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AI-designed active learning and STEM students' perceived success in higher education mathematics and statistics courses

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Abstract

This study examines the relationships between artificial intelligence (AI)-designed active learning and science, technology, engineering, and mathematics (STEM) students' perceived course success in higher education mathematics and statistics courses. A correlational research design was utilized which included 330 undergraduate students undertaking mathematics and statistics courses. A 47-item questionnaire was developed to collect data, which were analyzed using exploratory and confirmatory factor analysis, correlation analysis, and multiple regression analysis. The findings indicate that AI-designed active learning dimensions are strongly and positively correlated with students' perceived success (PS) in mathematics and statistics courses. The predictive variables including attitudes toward courses, interest, enjoyment, and cooperative learning were significantly associated with PS and together accounted for 74.3% of the variance in students' PS that can be predicted by the regression model. The results are interpreted at the correlational level and propose that AI-designed active learning may facilitate promising learning experiences and perceived course success in higher education STEM learning environments.

Keywords: mathematics and statistics courses, AI-designed active learning, STEM education, higher education, correlational research design

INTRODUCTION

Mathematics and statistics play a vital role in higher education in science, technology, engineering, and mathematics (STEM) programs. For example, Agah and Sule (2015) state that solving multi-step mathematical problems requires logical thinking and mathematical reasoning, which directly supports the critical thinking skills needed to handle more complex situations in life. Moreover, mathematics and statistics serve as a core scientific discipline with intrinsic value and functions as a powerful tool for advancing knowledge across numerous STEM professions in the future (Hammoudi, 2020). The importance of mathematics and statistics goes beyond the scope of academics as it helps to mold workforce readiness and innovation in the increasingly data-driven global economies. The improvement of mathematical and statistical skills among university students is very vital for the countries in the Gulf Cooperation Council (GCC) and North Africa in order to sustain the programs of change through which they are going to become knowledge-based, technology-oriented economies (Kayan-Fadlelmula et al., 2022). This research study examines the associations between students' perceptions of AI-designed active learning and their perceived course success in mathematics and statistics courses within contexts of higher education learning.

Several undergraduate students experience mathematics and statistics courses as demanding and cognitively intense, which may decrease motivation, engagement, and confidence. Different education systems report the same problem of high dropout rates and low retention in math-intensive programs. Foundational mathematics courses are the main factors that determine students' persistence in STEM majors and general academic success (Gottfried, 2015; Kopparlo, 2024; Tyson, 2011). Latest data imply that as much as 40% to 60% of STEM students worldwide have an extremely hard time to finish required mathematics courses in a satisfactory manner which is the main reason for the decline in graduation rates in these fields

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Contribution to the literature

- This study examines the integration of AI-designed active learning in higher education courses of mathematics and statistics amongst STEM students in a regional context that is currently underrepresented in existing literature.
- Using a quantitative correlational research design, it investigates specific dimensions of students' learning experiences, including clarity and organization, importance and necessity, interest, enjoyment, course attitudes, and cooperative learning.
- The research offers empirical evidence identifying which particular dimensions are most strongly associated with students' perceived course success, providing actionable guidance for instructors aiming to build engaging mathematics and statistics environments.

when compared to non-STEM ones (Wagner, 2024). Additionally, structural analyses of STEM education in the GCC reveal that students' low confidence in mathematics, instructors' reliance on traditional teaching methods, and the minimal use of active learning methods have resulted in students being less engaged and their performance dropping (Kayan-Fadlelmula et al., 2022).

AI has been a major driver of change to these long-standing issues in mathematics education. AI-based technologies such as intelligent tutoring, adaptive testing, and predictive analytics enable teachers with the capacity to personalize learning experiences, detect student misconceptions instantly, and enhance general academic outcomes (Awang, 2025; Leon et al., 2025). For example, Kestin et al. (2025) found that students who were taught using artificial intelligence (AI) assistance were able to perform better than those in traditional active learning settings with a learning gain of up to 1.3 standard deviations. Similarly, Wang et al. (2024) found that AI-assisted human tutoring by means of a platform like Tutor CoPilot enhanced the quality of feedback and the depth of learning in a number of quantitative subjects to a great extent. These discoveries point to the educational potential of using AI in mathematics instruction while at the same time, putting forward the issues of ethics, access, and faculty preparedness in the developing world.

