Undergraduate Students' Attitudes Toward the Use of Generative AI as Peer Instruction in an Abstract Algebra Course

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Abstract

This study investigated undergraduate students' attitudes toward the integration of Generative Artificial Intelligence (Generative AI) as a Peer Instruction (PI) tool in an Abstract Algebra course at a university in Thailand. Guided by the TPACK framework and the Technology Acceptance Model (TAM), the study employed a quantitative survey design. The participants were two groups of students—teacher education and science students—totaling 69 individuals enrolled in the course during the first semester of the 2025 academic year. Over a three-week intervention, Generative AI served as a "peer-like learning assistant," providing conceptual explanations, worked examples, and step-by-step reasoning to support engagement with abstract mathematical concepts. Data were collected via a validated questionnaire measuring demographics and attitudes across four dimensions: cognitive, affective, behavioral, and perceptions of AI's peer-instruction role. The results showed that students held a high overall level of positive attitudes toward using Generative AI as a Peer Instructor ($M = 4.03$, $SD = 0.51$, on a 5-point scale). All four dimensions—role perception, cognitive understanding, behavioral engagement, and affective motivation—showed consistently high mean scores. The overall attitude level was significantly higher than the benchmark for a high level (3.55; $t(65) = 7.74$, $p < .001$). These findings suggest that Generative AI effectively supported conceptual understanding, enhanced motivation, and fostered peer-like interaction in line with Peer Instruction principles. The study highlights the potential of integrating Generative AI to strengthen active learning in mathematically demanding courses.

Keywords: generative AI, peer instruction, abstract algebra, student attitudes

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Introduction

In the contemporary era of the digital world, artificial intelligence (AI) technologies have rapidly evolved, becoming a primary driving force transforming the structure of 21st-century educational systems (Mhlanga, 2023). In particular, the emergence of Generative Artificial Intelligence (Generative AI or GenAI), built upon advanced large language models (LLMs), has introduced unprecedented capabilities in natural language processing, content generation, and sophisticated human-like interactions (Kasneci et al., 2023). With these distinctive features, Generative AI has transcended its traditional role as a simple information retrieval tool to become a highly potent innovation capable of elevating educational delivery to a personalized learning level (Kasneci et al., 2023; Mollick & Mollick, 2023). It serves as an intelligent companion that can immediately adapt conceptual content, provide step-by-step reasoning, and deliver instantaneous feedback tailored to individual learning paces, thereby reducing learning gaps and unlocking students' academic potential (Baidoo-Anu & Ansah, 2023; Kasneci et al., 2023).

For undergraduate students pursuing degrees in mathematics—whether enrolled in teacher education or pure science streams—mastering pure mathematics courses is essential for fostering high-level mathematical maturity and analytical thinking (Weber, 2001). Among these mathematically demanding courses, Abstract Algebra stands out as a notoriously formidable subject for many undergraduate students (Leron & Dubinsky, 1995; Weber, 2001). Unlike secondary-level algebra that heavily prioritizes numerical computations and standard algebraic equations, Abstract Algebra focuses on the conceptual properties, axiomatic structures, and internal relationships of mathematical systems, involving highly abstract objects such as groups, rings, and fields (Gallian, 2021). When students attempt to review these dense concepts independently, they often encounter immense cognitive barriers, finding the symbols and formal definitions detached from their prior experiences (Hazzan, 1999). This conceptual leap frequently leads to academic anxiety, misconceptions, and a decrease in learning motivation (Hazzan, 1999; Weber, 2001).

To address these cognitive difficulties, research in mathematics education has strongly advocated for active learning strategies, particularly Peer Instruction (PI) (Mazur, 1997). Developed by Eric Mazur, Peer Instruction is an active learning pedagogy designed to shift students from passive listeners into active conceptual thinkers through collaborative discussion (Mazur, 1997). The cognitive process of explaining mathematical arguments, debating logic, and identifying counterexamples with peers significantly sharpens and deepens conceptual understanding (Crouch & Mazur, 2001; Weber, 2001). However, traditional human-to-human peer interaction outside the classroom often faces constraints, including scheduling conflicts, unequal peer knowledge levels, and psychological barriers such as the fear of being judged or exposed for making mistakes (Khan, 2023).

