learning may strengthen students' self-efficacy through immediate feedback and guided learning support, while positive learning experiences may further reinforce their confidence in solving mathematical problems (Bandura, 1997).

Trust, satisfaction, and future use intention

Trust and satisfaction are important determinants of students' continued use of AI-supported learning technologies. Students' willingness to rely on AI-generated information is shaped by perceptions of reliability and accuracy (Dignum, 2019; Zawacki-Richter et al., 2019). Positive academic experiences may therefore strengthen trust in AI-generated outputs.

ECT suggests that positive learning experiences and fulfilled expectations contribute to satisfaction and continued technology use (Bhattacherjee, 2001). Students experiencing meaningful academic benefits may be more likely to continue using AI-supported learning technologies.

Research gap and contextual relevance

Although previous studies provide valuable insights into AI-supported learning, research focusing specifically on higher education mathematics students remains limited. Much of the literature treats educational technologies as discipline-neutral despite the distinctive demands of mathematics learning. Furthermore, research examining AI-supported mathematics learning in regional contexts such as Assam, India, remains scarce.

The present study addresses these gaps by examining relationships among PU, PEOU, EM, PAP, SE, TR, SAT, and FU in AI-supported learning in higher education mathematics.

Research Hypotheses

This section develops the research hypotheses based on the integrated theoretical framework comprising TAM, ECT, EP, and prior empirical evidence on AI-supported learning.

Perceived ease of use and perceived usefulness

According to TAM, technologies perceived as easier to use are more likely to be perceived as useful (Davis, 1989). In higher education mathematics, AI-supported tools that are easy to access and operate may reduce technological barriers and improve students' perceptions of their usefulness for conceptual understanding and mathematical problem-solving. Previous studies similarly suggest that PEOU positively influences PU in AI-supported educational environments (Alhumaid et al., 2023; Malik et al., 2023).

H1: PEOU positively influences PU in higher education mathematics.

Perceived ease of use and engagement and motivation

Ease of use may foster students' EM in AI-supported mathematics learning. According to TAM, technologies that are easier to learn and operate reduce user effort and encourage greater interaction (Davis, 1989). In mathematics, user-friendly AI tools may reduce technological barriers and enable students

to focus on learning activities. Previous studies similarly suggest that accessible educational technologies contribute to positive learning experiences and learner participation (Alhumaid et al., 2023; Liu et al., 2024).

H2: PEOU positively influences EM in higher education mathematics.

Perceived usefulness and engagement and motivation

Students who perceive AI tools as educationally valuable may become more engaged and motivated during learning activities. Previous educational technology research suggests that PU contributes positively to learning participation, motivation, and academic engagement (Alhumaid et al., 2023; Malik et al., 2023).

H3: PU positively influences EM in higher education mathematics.

Perceived usefulness and perceived academic performance

PU has frequently been associated with improved learning effectiveness and academic performance (Davis, 1989; Kulik & Fletcher, 2016). Students who perceive AI tools as beneficial for mathematical understanding and problem-solving may use them more effectively during learning. AI-supported systems that provide adaptive feedback and guided explanations may therefore enhance students' perceived academic performance.

H4: PU positively influences PAP in higher education mathematics.

Engagement and motivation and perceived academic performance

EM has consistently been recognised as an important predictor of academic achievement and learning effectiveness (Fredricks et al., 2004; Liu et al., 2024). Active engagement and motivation during AI-supported mathematics learning may contribute to higher perceived academic performance.

H5: EM positively influences PAP in higher education mathematics.

Engagement and motivation and self-efficacy

EP literature suggests that positive learning experiences can strengthen students' self-efficacy (Bandura, 1997). In AI-supported mathematics learning, sustained EM may reinforce students' self-efficacy through guided support and immediate feedback.

H6: EM positively influences SE in higher education mathematics.

Perceived academic performance and self-efficacy

Bandura's self-efficacy theory suggests that successful learning experiences strengthen learners' efficacy beliefs (Bandura, 1997). Within AI-supported mathematics learning, higher perceived academic performance may reinforce students' confidence in their mathematical abilities.

H7: PAP positively influences SE in higher education mathematics.

Perceived academic performance and trust in AI outputs

Students' trust in AI-generated explanations and outputs may be shaped by their experiences with AI-supported learning. Previous studies suggest that perceptions of reliability, transparency, and responsible AI use influence trust in technology-supported learning environments (Dignum, 2019; Zawacki-Richter et al., 2019). In AI-supported mathematics learning, students who perceive improvements in their academic performance may develop greater trust in AI-generated explanations and outputs.

H8: PAP positively influences TR in higher education mathematics.

Perceived ease of use and satisfaction

Previous studies on technology acceptance and expectation-confirmation suggest that technologies perceived as easy to use are more likely to foster positive user experiences and greater satisfaction (Bhattacherjee, 2001). In AI-supported mathematics learning, user-friendly systems may contribute to more satisfying learning experiences.

H9: PEOU positively influences SAT in higher education mathematics.

Engagement and motivation and satisfaction

Students who experience greater EM during learning activities are more likely to report higher satisfaction with educational technologies (Fredricks et al., 2004; Liu et al., 2024). In AI-supported mathematics learning, greater EM may similarly contribute to satisfaction with AI-supported learning systems.

H10: EM positively influences SAT in higher education mathematics.

Perceived academic performance and satisfaction

ECT suggests that positive learning outcomes and fulfilled expectations contribute significantly to user satisfaction (Bhattacherjee, 2001). Students who

perceive improvements in their academic performance through AI-supported mathematics learning may report greater satisfaction with AI-supported learning tools.

H11: PAP positively influences SAT in higher education mathematics.

Satisfaction and trust in AI outputs

Positive experiences with AI-supported mathematics learning may strengthen students' trust in AI-generated explanations and outputs. The broader educational technology literature suggests that favourable perceptions, ethical reliability, and positive academic experiences contribute to building and sustaining students' trust in AI-supported educational technologies (Shahzad et al., 2024; Zawacki-Richter et al., 2019). In mathematics learning, satisfactory experiences with AI-generated explanations and problem-solving support may strengthen trust in AI-generated outputs.

H12: SAT positively influences TR in higher education mathematics.

Perceived academic performance and future use intention

ECT identifies satisfaction as a key determinant of continued technology use following post-adoption experiences (Bhattacherjee, 2001). In AI-supported mathematics learning, students who perceive improvements in their academic performance may be more willing to continue using AI tools in future mathematics learning.

H13: PAP positively influences FU regarding AI-supported mathematics learning.

Satisfaction and future use intention

ECT suggests that satisfaction is a major predictor of continued technology use and future use intention (Bhattacherjee, 2001). Students who are satisfied with AI-supported mathematics learning experiences are more likely to continue using AI-supported learning tools.

H14: SAT positively influences FU regarding AI-supported mathematics learning.