Alongside AI a creative and effective change in the teaching methods especially through active learning in mathematics and statistics has been observed. Active learning focuses more on problem-solving, discussion, and collaboration rather than students passively receiving information. Saadeghvaziri et al. (2025) found that students' learning models, particularly ones that are mastery-based and inquiry-driven, profoundly affect the motivation, self-concept, and achievement in STEM areas of students. These educational strategies, if used with AI, can produce a great harmony effect which means they can instantly adjust to the requirements of students and at the same time stimulate their cognitive functions (Létourneau et al., 2025; Nguyen & Pham, 2025). However, the local situation is quite different as the implementation of AI-designed active learning in mathematics education in universities in the GCC and North Africa still seems to be a very limited area of research.

Hence, this study focuses on the relationship between the dimensions of AI-designed active learning and the perceived success (PS) of STEM students in courses of mathematics and statistics in academic institutions of higher education. The research, by bridging this gap, becomes a part of the expanding scholarly works that lie in the confluence of AI, teaching, and students' performance in mathematics and statistics. Therefore, this study aims to answer the following research questions: Which dimensions of AI-designed active learning are most strongly associated with STEM students' PS in courses of mathematics and statistics? The study becomes a source of insightful information for the local educational community on the adoption of digital technologies as a mean of enhancing active learning strategies for better performance and retention of students.

The rest of the paper follows this outline: we first provide the value-added and contribution of the study. We then present the literature on instruction and learning of mathematics and statistics, student retention, integration of AI, and active learning practices. After that we provide the theoretical framework for the study. Next, we provide the research design, factor analysis, correlation analysis, regression analysis, and mathematical modeling. Finally, we provide discussion and give the conclusions, recommendations, and implications for GCC and North African higher education policymakers and educators.

SIGNIFICANCE OF RESEARCH

The significance of this research stems from three main reasons. Firstly, AI-designed active learning in higher education STEM courses is examined in this study within a regional context which is considered underrepresented in the relevant literature. Secondly, the study goes above the general claims about AI by examining specific dimensions of students' learning experiences, including importance and necessity (IN), clarity and organization (CO), interest, enjoyment, attitudes toward the course, and cooperative learning

(CL). Thirdly, the research offers practical guidance to instructors willing to create more engaging mathematics and statistics environments by providing evidence which dimensions are more strongly associated with students' perceived course success.

LITERATURE REVIEW

AI creates interactive personalized learning environments for students in mathematics and statistics and enhances problem solving skills via instant feedback (Hwang & Tu, 2021; Maulida et al., 2024; Zhai & Krajcik, 2024). Various studies addressed how to successfully implement and organize active learning STEM activities using effective strategies. According to Maričić et al. (2025), using direct and indirect instruction and implementing self-explanation effect are effective ways to organize STEM activities. Lugosi and Uribe (2022) found several other strategies that raise students' achievements in mathematics including interactive presentation styles and group work that involves discussion and feedback. Moreover, Ting et al. (2019) emphasized that active learning via problem-based collaborative games increases students' conceptual understanding, and therefore their exam performance in a first-year calculus course in Hong Kong. Furthermore, Chen et al. (2018) presented the success of 537 students in online STEM courses offered in US through active learning activities by relating the course materials to real life situations. These approaches can be adapted within AI active learning activities because AI tools can facilitate and refine those strategies. Apkarian et al. (2021); however, indicate that the efficiency of numerous active learning strategies differs depending on several factors that determine their compatibility with the classroom environment.