In light of these challenges, utilizing Generative AI as a "peer-like learning assistant" represents a timely and vital educational innovation (Khan, 2023). Acting as a dedicated peer instructor, Generative AI offers unique advantages: it is endlessly patient, available 24/7, and generates a safe, pressure-free learning environment where students can freely test logical proofs, clarify basic definitions, and embrace errors without fear of academic or social judgment (Khan, 2023). This integration bridges the cognitive gap by supporting active learning and conceptual modeling in highly abstract courses.

Nevertheless, the successful adoption of any educational technology ultimately hinges upon the core psychological factor of user acceptance and student attitudes (Davis, 1989). Grounded in established technology integration frameworks—including the Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006), the Technology Acceptance Model (TAM) (Davis, 1989), the Theory of Planned Behavior (TPB) (Ajzen, 1991), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003)—a student's willingness to use a tool is driven by their perceived usefulness, cognitive engagement, affective response, and behavioral control. While extensive literature covers the general application of AI in language acquisition or coding, there is a prominent research gap concerning the use of GenAI as a peer instructor in mathematically rigorous and abstract domains (Weber, 2001).

Therefore, this study aimed to investigate undergraduate students' attitudes toward the integration of Generative AI as a Peer Instruction tool in an Abstract Algebra course at a university in Thailand. By examining student perspectives across four distinct dimensions—cognitive, affective, behavioral, and perceptions of AI's peer-instruction role—the findings of this research provide critical baseline insights for university instructors. This knowledge can guide the development of effective instructional strategies and pedagogical models that responsibly integrate artificial intelligence to foster deep mathematical reasoning in higher education.

Literature Review

Nature and Challenges of Abstract Algebra

Abstract Algebra is a foundational branch of higher mathematics that investigates algebraic structures—such as groups, rings, and fields—comprising a set equipped with one or more binary operations (Dummit & Foote, 2004; Gallian, 2021). Unlike secondary-level algebra which emphasizes procedural computations and numeric problem-solving, Abstract Algebra shifts the mathematical paradigm toward structural analysis, formal definitions, and rigorous proof construction based entirely on axiomatic systems (Gallian, 2021; Weber, 2001). This mathematical maturity is critical for advanced studies in topology, algebraic geometry, and number theory, as well as practical applications in cryptography and physics (Gallian, 2021; Weber, 2001).

Despite its importance, undergraduate students frequently find Abstract Algebra uniquely challenging (Leron & Dubinsky, 1995; Weber, 2001). Educational researchers note that students must undergo a drastic cognitive transition from operational thinking to object-oriented thinking, conceptualizing abstract properties as concrete entities (Sfard, 1991). Furthermore, students struggle with formal symbolic notation, which creates a barrier to connecting rigorous definitions with intuitive mental representations (Hazzan, 1999). As it is often the first course requiring intensive proof construction, students frequently lack the strategic knowledge needed to initiate proofs or apply theorems correctly, leading to reduced motivation and cognitive detachment (Hazzan, 1999; Weber, 2001). These difficulties highlight the urgent need for pedagogical interventions that can bridge abstract theory with active learning.

Generative AI and Peer Instruction Pedagogy

Peer Instruction (PI), originally developed by Eric Mazur (1997), is an active learning strategy that replaces passive lecturing with intellectual interaction among students to cultivate deep conceptual understanding. The core premise is that a student who has recently mastered a concept is uniquely equipped to explain it to a struggling peer in a language that is highly relatable (Mazur, 1997). The process of articulating reasoning, debating mathematical proofs, and defending arguments with peers actively sharpens conceptual clarity (Crouch & Mazur, 2001). In abstract domains, peer interactions regarding definition checks and counterexamples significantly enhance mathematical cognition (Weber, 2001).

With the rise of Generative Artificial Intelligence (Generative AI) powered by Large Language Models (LLMs), technology can now effectively step into the role of a peer-like assistant (Kasneci et al., 2023; Mhlanga, 2023). Generative AI can personalize learning by translating dense mathematical abstractions into simplified language or tailored examples (Kasneci et al., 2023). While AI can act as an intelligent tutor providing direct solutions (Mollick & Mollick, 2023), its application as a collaborative "peer instructor" or dialogue companion encourages students to actively critique information, check logic, and co-create mathematical scenarios (Khan, 2023). Crucially, AI establishes a safe psychological space where students can ask basic questions or evaluate unrefined proof arguments without the fear of social judgment, facilitating a continuous active learning experience outside classroom boundaries (Khan, 2023).