Taken together, the hypotheses represent an integrated conceptual framework informed by TAM, ECT, EP, and contemporary empirical studies on AI-supported learning in higher education.

Figure 1 presents the theoretical model and hypothesised relationships examined in this study.

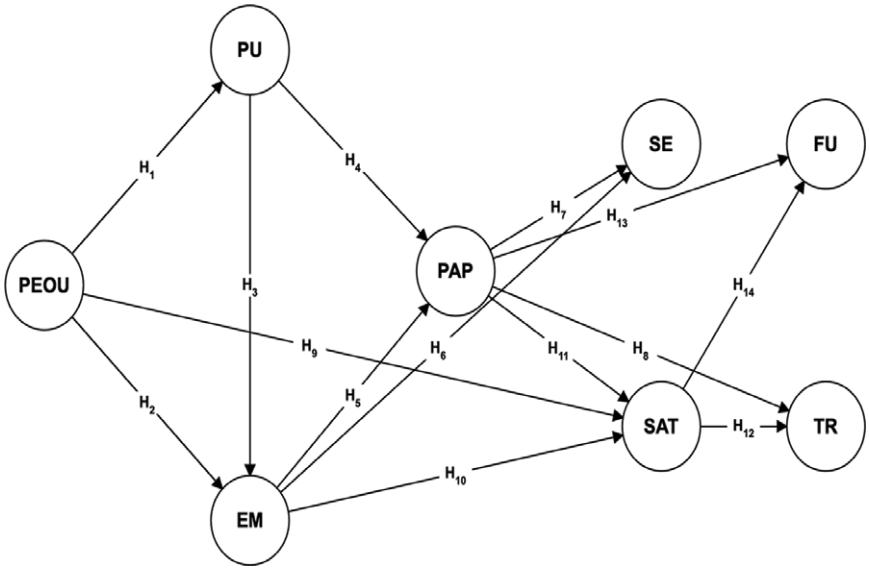

Figure 1. Theoretical model of the study

Methodology

This section describes the structured literature review, thematic analysis, survey design, instrument development, conceptual and measurement model development, data collection, analytical procedures, and ethical considerations adopted in the study.

Structured literature review

A structured literature review was undertaken to identify theoretical and empirical studies on AI-supported mathematics learning in higher education and to inform the development of the proposed conceptual framework. The structured literature review strategy, including the study selection criteria, is summarised in Table 1.

The reviewed literature provided the theoretical and empirical foundation for the proposed conceptual framework and hypothesis development, drawing on evidence from TAM, ECT, EP, and AI-supported learning.

To complement the broader literature review, five empirical studies were purposively selected for focused thematic synthesis (Table 1). Together, these studies addressed multiple constructs represented in the proposed framework and provided empirical evidence relevant to the study objectives. Following

Table 1

Summary of the structured literature review strategy

Stage	Description
Databases searched	Scopus, Web of Science, ERIC, and Google Scholar
Publication period	2019–2024
Language	English
Publication type	Peer-reviewed empirical journal articles
Search terms	Artificial intelligence; AI-supported learning; higher education; mathematics education; student perceptions; Technology Acceptance Model (TAM); Expectation-Confirmation Theory (ECT); educational psychology; student engagement
Inclusion criteria	Empirical studies investigating AI adoption or AI-supported learning in higher education and examining one or more constructs represented in the proposed conceptual framework
Exclusion criteria	School-level studies, technical AI development without educational application, review articles, opinion papers, conference abstracts, and non-peer-reviewed publications
Study identification	Relevant studies were identified based on titles, abstracts, and relevance to the study objectives.
Study selection	Potentially eligible studies were assessed against the inclusion and exclusion criteria.
Duplicate records	Duplicate records identified during screening were removed.
Empirical studies purposively selected for focused thematic synthesis	Ahmed et al. (2022); Chan & Hu (2023); Sanusi et al. (2024); Sun et al. (2024); and Al-Zahrani (2024).

Braun and Clarke's (2006) six-phase thematic analysis framework, the resulting themes informed refinement of the conceptual framework and interpretation of the literature.

Survey research

This study employed a quantitative cross-sectional survey to examine higher education mathematics students' perceptions of AI-supported learning. Data

were collected between 25 June and 22 July 2024 using Google Forms across multiple universities in Assam, India.

Convenience sampling was adopted because of the exploratory nature of the study and the absence of an institution-wide sampling frame for mathematics students across the participating universities. Participants were recruited through coordination with Departments of Mathematics, where faculty members distributed the survey link to students who voluntarily participated.

A total of 145 responses were received. After excluding incomplete or inconsistent submissions and responses from students not formally enrolled in mathematics programmes, 105 valid responses remained for analysis.

The final sample included students from six universities in Assam (Table 2); however, institutional representation was uneven, with one university contributing only one respondent.

Table 2

Participant demographics (n = 105)

Variable	Categories	Frequency (N)	Percentage (%)
Gender	Male	61	58.10
	Female	44	41.90
Age	16-20	40	38.10
	21-25	49	46.67
	26-30	11	10.48
	>31	5	4.76
Name of your Institution	Assam Don Bosco University	17	16.19
	Assam University, Silchar	10	9.52
	Dibrugarh University	35	33.33
	Gauhati University	14	13.33
	Tezpur University	28	26.67
	The Assam Royal Global University	1	0.95
Level of Education	Undergraduate	61	58.10
	Postgraduate	26	24.76
	Research Scholar	18	17.14

Continued on next page

Table 2 continued

Variable	Categories	Frequency (N)	Percentage (%)
Major/Field of Study	Mathematics	105	100.00
Have you ever used AI Technologies/ Tools like ChatGPT, Gemini, CoPilot etc.	Always	18	17.14
	Often	26	24.76
	Sometimes	49	46.67
	Rarely	8	7.62
	Never	4	3.81

Model Development

The proposed research model was developed by integrating the theoretical foundations of the TAM, ECT, relevant EP constructs, and evidence identified through the structured literature review and focused thematic synthesis. The model development process comprised two complementary stages. First, the study constructs were operationalised using a structured questionnaire. Second, the conceptual framework and measurement model were established through theory-driven conceptual revisions and measurement model evaluation to ensure theoretical coherence and satisfactory psychometric quality.

Instrument Development and Construct Operationalisation

The study constructs were operationalised using a structured questionnaire comprising measurement items adapted from validated theoretical and empirical studies in educational technology, AI-supported learning, and EP.

The questionnaire was pilot-tested at the authors' home institution with 15 undergraduate students from the Departments of Mathematics and Physics. Physics students were included because Physics represents a closely related STEM discipline with substantial mathematical content. The pilot study assessed questionnaire clarity, wording, sequencing, and administration rather than the measurement model. Minor refinements were made following the pilot study, and the pilot responses were excluded from the final analysis.