In a study conducted in Indonesia, Amelia and Harahap (2021) found that interactive multimedia learning process increases students' interest in learning mathematics owing to students' low interest in mathematics courses during COVID-19 pandemic. Likewise, it is reported by Ribeirinha et al. (2024) that STEM activities nourished 191 Portuguese students' interest and enthusiasm in STEM fields which contributes to individual growth and confidence. According to Hammoudi (2019), the use of active learning activities promotes students' interest and ultimately their success in courses of mathematics. Nzaramyimana et al. (2021) revealed that interactive dynamic software such as GeoGebra is a key factor in increasing students' interest in learning mathematics in a study held in Rwanda. Grira et al. (2025) found that students' enjoyment of mathematics is a significant predictor of academic success. In a study that was held on 144 German students by Schukajlow and Rakoczy (2016), it was found that students' enjoyment has a positive correlation with students' interest and performance in mathematics. It is emphasized by Hammoudi et al. (2025) that the appropriate implementation of active learning activities enhances students' enjoyment and achievement in statistics and data science courses.

Although CL and collaborative learning have distinct features, they share a lot in common; therefore, both approaches can be used interchangeably. CL is found to be beneficial in improving mathematical problem-solving skills in classrooms with different ability levels, yet social dynamics, such as social acceptance and friendships, play a significant role in students' success (Klang et al., 2021). Furthermore, Turgut and Gülşen Turgut (2018) infer that CL has a positive effect on mathematics achievement in Turkey. Despite the great advantage of CL, Retnowati et al. (2018) conclude that when learning mathematics, students' similar knowledge bases make collaboration redundant; however, their study also found that CL during mathematical problem solving was superior to individual learning when group members had gaps in their knowledge bases. AI can play a role in forming adaptive groups that promote effective CL since it is capable of personalizing learning for individual students (Zawacki-Richter et al., 2019). To implement this, methods like jigsaw (Tran, 2012), interactive gamification (Duran et al., 2024; Zhao et al., 2021), or AI learning platforms (Thongprasit & Wannapiroon, 2022) can be utilized. With this in mind, students' learning behaviors and group dynamics analysis will be used to improve the AI's performance.

Since enjoyment and attitude have been shown to significantly predict students' performance in mathematics, it becomes essential to explore tools that can enhance these aspects (Mazana et al., 2019). A study involving first year STEM students at the University of Manchester shows that immediate online feedback significantly improves students' attitudes towards mathematical assessments by increasing their enjoyment and engagement (Acosta-Gonzaga & Walet, 2018). The results of a study conducted by Castillo et al. (2024) indicate that an innovative active learning calculus approach has a positive impact on attitudes compared to traditional instruction. It is found by Hammoudi and Grira (2023b) that solving challenging mathematical problems optimized students' enjoyment and motivation for success in courses of mathematics. The use of AI active learning can be utilized to create such challenging mathematical problems. In addition, Soesanto et al. (2022) examined Indonesian students' expectations of AI based learning and found that students consider AI as a helpful tool for solving and visualizing mathematical problems related to calculus and statistics. In order to keep them motivated, they emphasized the need for step-by-step feedback on their mistakes.

Based on the revised literature review, it is found that engagement and participation in mathematically

demanding courses can be improved through active learning, while AI-supported environments may promote personalization, feedback, and access to adaptive practice. However, there is less clarity within the literature about which dimensions of AI-designed active learning are most closely associated with students' PS in the context of higher education mathematics and statistics courses. This gap is addressed in the current research study by analyzing six dimensions of AI-designed active learning and their association with the perceived course success among STEM students.