Theoretical Frameworks on Technology Acceptance

The successful integration of AI into mathematically demanding classrooms depends heavily on student attitudes and user acceptance (Davis, 1989). To evaluate this, researchers rely on established psychological models, starting with the classical three-component attitude model, which breaks user attitude down into cognitive (knowledge and utility beliefs), affective (emotional feelings and motivation), and behavioral (usage intentions and actual habits) dimensions (Ostrom, 1969).

To systematically map these dimensions onto technology usage, this study synthesizes three prominent frameworks. The Technology Acceptance Model (TAM) asserts that Attitude Toward Use (ATU) and Behavioral Intention (BI) are determined by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) (Davis, 1989). The Theory of Planned Behavior (TPB) expands this by introducing Perceived Behavioral Control (PBC), which measures a student's confidence in their capacity and resources to control their own learning through the technology (Ajzen, 1991). Finally, the Unified Theory of Acceptance and Use of Technology (UTAUT) integrates Performance Expectancy (PE) and Effort Expectancy (EE) as direct drivers of user intention, alongside facilitating environmental conditions (Venkatesh et al., 2003). By synthesizing TAM, TPB, and UTAUT, this study constructs a comprehensive framework to assess how undergraduate students perceive the cognitive utility, affective security, and behavioral control of adopting Generative AI as a peer instructor in Abstract Algebra courses.

Methodology

Research Design and Participants

This study adopted a quantitative survey research design to investigate undergraduate students' attitudes toward using Generative AI as a peer instructor in an Abstract Algebra course. The target population comprised undergraduate university students enrolled in Abstract Algebra courses in Thailand. The actual research sample consisted of 66 undergraduate students in their 3rd to 5th years who were registered across two separate class sections during the first semester of the 2025 academic year at Burapha University.

A stratified random sampling technique was employed to select the sample, ensuring proportional representation based on the students' institutional affiliation across two primary faculties: the Faculty of Science and the Faculty of Education. The inclusion criteria specified that all participants must be enrolled in the Abstract Algebra course during the semester of the study, possess a foundational background in higher-level mathematical analysis, and demonstrate the cognitive capacity to engage with abstract proof reasoning.

Research Instruments

The primary research instrument was a validated quantitative online questionnaire constructed explicitly around the synthesized TAM, TPB, and UTAUT frameworks. The questionnaire was divided into two main parts:

Part 1 gathered demographic information, including gender, academic year, faculty affiliation, and the student's self-reported level of prior familiarity with Generative AI applications (ranging across five descriptive levels from “Never Used” to “Regularly Used”).

Part 2 evaluated students' attitudes toward Generative AI in its specific capacity as a peer instructor, comprising a total of 30 items uniformly distributed across four theoretical dimensions:

Cognitive Domain (8 items): Measured students' beliefs regarding the cognitive utility of AI in clarifying abstract definitions, systemizing mathematical proofs, and summarizing complex lecture topics (e.g., Items A1–A8).

Affective Domain (7 items): Evaluated students' emotional responses, levels of enjoyment, academic confidence, and psychological comfort when asking questions to reduce classroom anxiety (e.g., Items B1–B7).

Behavioral Domain (8 items): Documented students' actual habits and future behavioral intentions, including using AI to cross-check answers against external sources, generate sample problems, and plan self-directed reviews (e.g., Items C1–C8).

Peer Instruction Role Perception (7 items): Gauged how students viewed the AI's specific role characteristics, such as extreme patience during repeated queries, providing immediate feedback, and acting as an unjudging spar partner (e.g., Items D1–D7).

Responses for Part 2 were captured using a 5-point Likert scale, with weights assigned as follows: 5 for *Strongly Agree*, 4 for *Agree*, 3 for *Moderate*, 2 for *Disagree*, and 1 for *Strongly Disagree*.