The research model comprised eight latent constructs: PU, PEOU, EM, PAP, SE, TR, SAT, and FU. These constructs were measured using a questionnaire comprising 21 closed-ended items rated on a five-point Likert scale, in addition to six demographic questions and one open-ended question on AI-supported mathematics learning. Although the questionnaire was

administered to higher education mathematics students, the measurement instrument was designed to assess their general perceptions of AI-supported learning within the context of higher education mathematics. It was not intended to directly measure mathematics-specific cognitive processes, such as proof verification, symbolic accuracy, or formal reasoning. Table 3 presents the latent constructs, their corresponding measurement items, and the theoretical and empirical sources used for construct operationalisation.

Conceptual Framework and Measurement Model Development

The conceptual framework and measurement model were developed through two complementary stages. First, the conceptual framework was refined by removing the Awareness and Understanding and Bias and Fairness constructs, which consequently eliminated the structural relationships AU → PU and TR → BF. The relationship between perceived usefulness and perceived ease of use was also reoriented from PU → PEOU to PEOU → PU in accordance with the original TAM. The framework also incorporated seven theory-driven structural relationships (PU → EM, PU → PAP, PAP → SE, PEOU → SAT, EM → SAT,

Table 3

Latent constructs and measurement items

Latent Construct	Item Code	Measurement Item	Key Theoretical/ Empirical Sources
PU	PU1	AI tools help me to understand mathematical concepts better	Davis (1989); Ahmed et al. (2022)
	PU2	AI tools make my learning more efficient	
	PU3	AI tools provide personalised feedback that is helpful	
PEOU	PEOU1	AI tools used in my courses are easy to navigate	Davis (1989); Sun et al. (2024)
	PEOU2	I can easily access AI tools when needed	
	PEOU3	The interface of AI tools is user-friendly	

Continued on next page

Table 3 continued

Latent Construct	Item Code	Measurement Item	Key Theoretical/ Empirical Sources
EM	EM1	AI tools make learning mathematics more engaging	Fredricks et al. (2004); Chan & Hu (2023)
	EM2	I am more motivated to study mathematics when using AI tools	
PAP	PAP1	My understanding of mathematics has improved due to AI tools	Kulik & Fletcher (2016)
	PAP2	AI tools help me achieve better grades in mathematics	
	PAP3	Personalised learning through AI tools has enhanced my problem-solving skills	
SE	SE1	I feel more confident in my mathematical abilities when using AI tools	Bandura (1997); Cukurova et al. (2019)
	SE2	AI tools help me identify my strengths and weaknesses in mathematics	
TR	TR1	I trust the information provided by AI tools	Dignum (2019); Shahzad et al. (2024)
	TR2	AI tools provide reliable and factual information	
	TR3	I feel confident using the outputs from AI Tools	
SAT	SAT1	Overall, I am satisfied with the AI tools used in my mathematics courses	Oliver (1980); Bhattacherjee (2001); Recalde Drouet et al. (2024)
	SAT2	AI tools meet my learning needs effectively	

Continued on next page

Table 3 continued

Latent Construct	Item Code	Measurement Item	Key Theoretical/ Empirical Sources
FU	FU1	I am likely to continue using AI tools in future mathematics courses	Bhattacherjee (2001); Duong et al. (2024)
	FU2	I believe AI tools will become an essential part of mathematics education	
	FU3	I am interested in exploring more AI tools for learning mathematics	

Note: TAM and ECT informed the conceptualisation of the study constructs, whereas EP and the literature on AI-supported learning informed the operationalisation of the constructs and the development of the measurement items.

SAT → TR, and PAP → FU) to enhance its explanatory scope. These structural relationships were specified a priori and informed by the integrated theoretical framework comprising TAM, ECT, EP, and prior empirical evidence from AI-supported learning research rather than being derived from data-driven or post hoc model modification. Second, the measurement model underwent iterative refinement, with indicators that weakened construct validity being removed based on assessments of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity in accordance with established PLS-SEM guidelines (Hair et al., 2022).

The resulting research model comprised eight latent constructs, 21 indicators, and 14 hypotheses. Table 4 summarises the conceptual and measurement model development decisions by documenting the constructs, indicators, and structural relationships that were removed, modified, or introduced, together with the rationale for each decision.

The conceptual and measurement model refinements enhanced the psychometric properties of the research model. The lowest Cronbach's α increased from 0.454 to 0.706, the lowest composite reliability increased from 0.733 to 0.826, and the AVE increased from 0.489 to 0.613. In addition, all HTMT values were reduced to within the recommended threshold. The reported supplementary model fit indices also improved, with SRMR decreasing from 0.252 to 0.096 and NFI increasing from 0.597 to 0.740. Consistent with contemporary PLS-SEM recommendations, SRMR and NFI are reported as supplementary descriptive indices rather than primary model evaluation criteria (Hair et al., 2022).

Table 4

Conceptual and Measurement Model Development Decisions

Model component	Removed constructs/ indicators	Action taken	Reason for modification	Effect on model quality
Awareness and understanding of AI Tools (AU)	AU (Construct) AU1: I am aware of the basic features and functions of AI tools used in my courses AU2: I understand how AI tools personalize my learning experience AU3: I find AI concepts easy to understand	Construct removed	Theoretical refinement; the construct represented students' prior awareness and understanding of AI tools rather than post-adoption perceptions of AI-supported learning and was therefore removed to improve the conceptual parsimony of the revised framework.	Reduced conceptual redundancy and improved model parsimony.

Continued on next page

Table 4 continued

Model component	Removed constructs/ indicators	Action taken	Reason for modification	Effect on model quality
Bias and Fairness (BF)	BF (Construct) BF1: AI tools provides unbiased responses BF2: I am concerned about potential biases in the responses from AI Tools BF3: AI tools handles sensitive topics appropriately	Construct removed	Theoretical refinement; although conceptually relevant, the construct was peripheral to the primary focus of the revised framework. Its removal was further supported by inadequate psychometric properties, including internal consistency reliability below the recommended threshold (Cronbach's α = 0.454) and an average variance extracted (AVE) of 0.489.	Improved internal consistency reliability, convergent validity (AVE), discriminant validity (HTMT), and the overall psychometric quality of the measurement model.
Engagement and Motivation (EM)	EM (Indicators) EM3: AI make the learning process more enjoyable EM4: AI helps me understand complex topics better	Indicators removed	Measurement refinement; during iterative measurement model assessment, EM3 was found to emphasise learning enjoyment, whereas EM4 primarily reflected perceived learning benefit rather than the broader engagement and motivation construct. Their removal improved construct validity and psychometric performance.	Improved internal consistency reliability, AVE, HTMT, and the overall psychometric quality of the measurement model.