THEORETICAL FRAMEWORK

The research is based on the impact of AI-designed active learning on STEM students' success in mathematics, which focuses on discussing the application of AI-based technologies in the teaching process. The core area of concern is the implications of AI on mathematics performance, affective orientations, and motivation of students. The analysis of enthusiasm, cognitive processes, and social interaction confirms that the intersection between technology and STEM education inherently activates interest in students, maintains the interest, and boosts performance. The research relies on self-determination theory and control-value theory since both frameworks give a focused basis for interpreting how AI-designed active learning may be related to students' perceived courses success in mathematics and statistics courses. The relevance of self-determination theory happens through the use of AI-designed active learning to promote students' competence, autonomy, and engagement through structured feedback, collaborative participation, and adaptive practice (Shank et al., 2025). The appropriateness of control-value theory is justified since students' interest, enjoyment, and attitudes toward the course are closely related to their perceptions of control and task value in achievement settings (Liu et al., 2024). The other theoretical perspectives are presented in this study as supporting rather than primary explanatory lenses and they are discussed in the broader literature.

Students' Interest in Learning

Interest or curiosity is described as liking an object that drives one to put forth more effort and develop emotional attachment to the learning process. According to Hidi and Renninger (2006), interest is a psychological state, which involves a combination of both concentration and pleasant affect, such that meaningful learning situations can lead to the development of long-term individual interest. Krapp (2002) also argues that interest consists of affective and cognitive components and postulates that both contribute to motivation and a long-term commitment to learning.

The situated learning theory (Lave & Wenger, 1991) also provides a process with the help of which learners are able to perceive the applicability of STEM activities into real-world situations. When AI can show the practical relevance of mathematics in the local industries, students can see the direct benefits, thereby contributing to their interest. The self-determination theory (Deci & Ryan, 2013) believes that learners who independently solve difficulties with the help of AI have a higher degree of confidence and intrinsic motivation.

Students' Enjoyment of Learning

Students should be capable and interested in the subjects they are learning; this makes learning to be enjoyable. The attitude toward mathematics when positive, enables students to remain persistent even when they have challenges. The learning enjoyment is conceptualized in several studies as a positive and stimulating emotion, which increases intrinsic motivation and immerses cognition (Hammoudi & Grira, 2023a; Hammoudi et al., 2023; Pekrun et al., 2002). As it turned out, enjoyment in school was highly associated with perceived competence and favorable teacher-student interaction, which could be improved with the help of technology and AI-mediated feedback (Deif et al., 2026; Frenzel et al., 2009).

The control-value theory (Pekrun, 2006) asserts that the school activities give enjoyment to students when they have a belief that they can master the material. Short-term AI-responses to exercises strengthen the confidence of learners in performing complex mathematical problems. The self-efficacy theory (Bandura, 1997) underlines that intelligent tutoring systems should not merely make learners successful in doing things and learners should also receive skills and experiences that make them enjoy long-term learning.

Students' Attitudes Toward Learning

Attitudes of students toward classroom is how students react positively or negatively to the subjects being studied as a result of their cognitions, affect, and actions. According to Ajzen (1991), attitudes result in the acquired predisposition to act consistently in the direction of a reaction to an object or thing. According to Osborne et al. (2003), the attitude towards science and mathematics is absolutely decisive in determining whether a person is engaged and can succeed in various fields as the result of the classroom experiences and relevance.

Active Learning

Active learning is a pedagogical approach in which learners are involved in more demanding thinking including problem solving, creative thinking, and reflective thinking as opposed to passive receipt of information.

According to Bonwell and Eison (1991), active learning is considered an instructional approach that engages students mentally and makes them question their engagements. Prince (2004) claims that active learning helps to gain a profound understanding of concepts, as well as interest in STEM subjects. One of the underlying constructions, situated learning (Lave & Wenger, 1991), underlines the importance of knowledge construction through self-action. The cognitive load theory by Sweller (1988) is applicable in this case as well, where active teaching facilitated by intelligent tutoring systems will reduce extraneous cognitive load, and the learners can focus on complicated issues without being distracted.