To ensure instrument validity, the questionnaire was thoroughly evaluated by a panel of independent experts specializing in educational research methodologies, computer education, and academic measurement. Content validity was verified using the Index of Congruence (IOC), yielding a high overall scale average of 0.96, with individual items falling below the acceptable threshold of 0.50 being discarded. Additionally, the Content Validity Index (CVI) for the overall manuscript instrument was computed at 0.97, confirming that the remaining 30 items possessed high professional and theoretical alignment. The resulting mean scores were interpreted across five intervals: 4.51–5.00 (*Highest*), 3.51–4.50 (*High*), 2.51–3.50 (*Moderate*), 1.51–2.50 (*Low*), and 1.00–1.50 (*Lowest*).

Data Collection and Analysis

The quantitative data collection was executed electronically using Google Forms to guarantee distribution speed, cost-efficiency, and error-free recording. The digital questionnaire link was distributed to the participants during their final class session of the first semester of the 2025 academic year, directly following a structured three-week classroom intervention where Generative AI tools (e.g., ChatGPT, Gemini, Claude) were actively utilized by the students as peer assistants to complete abstract homework exercises and prepare for final exams. The final deadline for form submissions was synchronized with the official final examination date of the course. Full transparency regarding research objectives and explicit participant consent were provided and obtained on the introductory page of the form before any data collection commenced.

The collected data were formally analyzed using Jamovi statistical software. Descriptive statistics, including frequency distributions, percentages, mean scores (*M*), and standard deviations (*SD*), were calculated to outline the demographic profile and evaluate the baseline attitude levels for each dimension. For inferential statistical analysis, a One-Sample t-Test was performed to evaluate whether the students' overall attitude score significantly exceeded the pre-established "High" level benchmark of 3.50. Furthermore, Independent Samples t-Tests were conducted at a statistical significance level of $\alpha = .05$ to examine whether students' overall attitudes varied significantly based on their gender or their specific faculty affiliation.

Results

Demographic Profile of the Participants

The demographic characteristics of the 66 undergraduate students who participated in this study were analyzed using descriptive statistics, including frequencies and percentages. The data obtained from Part 1 of the online questionnaire are presented in Table 1.

Table 1
Demographic Characteristics of the Participants (N = 66)

Demographic Variables	Frequency (n)	Percentage (%)
Gender		
Male	21	31.82
Female	45	68.18
Academic Year		
3rd Year	63	95.45
4th Year	1	1.52
5th Year	2	3.03
Faculty Affiliation		
Faculty of Science	37	56.06
Faculty of Education	29	43.94
Prior Generative AI Experience		
Regularly Used	28	42.42
Frequently Used	30	45.45
Occasionally Used	8	12.12

As illustrated in Table 1, the majority of the participants were female (68.18%), with male participants accounting for 31.82%. In terms of academic status, an overwhelming majority were 3rd-year students (95.45%), while 4th-year (1.52%) and 5th-year students (3.03%) constituted a smaller fraction of the sample. Regarding institutional affiliation, 56.06% of the students belonged to the Faculty of Science, and 43.94% were from the Faculty of Education. Interestingly, all participants had prior experience with Generative AI technologies; 45.45% reported using it frequently, 42.42% used it regularly, and 12.12% utilized it occasionally. None of the students selected the “rarely” or “never” options, indicating a high level of technical familiarity within the selected sample.

Attitude Levels Toward Generative AI as a Peer Instructor

The quantitative evaluation of student attitudes was partitioned into four baseline dimensions: Cognitive Domain (A), Affective Domain (B), Behavioral Domain (C), and Peer Instruction Role Perception (D). Mean scores (M) and standard deviations (SD) were calculated for each dimension to determine the general agreement level.

In the Cognitive Domain (Dimension A), the overall descriptive results revealed a high level of positive attitude (M = 4.05, SD = 0.57). The items that received the highest consensus were Item A3 (“GenAI helps me connect different concepts in the lesson effectively”) and Item A8 (“GenAI helps summarize the essence of complex topics to be easily understood”), both yielding an identical mean score of 4.21 (SD = 0.64 and 0.69, respectively). This was closely followed by Item A5 (“I can use GenAI to help generate examples or clarify abstract concepts easily") (M = 4.14, SD = 0.74). Conversely, the lowest-rated item in this domain was Item A7 ("I believe using GenAI enables me to perform deep analytical thinking regarding structures") (M = 3.85, SD = 0.86), though it remained well within the "High" agreement tier.