Continued on next page

Table 4 continued

Model component	Removed constructs/ indicators	Action taken	Reason for modification	Effect on model quality
Self-Efficacy (SE)	SE (Indicator) SE3: I am more likely to seek help from AI tools than from human tutors	Indicator removed	Measurement refinement; during iterative measurement model assessment, the indicator was found to emphasise AI help-seeking behaviour rather than confidence in one's own academic capability, thereby weakening its alignment with the intended self-efficacy construct. It also demonstrated comparatively weaker psychometric performance during the iterative measurement model assessment.	Improved internal consistency reliability, AVE, HTMT, and the overall psychometric quality of the measurement model.

Continued on next page

Table 4 continued

Model component	Removed constructs/ indicators	Action taken	Reason for modification	Effect on model quality
Satisfaction (SAT)	SAT (Indicator) SAT3: I would recommend the use of AI tools to other students	Indicator removed	Measurement refinement; during iterative measurement model assessment, the indicator was found to emphasise recommendation intention, representing a behavioural outcome more closely aligned with future use intention than satisfaction. It also demonstrated comparatively weaker psychometric performance during the iterative measurement model assessment.	Improved internal consistency reliability, AVE, HTMT, and the overall psychometric quality of the measurement model.

Continued on next page

Table 4 continued

Model component	Removed constructs/ indicators	Action taken	Reason for modification	Effect on model quality
Structural model	–	Structural model revised	Theoretical refinement; the structural model was refined by removing the relationships AU → PU and TR → BF as a consequence of removing the corresponding latent constructs from the conceptual framework, reorienting the relationship from PU → PEOU to PEOU → PU in accordance with the original TAM, and introducing seven additional theory-driven relationships (PU → EM, PU → PAP, PAP → SE, PEOU → SAT, EM → SAT, SAT → TR, and PAP → FU). All structural modifications were theory-driven and specified a priori based on TAM, ECT, EP, and prior empirical evidence rather than being derived from data-driven or post hoc model modification.	Improved theoretical coherence and explanatory capability while maintaining consistency with the revised integrated framework.

Data analysis procedure

Data were analysed using SmartPLS 4 (Ringle et al., 2024) following the PLS-SEM approach. The standard PLS-SEM algorithm was employed because the study focused on exploratory, prediction-oriented analysis involving multiple latent constructs. PLS-SEM is particularly appropriate for such research because it emphasises variance explanation and predictive relationships (Hair et al., 2022).

The analysis followed a two-stage procedure comprising measurement model and structural model assessment. The measurement model was evaluated using indicator reliability, internal consistency reliability, convergent validity, and discriminant validity through factor loadings, Cronbach's alpha (α), Dijkstra-Henseler's rho_a reliability coefficient (rho_a), composite reliability (rho_c), average variance extracted (AVE), variance inflation factor (VIF), and the Heterotrait-Monotrait ratio (HTMT).

Structural model assessment included path coefficients, hypothesis testing, coefficient of determination (R^2), predictive relevance (Q^2), and supplementary model evaluation indices. Bootstrapping with 5,000 subsamples assessed the significance of the hypothesised relationships. Because the study employed variance-based PLS-SEM, structural model evaluation followed the prediction-oriented criteria recommended for PLS-SEM rather than the global goodness-of-fit measures commonly associated with covariance-based SEM (e.g., χ^2/df, CFI, TLI, and RMSEA). Accordingly, the analysis focused on measurement quality, structural relationships, R^2, and Q^2, while SRMR and NFI were reported only as supplementary descriptive indices (Hair et al., 2022).

Sample size adequacy (n = 105) was assessed using the Inverse Square Root Method proposed by Kock and Hadaya (2018), consistent with contemporary PLS-SEM recommendations (Hair et al., 2022). The weakest significant path coefficient in the structural model was H10 (EM →SAT: β = 0.256, p = 0.022). Applying the inverse square root method at α = 0.05 and statistical power (1−β) = 0.80 yielded a minimum sample size requirement of approximately 95 observations.

$$N_{min} = \left(\frac{2.489}{|\beta_{min}|}\right)^2 = \left(\frac{2.489}{0.256}\right)^2 \approx 94.53$$

The final sample of 105 valid responses exceeded this minimum requirement, supporting the adequacy of the sample for exploratory PLS-SEM estimation. However, this should not be interpreted as evidence of population representativeness or statistical generalisability because the study employed convenience sampling and uneven institutional representation.

A post-hoc power analysis was conducted using G*Power 3.1 (Faul et al., 2009). Using an F-test for multiple regression (fixed model, R^2 deviation from zero), a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, a total sample size of 105, and three predictors corresponding to the maximum number of predictors for a single endogenous construct (SAT), the achieved statistical power was approximately 92.0% ($1-\beta = 0.920$). This exceeds the commonly recommended 0.80 threshold (Cohen, 1988), indicating adequate power to detect medium effects. Similarly, the achieved statistical power should not be interpreted as evidence of sample representativeness or broader generalisability because the study employed convenience sampling, uneven institutional representation, and unequal subgroup sizes.

Ethical and methodological considerations

Participation was voluntary, and respondents were informed about the study purpose before participation. No personally identifiable information was collected, and responses were analysed anonymously.

The study employed convenience sampling and relied on self-reported perceptions. Nevertheless, it provides context-sensitive insights into AI-supported mathematics learning within a regionally underrepresented setting.

Results

Descriptive statistics

Descriptive statistics were analysed to examine the overall response distribution for the retained measurement items. Mean scores indicated generally positive perceptions of perceived usefulness, perceived ease of use, engagement and motivation, and perceived academic performance. Participants also reported moderate confidence in using AI-supported systems for conceptual understanding, mathematical problem-solving, and independent learning, together with positive perceptions of trust and satisfaction and a favourable intention to continue using AI tools.

In summary, the descriptive findings indicate generally positive perceptions of AI-supported learning among mathematics students across undergraduate, postgraduate, and research levels.

Measurement model assessment

The measurement model was evaluated using indicator reliability, internal consistency reliability, convergent validity, and discriminant validity criteria following contemporary PLS-SEM guidelines (Hair et al., 2022).

Indicator reliability and internal consistency reliability

Indicator reliability was assessed using outer factor loadings. All retained indicators demonstrated loadings above 0.70. Internal consistency reliability was evaluated using α, rho_a, and rho_c.

As shown in Table 5, Cronbach's α ranged from 0.706 to 0.920, rho_a values from 0.758 to 0.936, and rho_c values from 0.826 to 0.951. All reliability coefficients exceeded the recommended threshold of 0.70, indicating acceptable internal consistency reliability.

Convergent validity

Convergent validity was assessed using the AVE. As presented in Table 6, all constructs demonstrated AVE values above the recommended threshold of 0.50, ranging from 0.613 to 0.906. These findings indicate that the constructs explained more than half of the variance in their respective indicators.

Discriminant validity

Discriminant validity was assessed using the HTMT. Table 6 shows that all HTMT values in the model were below the recommended threshold of 0.90, ranging from 0.594 to 0.883, indicating acceptable discriminant validity among the constructs. The observed HTMT values demonstrate acceptable construct distinctiveness and support subsequent structural model assessment.

Structural model assessment

Following confirmation of the measurement model, the structural model was evaluated using collinearity diagnostics, path coefficients, and bootstrapping procedures.

Collinearity assessment

Inner model collinearity was assessed using VIF values. As presented in Table 5, all VIF values were below the recommended threshold of 5.0, indicating that multicollinearity was not a concern.

Hypothesis testing

The significance of the hypothesised relationships was evaluated using bootstrapping with 5,000 subsamples. As presented in Table 7, PEOU exerted a significant positive effect on PU ($\beta = 0.691$, $p < 0.001$), consistent with TAM.

Table 5

Measurement model statistics

	Mean	SD	α	rho_a	rho_c	AVE	Loadings	VIF	R^2
PU			0.784	0.789	0.874	0.698			0.478
PU1	3.343	0.893					0.856	1.697	
PU2	3.610	0.669					0.851	1.787	
PU3	3.581	0.687					0.798	1.501	
PEOU			0.706	0.758	0.826	0.613			
PEOU1	3.371	0.772					0.828	1.192	
PEOU2	3.895	0.716					0.751	1.667	
PEOU3	3.876	0.686					0.767	1.658	
EM			0.889	0.891	0.947	0.900			0.533
EM1	3.400	0.788					0.952	2.774	
EM2	3.190	0.937					0.945	2.774	
PAP			0.920	0.921	0.950	0.862			0.651
PAP1	3.114	0.969					0.939	3.854	
PAP2	3.010	0.941					0.934	3.745	
PAP3	3.286	0.943					0.912	2.873	

Continued on next page

Table 5 continued

	Mean	SD	α	rho_a	rho_c	AVE	Loadings	VIF	R^2
SE			0.897	0.897	0.951	0.906			0.709
SE1	3.105	0.935					0.954	2.942	
SE2	3.114	0.949					0.950	2.942	
TR			0.825	0.852	0.895	0.741			0.526
TR1	3.229	0.831					0.886	2.187	
TR2	3.562	0.816					0.778	1.563	
TR3	3.314	0.734					0.912	2.379	
SAT			0.892	0.893	0.949	0.903			0.700
SAT1	3.305	0.782					0.949	2.850	
SAT2	3.324	0.811					0.951	2.850	
FU			0.904	0.936	0.939	0.838			0.475
FU1	3.638	0.818					0.939	3.534	
FU2	3.524	0.852					0.942	3.714	
FU3	3.705	0.861					0.862	2.324	

Note: SD = Standard deviation

Table 6

Discriminant validity

Construct	PU	PEOU	EM	PAP	SE	TR	SAT	FU
PU								
PEOU	0.863							
EM	0.866	0.633						
PAP	0.850	0.709	0.848					
SE	0.760	0.594	0.872	0.883				
TR	0.801	0.782	0.677	0.740	0.678			
SAT	0.841	0.862	0.799	0.836	0.752	0.807		
FU	0.759	0.827	0.696	0.707	0.622	0.659	0.690	

PU, in turn, had significant positive effects on EM (β = 0.652, $p < 0.001$) and PAP (β = 0.359, $p < 0.001$). EM also showed significant positive effects on PAP (β = 0.508, $p < 0.001$), SE (β = 0.397, $p = 0.001$), and SAT (β = 0.256, $p = 0.022$). Furthermore, PAP significantly influenced SE (β = 0.498, $p < 0.001$), TR (β = 0.286, $p = 0.022$), SAT (β = 0.318, $p = 0.002$), and FU (β = 0.421, $p = 0.001$), while SAT exerted significant positive effects on TR (β = 0.484, $p < 0.001$) and FU (β = 0.313, $p = 0.013$), consistent with ECT.

The relationship between PEOU and EM was not statistically significant (β = 0.106, $p = 0.290$), indicating that perceived ease of use alone may not directly enhance students' engagement and motivation in AI-supported mathematics learning. Overall, thirteen of the fourteen hypothesised relationships were supported. Figures 2 and 3 illustrate the structural model, presenting the standardized path coefficients and corresponding p values, respectively, for the hypothesised relationships among the study constructs.

Coefficient of determination

The coefficient of determination (R^2) was examined to assess the explanatory power of the structural model. The model explained 47.8% of the variance in PU, 53.3% in EM, 65.1% in PAP, 70.9% in SE, 52.6% in TR, 70.0% in SAT, and 47.5% in FU. These findings indicate moderate to substantial explanatory power across the endogenous constructs.

Predictive relevance assessment (Q^2)

Q^2 of the structural model was assessed using the blindfolding procedure and Stone-Geisser's Q^2 values (Hair et al., 2022). As presented in Table 8, all

Table 7

Structural model results

Hypothesis	Paths	Original sample (O)	Sample mean (M)	SD	T statistics	*p* values	Remarks
H1	**PEOU → PU**	0.691	0.697	0.056	12.446	< 0.001	Supported
H2	**PEOU → EM**	0.106	0.108	0.101	1.058	0.290	Not supported
H3	**PU → EM**	0.652	0.653	0.086	7.592	< 0.001	Supported
H4	**PU → PAP**	0.359	0.359	0.094	3.830	< 0.001	Supported
H5	**EM → PAP**	0.508	0.507	0.107	4.738	< 0.001	Supported
H6	**EM → SE**	0.397	0.396	0.124	3.203	0.001	Supported
H7	**PAP → SE**	0.498	0.500	0.128	3.882	< 0.001	Supported
H8	**PAP → TR**	0.286	0.287	0.125	2.292	0.022	Supported
H9	**PEOU → SAT**	0.380	0.384	0.062	6.162	< 0.001	Supported
H10	**EM → SAT**	0.256	0.243	0.112	2.287	0.022	Supported
H11	**PAP → SAT**	0.318	0.326	0.103	3.078	0.002	Supported
H12	**SAT → TR**	0.484	0.482	0.132	3.682	< 0.001	Supported
H13	**PAP → FU**	0.421	0.415	0.124	3.407	0.001	Supported
H14	**SAT → FU**	0.313	0.317	0.126	2.490	0.013	Supported