For the Affective Domain (Dimension B), students reported a consistently positive emotional response, with a composite score falling into the high range (M = 3.89, SD = 0.55). The top-rated item was Item B4 ("I feel comfortable asking basic or unrefined questions to GenAI that I might not dare to ask the professor in class") (M = 4.15, SD = 0.85), followed by Item B6 ("I feel that using GenAI helps reduce learning stress in difficult topics") (M = 4.08, SD = 0.83). Notably, Item B7 ("Using GenAI makes me feel that learning Abstract Algebra is not as difficult as I thought") received the lowest mean rating in the entire questionnaire (M = 3.50, SD = 0.81), indicating a moderate level of agreement due to the inherently challenging nature of the course content.

Regarding the Behavioral Domain (Dimension C), the data showed high actionable intent and usage habits among the undergraduate participants (M = 4.05, SD = 0.55). Item C3 ("Using GenAI as a companion to check answers helps me cross-verify my own mathematical concepts better") registered the highest mean score (M = 4.21, SD = 0.67), closely trailed by Item C6 ("I often use GenAI to inspect or compare answers with correct problem-solving guidelines") (M = 4.20, SD = 0.77). The lowest average score belonged to Item C7 ("I use GenAI to help plan my learning schedule and conduct self-directed reviews") (M = 3.86, SD = 0.78).

In the final dimension, Peer Instruction Role Perception (Dimension D), students displayed the highest overall positive attitude across all domains (M = 4.13, SD = 0.56). Item D1 ("GenAI acts like a highly patient friend, showing no boredom even when I ask the same question repeatedly") scored the highest average in the study (M = 4.42, SD = 0.72). This was supported by two equally rated secondary items: Item D2 ("I believe having GenAI as a peer instructor helps me learn difficult course content more easily") and Item D6 ("Communicating with GenAI makes me feel like I have a peer tutoring me without the fear of being judged") (M = 4.17; SD = 0.71 and 0.80, respectively). Item D4 ("Using GenAI as a conversation partner helps design learning that forces me to think critically and interact more than learning with human peers") scored the lowest within this domain (M = 3.97, SD = 0.91).

A summary of the baseline mean scores, standard deviations, and general descriptive interpretations across all four distinct sub-dimensions and the overall framework is provided in Table 2.

Table 2
Summary of Attitudinal Mean Scores and Interpretations Across Dimensions (N = 66)

Attitudinal Dimensions	Mean (M)	Standard Deviation (SD)	Descriptive Level
Dimension A: Cognitive Domain	4.05	0.57	High Level
Dimension B: Affective Domain	3.89	0.55	High Level
Dimension C: Behavioral Domain	4.05	0.55	High Level
Dimension D: Peer Instruction Role Perception	4.13	0.56	High Level
Overall Attitudinal Framework	**4.03**	**0.51**	**High Level**

Hypothesis Testing and Inferential Statistics

To empirically addresses the research questions, three statistical hypotheses were tested using inferential statistics.

Hypothesis 1: The first hypothesis stated that the undergraduate students' overall attitude score toward using Generative AI as a peer instructor would be statistically higher than the pre-established “High” descriptive tier threshold of 3.50 (H_0: $\mu \leq 3.50$; H_1: $\mu > 3.50$). A One-Sample *t*-Test was performed to evaluate this claim against the constant test value. The results are summarized in Table 3.

Table 3
One-Sample t-Test Results Comparing Overall Attitude Against the Benchmark Tier

Variable	Mean (M)	SD	t	df	p	Cohen's d
Overall Student Attitude	4.03	0.51	8.54	65	< .0001	1.05

The inferential data from Table 3 indicates that the participants' overall attitude mean (M = 4.03, SD = 0.51) significantly exceeded the 3.50 threshold, $t(65) = 8.54$, $p < .0001$. Therefore, the null hypothesis was rejected, confirming that students held a statistically high level of positive attitude. Furthermore, the calculated effect size was exceptionally high (Cohen's d = 1.05), demonstrating that the statistical difference is highly robust and practically meaningful in educational contexts.

Hypothesis 2 & 3: The second and third hypotheses anticipated that students' overall attitudes would remain statistically invariant regardless of their institutional faculty affiliation or their biological gender, respectively. Two independent samples *t*-tests were performed at an alpha level of .05 to evaluate these demographic differences. Prior to execution, the data distributions were confirmed to satisfy parametric assumptions, showcasing normal distribution properties via the Shapiro-Wilk test ($p > .05$) and homogeneous variances via Levene's test ($p > .05$). The comparative results are presented in Table 4.