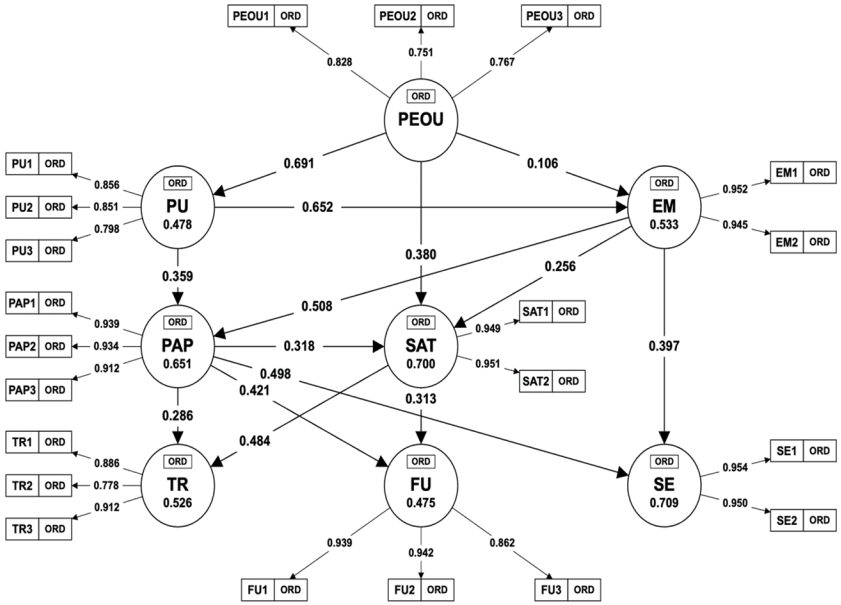

Figure 2. Structural model with standardized path coefficients

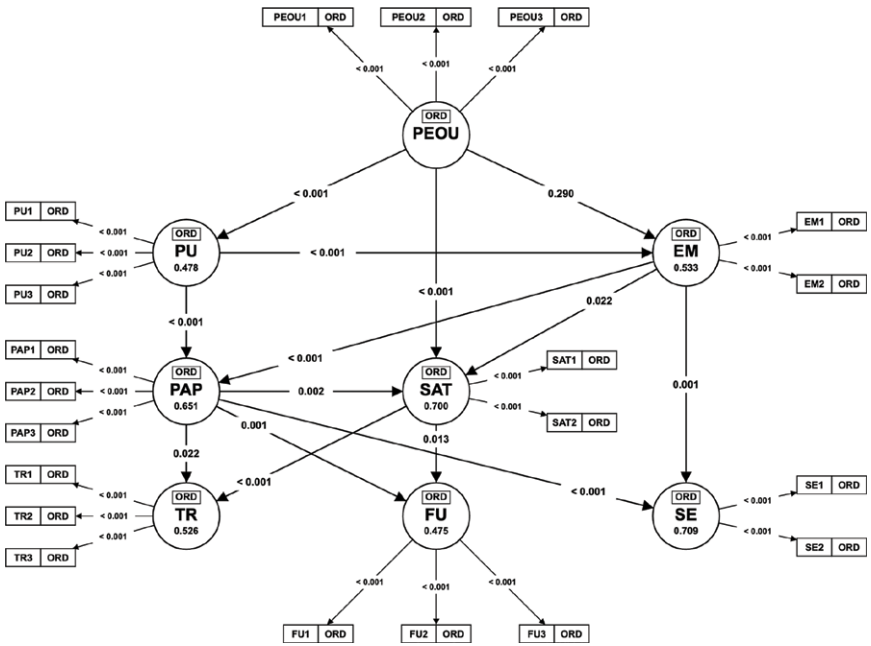

Figure 3. Structural model with *p* values

Table 8

Predictive relevance

Indicators	Q^2 predict
PU	0.527
EM	0.477
PAP	0.420
SE	0.311
TR	0.352
SAT	0.581
FU	0.454

endogenous constructs demonstrated positive Q^2 values ranging from 0.311 to 0.581, indicating acceptable predictive relevance. The highest predictive relevance was observed for SAT ($Q^2 = 0.581$), followed by PU ($Q^2 = 0.527$) and EM ($Q^2 = 0.477$).

Model fit assessment

Table 9 shows that the saturated model yielded an SRMR of 0.083, whereas the estimated model produced an SRMR of 0.096 and an NFI of 0.740. Although the global fit indices remain below commonly suggested thresholds, they are interpreted only as supplementary descriptive indices, consistent with contemporary PLS-SEM recommendations (Hair et al., 2022). Consistent with the prediction-oriented evaluation adopted in this study, interpretation of the structural model focused on measurement quality, path coefficients, R^2, and Q^2. The positive Q^2 values reported in Table 8 indicate acceptable predictive relevance despite the global fit indices remaining below commonly suggested thresholds.

Exploratory thematic analysis of open-ended responses

Among the 105 respondents, 44 provided open-ended comments on the use of AI tools in education. After excluding 23 brief or non-informative responses (e.g., “No”, “NA”, “Nil”, or unrelated comments), 21 substantive responses were retained for exploratory thematic analysis. Given the brevity of many responses, the qualitative findings are presented as supplementary evidence alongside the quantitative results.

Table 9

Global model fit indices

	Saturated model	Estimated model
SRMR	0.083	0.096
d_ULS	1.597	2.128
d_G	0.825	0.896
Chi-square	528.121	531.315
NFI	0.742	0.740

The retained responses were analysed following the six-phase thematic analysis framework proposed by Braun and Clarke (2006). The analysis identified recurring themes reflecting both the perceived benefits and limitations of AI-supported mathematics learning. These themes, together with their frequencies and representative quotations, are summarised in Table 10.

Overall, the qualitative findings indicated generally positive perceptions of AI-supported mathematics learning while also highlighting concerns regarding the accuracy of AI-generated mathematical responses and the importance of maintaining independent mathematical reasoning.

Discussion

Technology acceptance and perceived usefulness

The findings support the central assumptions of TAM by demonstrating that PEOU positively influenced PU. Students who perceived AI tools as easy to use were more likely to regard them as useful for mathematics learning, suggesting that usability contributed to students' perceptions of the educational value of AI-supported learning. The significant relationship between PEOU and SAT further indicates that user-friendly AI tools contributed to more positive learning experiences. These findings are consistent with previous studies identifying PEOU and PU as important determinants of AI adoption in educational settings (Ahmed et al., 2022; Alhumaid et al., 2023; Sun et al., 2024).

PU also demonstrated significant positive effects on EM and PAP. These relationships suggest that students reported greater engagement and perceived improvements in their academic performance when AI tools were viewed as supporting effective mathematics learning rather than merely

Table 10

Themes identified from open-ended responses

Theme	Definition	Responses (n)	Representative quotation
AI as a learning support tool	AI supports understanding, explanations, and independent learning.	8	"AI is very helpful to us. It helps us to understand problems."
Mathematical accuracy and limitations	AI may generate inaccurate, incomplete, or unreliable mathematical solutions, particularly for conceptual or complex mathematics.	8	"The AI outputs are less accurate than a human solution."
Human guidance remains essential	AI should complement rather than replace teachers and human reasoning.	2	"AI will definitely be helpful but we always need a qualified human being to guide us."
Overdependence and reduced mathematical thinking	Excessive reliance on AI may weaken independent reasoning and creativity.	3	"Machine learning should not be allowed to dominate over the human brain."

providing technological convenience. This observation is consistent with previous research showing that AI-supported technologies are associated with greater engagement, independent learning, and improved educational outcomes (Chan & Hu, 2023; Malik et al., 2023). Within higher education mathematics, where conceptual understanding and structured problem-solving are fundamental, students perceived AI tools as particularly valuable for providing timely explanations, personalised feedback, and opportunities for independent mathematical learning.