Table 4
Independent Samples t-Test Results Comparing Overall Attitudes by Faculty and Gender

Independent Variables	Grouping Categories	n	Mean (M)	SD	t	df	p
Faculty Affiliation	Faculty of Science	37	4.10	0.54	1.24	64	.221
	Faculty of Education	29	3.94	0.45			
Gender Group	Male Participants	21	3.97	0.59	-0.64	64	.526
	Female Participants	45	4.06	0.46			

The inferential comparison in Table 4 shows that although students from the Faculty of Science reported a slightly higher mean score (M = 4.10, SD = 0.54) than those from the Faculty of Education (M = 3.94, SD = 0.45), this variance was not statistically significant, $t(64) = 1.24$, $p = .221$. Similarly, the comparison between male students (M = 3.97, SD = 0.59) and female students (M = 4.06, SD = 0.46) revealed no statistically significant difference, $t(64) = -0.64$, $p = .526$. Consequently, the null hypotheses for both demographic variables failed to be rejected, confirming that positive attitudes toward adopting Generative AI as a peer instructor are uniform across different faculties and genders within higher education.

Discussion

The quantitative findings of this study demonstrate an overwhelmingly positive attitude among undergraduate students toward the integration of Generative AI as a Peer Instruction tool in an Abstract Algebra course. The discussion focuses on synthesizing these statistical results with the theoretical foundations—specifically the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), the Unified Theory of Acceptance and Use of Technology (UTAUT), and Eric Mazur's Peer Instruction framework—while highlighting how this technical implementation successfully addresses the historical cognitive challenges inherent to pure mathematics education.

The empirical analysis revealed that students' overall positive attitude (M = 4.03, SD = 0.51) was statistically higher than the designated high-level benchmark of 3.50, backed by a powerful effect size (Cohen's d = 1.05). This robust acceptance can be explained primarily through the lens of the Peer Instruction Role Perception dimension (Dimension D), which achieved the highest composite mean score (M = 4.13, SD = 0.56) across the entire framework. Within this domain, Item D1 ("GenAI acts like a highly patient friend, showing no boredom even when I ask the same question repeatedly") scored the absolute highest average (M = 4.42, SD = 0.72). In traditional mathematics education, a primary barrier to successful Peer Instruction outside the classroom is the presence of social anxiety and the fear of negative evaluation by peers or professors when trying to articulate unrefined logical arguments (Hazzan, 1999; Khan, 2023). By assuming the role of an infinitely patient, completely unjudging dialogue partner, Generative AI eliminates these social risks. This finding directly supports Khan's (2023) assertion that AI provides a safe psychological harbor for academic experimentation. Students can repeatedly test flawed proof structures, clarify fundamental definitions, and embrace cognitive trial-and-error without experiencing social or academic embarrassment.

Furthermore, this psychological safety net directly explains the high ratings observed within the Affective Domain (Dimension B, $M = 3.89$, $SD = 0.55$), particularly Item B4 ("I feel comfortable asking basic or unrefined questions to GenAI that I might not dare to ask the professor in class") which scored $M = 4.15$ ($SD = 0.85$). According to the Technology Acceptance Model (TAM) and UTAUT frameworks, technology adoption is heavily moderated by performance expectancy and emotional comfort (Davis, 1989; Venkatesh et al., 2003). When students perceive that an AI assistant alleviates learning anxiety and creates a supportive environment, their intrinsic motivation increases. This is a critical pedagogical outcome because abstract mathematical courses like Abstract Algebra often cause cognitive overload and severe math anxiety due to their dense axiomatic nature (Leron & Dubinsky, 1995; Weber, 2001). Although Item B7 ("Using GenAI makes me feel that learning Abstract Algebra is not as difficult as I thought") received a lower, moderate rating ($M = 3.50$, $SD = 0.81$), this nuance confirms that while AI serves as an excellent supportive mechanism, it does not artificially diminish or dilute the objective rigor of pure mathematics content. Rather, it enhances the student's affective capacity to handle the difficulty.