Engagement, motivation, and academic outcomes

EM significantly influenced PAP, SE, and SAT, supporting EP literature that identifies engagement and motivation as important determinants of successful learning (Fredricks et al., 2004; Liu et al., 2024). In higher education mathematics, where students frequently encounter abstract concepts and multi-step problem-solving tasks, greater engagement and motivation were associated with higher perceived academic performance, stronger self-efficacy, and greater satisfaction with AI-supported learning.

PAP emerged as one of the strongest predictors in the structural model, significantly influencing SE, TR, SAT, and FU. These relationships suggest that students who perceived AI tools as supporting their mathematics learning also reported greater confidence in their mathematical abilities, stronger trust in AI-supported learning, higher satisfaction, and greater intention to continue using such technologies. The significant effects of SAT on TR and FU are also consistent with ECT, which proposes that positive post-adoption experiences encourage continued technology use (Bhattacherjee, 2001; Duong et al., 2024). Taken together, the findings suggest that students' continued acceptance of AI-supported mathematics learning depends not only on its ease of use, but also on the perceived educational value of AI tools and the quality of the learning experiences they facilitate.

Non-significant relationship between perceived ease of use and engagement and motivation

An important finding of the study was the non-significant relationship between PEOU and EM. Although AI tools that were easier to use were perceived as more useful and generated higher levels of satisfaction, ease of use alone was insufficient to enhance students' engagement and motivation. This finding may reflect the distinctive nature of higher education mathematics, where students are more likely to perceive AI tools as facilitating conceptual understanding, providing step-by-step guidance, and supporting

mathematical problem-solving than for their usability alone. Consequently, meaningful learning support appears to play a more important role than ease of use in fostering sustained engagement with AI-supported mathematics learning. These observations suggest that, within higher education mathematics, the perceived educational value of AI tools may be more influential than usability in promoting student engagement.

Thematic analysis and contextual interpretation

The qualitative findings complemented the quantitative results by providing additional insight into students' experiences of AI-supported mathematics learning. Students particularly valued AI tools for enhancing conceptual understanding, supporting independent learning, and assisting with mathematical problem-solving. At the same time, concerns regarding inaccurate AI-generated responses and excessive dependence emphasise the importance of responsible and pedagogically guided AI integration within higher education mathematics. These observations are consistent with recent studies highlighting both the educational opportunities and the limitations of generative AI in mathematics education (Pepin et al., 2025; Rizos & Gkrekas, 2025).

The study also contributes context-sensitive empirical evidence from higher education institutions in Assam, India, a region that remains underrepresented in AI-supported learning research. Although the findings may not be directly generalisable to other educational contexts, they provide valuable insight into students' perceptions and experiences of AI-supported mathematics learning within a regional higher education setting. Overall, the findings suggest that the integrated framework based on TAM, ECT, and EP constructs provides a useful basis for understanding students' perceptions, learning experiences, and future use intentions regarding AI-supported mathematics learning.

Practical Implications

The study has several practical implications for educators and higher education institutions seeking to integrate AI into mathematics education. Since PU significantly influenced EM and PAP, AI should be integrated as a learning support tool within pedagogically guided instruction that supports students' conceptual understanding, mathematical reasoning, and problem-solving rather than merely providing technological assistance. Educators should encourage students to use AI to complement conventional classroom instruction through guided practice, personalised feedback, and independent mathematical learning.

The significant relationships among PAP, SE, TR, SAT, and FU suggest that mathematics students' continued acceptance of AI was associated with their perceived academic benefits and positive learning experiences. Accordingly, higher education institutions should provide guidance on the responsible use of AI by encouraging students to critically evaluate AI-generated responses, verify mathematical solutions, and recognise the limitations of AI-generated content. Such practices may reduce overdependence on AI while supporting students' confidence and encouraging independent mathematical thinking.

Learning activities that require students to evaluate, justify, and verify AI-generated solutions alongside conventional mathematical reasoning may further support responsible AI integration within higher education mathematics. Such activities may maximise the educational benefits of AI while encouraging students to use AI as a learning support tool rather than a substitute for independent mathematical thinking.

Limitations

This study has several limitations. First, although the sample size (n = 105) satisfied contemporary PLS-SEM sample size and statistical power recommendations, the study employed convenience sampling with uneven institutional representation. Consequently, the findings should be interpreted as contextually informative rather than institutionally representative, limiting broader generalisability. Second, the cross-sectional design restricts causal interpretation of the observed relationships. Third, the study relied on self-reported perceptions, which may be influenced by response bias. Fourth, the qualitative analysis was exploratory because many open-ended responses were relatively brief. Finally, the model examined trust in AI outputs but did not directly measure perceptions of fairness or algorithmic bias. Accordingly, the findings should not be interpreted as providing a comprehensive empirical assessment of ethical AI adoption.

Although the study focused on higher education mathematics students, most measurement items assessed general perceptions of AI-supported learning rather than mathematics-specific learning processes. Consequently, the findings should be interpreted within this context. Future research should employ longitudinal designs, larger and more geographically diverse samples, comparative disciplinary analyses, and richer qualitative investigations. Mathematics-specific measurement instruments should also incorporate constructs such as proof verification, symbolic accuracy, step-by-step mathematical reasoning, interpretation of formal notation, identification of hallucinated solutions, and dependence on AI for mathematical problem-solving, while examining fairness, algorithmic bias, and discipline-specific differences in AI-supported learning.

Conclusion

This study investigated students' perceptions of AI-supported learning in higher education mathematics by integrating TAM, ECT, and EP to explain factors associated with learning experiences and continued AI use. The findings indicate that PU, EM, PAP, and SAT were key factors associated with mathematics students' perceptions of AI-supported learning and their future use intentions, whereas ease of use alone was insufficient to directly enhance engagement and motivation. Together, the quantitative and qualitative findings suggest that mathematics students perceived AI primarily as a valuable support for mathematics learning rather than valuing it solely for its ease of use.

Future research should employ longitudinal designs, larger and more diverse samples, and mathematics-specific measurement instruments to further investigate AI-supported mathematics learning while incorporating dimensions such as fairness, algorithmic bias, and mathematical reasoning.