In the Cognitive Domain (Dimension A, $M = 4.05$, $SD = 0.57$) and Behavioral Domain (Dimension C, $M = 4.05$, $SD = 0.55$), the high consensus on Item A3 and Item C3 regarding concept connection and cross-verifying mathematical proofs ($M = 4.21$) provides deep pedagogical insights. Under Mazur's (1997) Peer Instruction framework, deep learning occurs when a student actively externalizes their internal logic and defends their reasoning. The high behavioral scores indicate that undergraduate students did not treat Generative AI as a passive shortcut or an automated answer generator. Instead, they utilized it interactively as a collaborative tool to compare guidelines, review step-by-step logic, and check their own mathematical derivations against structured AI outputs. This active engagement corresponds with the Technological Pedagogical Content Knowledge (TPACK) model, demonstrating that when technology is correctly aligned with a specific pedagogy (Peer Instruction) and a specific content domain (Abstract Algebra), it successfully shifts students from operational copiers into reflective, meta-cognitive thinkers (Mishra & Koehler, 2006; Sfard, 1991).

Lastly, the inferential analysis utilizing Independent Samples *t*-Tests yielded no statistically significant differences in student attitudes based on biological gender ($p = .526$) or institutional faculty affiliation ($p = .221$). This statistical invariance is highly encouraging for educational policy. It indicates that the cognitive utility and affective benefits of employing Generative AI as a peer instructor are universal and accessible, benefiting pure science majors and teacher education majors equally. This uniform acceptance aligns with modern UTAUT research indicating that as technology becomes more intuitive, adaptive, and ubiquitous, historical demographic gaps in technology acceptance tend to close (Venkatesh et al., 2003). Ultimately, the study confirms that integrating Generative AI as a peer-like assistant is a highly effective, equitable strategy to promote active learning and deepen conceptual understanding in higher education mathematics.

Conclusion

This study confirms that the pedagogical integration of Generative AI as a "peer instructor" or dialogue companion fosters an exceptionally high level of positive attitudes among undergraduate mathematics and education students ($M = 4.03$, $SD = 0.51$). Grounded in synthesized frameworks of technology acceptance (TAM, TPB, UTAUT) and interactive learning (Peer Instruction), the empirical results reveal that the tool's primary value lies in establishing a completely safe, non-judgmental, and highly responsive psychological environment. This unique asset allows students to navigate the historically formidable and abstract proof-based structures of Abstract Algebra with enhanced cognitive confidence and reduced learning anxiety. The high agreement regarding the behavioral and cognitive utility of the tool underscores that students did not perceive AI as a simple shortcut for answers, but rather as an intellectual partner to cross-verify arguments, clarify dense definitions, and stimulate self-directed learning. Furthermore, the statistical invariance across biological genders and institutional faculty affiliations highlights that this tech-pedagogical intervention functions as an equitable and universally accessible learning aid in higher education.

Despite these promising insights, certain limitations must be acknowledged. First, this study relied entirely on a self-reported quantitative survey design, which captures student perceptions and attitudes but does not directly measure objective learning outcomes or long-term academic performance retention. Second, the sample was bounded within a specific regional university in Thailand over a structured three-week classroom intervention, which may limit the direct generalizability of the findings to different cultural settings or less technically familiar cohorts.

Based on these outcomes, several recommendations are proposed for future practice and research. For educational practitioners, university instructors should design explicit instructional prompts and structured training modules that teach students how to actively critically question and engage with AI as a collaborative companion, rather than using it for passive data extraction. For future academic inquiries, researchers are strongly encouraged to employ mixed-methods approaches, integrating qualitative thematic analysis from student interviews alongside longitudinal experimental or quasi-experimental designs. Such studies could directly evaluate the empirical impact of Generative AI peer tutoring on students' actual proof-construction abilities, conceptual mastery scores, and mathematical maturity over an extended academic period.

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Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work, the authors used Gemini in order to improve the English language expression and verify the grammatical accuracy of the manuscript. The usage was limited to correcting grammatical and spelling errors and rephrasing statements for accuracy and clarity. The authors further declare that, apart from Gemini, no other AI or AI-assisted technologies have been used to generate content in writing the manuscript. The ideas, design, procedures, findings, analyses, and discussion are originally written and derived from careful and systematic conduct of the research.

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