The study contributes to the growing literature on AI-supported mathematics education by applying an integrated theoretical framework based on TAM, ECT, and EP constructs to examine students' perceptions and continued use of AI within a regional higher education context. The findings provide context-sensitive evidence that may inform the pedagogically guided integration of AI into higher education mathematics.

Author Declarations

Author Contributions

Author 2 conceptualised the study, designed the methodology, and carried out the data analysis. Author 1 conducted the literature review, contributed to data collection, prepared the initial draft, and undertook the final editing. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare that there are no conflicts of interest associated with this work.

Data Availability Statement

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request. All shared data will be de-identified in accordance with institutional and ethical data protection protocols.

Declaration on Use of Generative AI and AI Tools

During the preparation of this manuscript, the authors used ChatGPT to assist with language editing, manuscript organisation, and clarity improvements. The authors reviewed and verified all content and accept full responsibility for its accuracy and integrity.

Ethics Approval

Ethical approval was not required for this study due to the anonymous and voluntary nature of participation. The study was conducted by the authors.

Funding Statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Informed Consent

Informed consent was secured from all participants. Participants were informed about the study's purpose, voluntary nature, and withdrawal rights, and consent was recorded through the online Google Form mode of data collection.

Welfare of Animals

This study did not involve animals and therefore does not require an animal welfare statement.

References

Ahmed, S., Khalil, M., Chowdhury, B., Haque, R., Senathirajah, A., & Omar Din, F. (2022). Motivators and barriers of artificial intelligent (AI) based teaching. *Eurasian Journal of Educational Research, 100*, 74–89. https://doi.org/10.14689/ejer.2022.100.006

All India Council for Technical Education. (2025). *AICTE declares 2025 as the Year of Artificial Intelligence in Education*. https://www.aicte.gov.in/downloads/initiatives/AICTE%20inputs%20on%20Artificial%20Intelligence%20-comprehensive.pdf

Alhumaid, K., Naqbi, A. S., Elsori, D., & Al Mansoori, M. A. (2023). The adoption of artificial intelligence applications in education. *International Journal of Data and Network Science, 7*(1), 457–466. https://doi.org/10.5267/j.ijdns.2022.8.013

Al-Zahrani, A. M. (2024). Unveiling the shadows: Beyond the hype of AI in education. *Heliyon, 10*(9), e30696. https://doi.org/10.1016/j.heliyon.2024.e30696

Baker, R., & Siemens, G. (2014). Educational data mining and learning analytics. In R. K. Sawyer (Ed.),*The Cambridge handbook of the learning sciences* (2nd ed., pp. 253–272). Cambridge University Press.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W. H. Freeman and Company.

Bhattacherjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly, 25*(3), 351–370. https://doi.org/10.2307/3250921

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education, 20*(1), 43. https://doi.org/10.1186/s41239-023-00411-8

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates. https://doi.org/10.4324/9780203771587

Cukurova, M., Kent, P., & Luckin, R. (2019). Artificial intelligence and multimodal data in the service of human decision-making: A case study in debate tutoring. *British Journal of Educational Technology, 50*(6), 3032–3046. https://doi.org/10.1111/bjet.12829

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Dignum, V. (2019). *Responsible artificial intelligence: How to develop and use AI in a responsible way*. Springer Nature. https://doi.org/10.1007/978-3-030-30371-6

Duong, C. D., Nguyen, T. D., Ngo, T. V. N., Dao, V. T., Diep, N., & Thanh, P. V. (2024). Exploring higher education students' continuance usage intention of ChatGPT: Amalgamation of the information system success model and the stimulus-organism-response paradigm. *International Journal of Information and Learning Technology, 41*(5), 556–584. https://doi.org/10.1108/IJILT-01-2024-0006

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research, 74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage Publications.

Handique, K. (2023). Problems and challenges of higher education in Assam. *Journal of Emerging Technologies and Innovative Research, 10*(10), f41–f45. https://www.jetir.org/papers/JETIR2310406.pdf

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal, 28*(1), 227–261. https://doi.org/10.1111/isj.12131

Kulik, J. A., & Fletcher, J. D. (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of Educational Research, 86*(1), 42–78. https://doi.org/10.3102/0034654315581420

Liu, Y., Ma, S., & Chen, Y. (2024). The impacts of learning motivation, emotional engagement, and psychological capital on **academic performance** in a blended learning university course. *Frontiers in Psychology, 15*, Article 1357936. https://doi.org/10.3389/fpsyg.2024.1357936

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson. https://edu.google.com/pdfs/Intelligence-Unleashed-Publication.pdf

Malik, A. R., Pratiwi, Y., Andajani, K., Numertayasa, I. W., Suharti, S., Darwis, A., & Marzuki. (2023). Exploring artificial intelligence in academic essay writing: Higher education students' perspectives. *International Journal of Educational Research Open, 5*, 100296. https://doi.org/10.1016/j.ijedro.2023.100296

Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research, 17*(4), 460–469. https://doi.org/10.2307/3150499

Pepin, B., Buchholtz, N., & Salinas-Hernández, U. (2025). Mathematics education in the era of ChatGPT: Investigating its meaning and use for school and university education. *Digital Experiences in Mathematics Education, 11*, 1–8. https://doi.org/10.1007/s40751-025-00173-0

Recalde Drouet, E. M., Tello Salazar, D. M., Charro Domínguez, T. L., & Catota Pinthsa, P. J. (2024). Analysis of the repercussions of artificial intelligence in the personalization of the virtual educational process in higher education programs. *Data and Metadata, 3*, 386. https://doi.org/10.56294/dm2024386

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). *SmartPLS 4* [Computer software]. SmartPLS. https://www.smartpls.com

Rizos, I., & Gkrekas, N. (2025). The impact of LLMs on mathematics education and research at the university. *Social Sciences & Humanities Open, 11*, 101969. https://doi.org/10.1016/j.ssaho.2025.101969

Sanusi, I. T., Ayanwale, M. A., & Tolorunleke, A. E. (2024). Investigating pre-service teachers' artificial intelligence perception from the perspective of planned behavior theory. *Computers and Education: Artificial Intelligence, 6*, 100202. https://doi.org/10.1016/j.caeai.2024.100202

Shahzad, M. F., Xu, S., & Javed, I. (2024). ChatGPT awareness, acceptance, and adoption in higher education: The role of trust as a cornerstone. *International Journal of Educational Technology in Higher Education, 21*, 46. https://doi.org/10.1186/s41239-024-00478-x

Sun, F., Tian, P., Sun, D., Fan, Y., & Yang, Y. (2024). Pre-service teachers' inclination to integrate AI into STEM education: Analysis of influencing factors. *British Journal of Educational Technology, 55*(6), 2574–2596. https://doi.org/10.1111/bjet.13469

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 39. https://doi.org/10.1186/s41239-019-0171-0