AI in Learning

Educational uses of AI have been in the form of intelligent tutoring systems that replicate the thinking capabilities of human tutors to provide more personalized instruction, produce bespoke feedback or assess the degree of engagement. According to Luckin et al. (2016), AI in the educational context is the system based on the continuous modeling, representation, and adaptation of the knowledge and behavior of learners in real time to provide optimal learning opportunities. Holmes et al. (2019) also indicate that AI-powered tools facilitate customization, feedback in a timely manner, and lasting interaction in adaptable learning scenarios. The self-regulated learning (Zimmerman, 2000) is significantly improved by AI as it offers guidance that helps STEM students monitor their problem-solving processes. This technology scaffold also promotes the self-learning process in learners and eventually enhances it.

Cooperative Learning

The occurrence of CL happens when students work together in teams to achieve common goals, but each student is still responsible for his or her part. The social interdependence theory (Deutsch, 1949) is related to CL and it proposes that teamwork setups promote common goals. Students can be arranged into groups through the use of certain AI tools. This matches with situated learning (Lave & Wenger, 1991) in which real-life practice teams are the essence of the learning process.

Students' Success

There are several definitions of students' success. Most definitions agree that students' success occurs when students achieve the learning outcomes, stay motivated and convert challenges into opportunities, and develop their skills to manage their own study habit. Several theories are related to students' success such as the self-efficacy (Bandura, 1997) which proposes that students end up doing better in mathematics if they believe they can do mathematics. In addition to that, it takes time and effort to master mathematical issues which fit the pace of each learner. The current study investigates how students can be engaged in mathematics through the integration of AI technologies in the learning process.

Comparative Analysis of Theoretical Perspectives

The theoretical framework of this study is summarized in **Table 1**. The key idea of each theory, the integration of AI-designed active learning within each theory, and the relation of each theory to the core of this research are summarized in **Table 1**.

Table 1. Summary of theories related to AI-designed active learning in STEM

Theory	Key idea	AI-active learning integration	Study relation (STEM/GCC situation)
Situated learning (Lave & Wenger, 1991)	Knowledge is built in the real-life situations.	The simulated AI and virtual laboratories provide students with a real-life experience of solving problems in STEM.	Relates mathematics learning to real-life GCC industrial and engineering applications.
Cognitive load theory (Sweller, 1988)	The optimum of learning occurs when the cognitive resources are used in an effective manner.	Scaffolding and sequence of material by AI tutors minimizes extraneous load.	Helps students to perform multifaceted calculations and abstract thinking.
Self-regulated learning (Zimmerman, 2000)	Students have control over their thoughts, motivation, and actions.	Self-tracking and reflection AI dashboards provide real-time self-reflections and analytics.	Promotes independence and responsibility in STEM learning among students in universities.
Self-determination theory (Deci & Ryan, 2013)	It offers quicker customized tasks to the user, which encourages decision-making and meaningful interaction by AI systems.	Enhances self-drive and determination in challenging STEM disciplines.	Boosts intrinsic drive in rigorous STEM fields.
Self-efficacy theory (Bandura, 1997)	Performance and persistence are dependent on belief in the ability to do it.	The mastery feedback offered by AI tools is incremental and increases confidence.	Anticipates retention and improvement of performance in learners in GCC and North Africa.

Table 1 (Continued).

Theory	Key idea	AI-active learning integration	Study relation (STEM/GCC situation)
Control-value theory (Pekrun, 2006)	The achievement emotions are based on the perceived control and value of the task.	AI-based feedback enhances competence and pleasure in the learners.	Helps to become emotional and resilient to mathematics problems.
CL (Deutsch, 1949; Johnson & Johnson, 2009)	Students learn in an organized group partaking and interdependence.	Artificial intelligence systems maximize the formation of groups and track equal participation.	Promotes group work and instructional leadership in the GCC and the North African classrooms.
AI-in-learning framework (Luckin et al., 2016)	AI learners are instructed using adaptive feedback and smart systems.	Machine learning software customize mathematics problems and can change the pace dynamically.	Assures culture specific STEM participation in GCC/North African institutions.

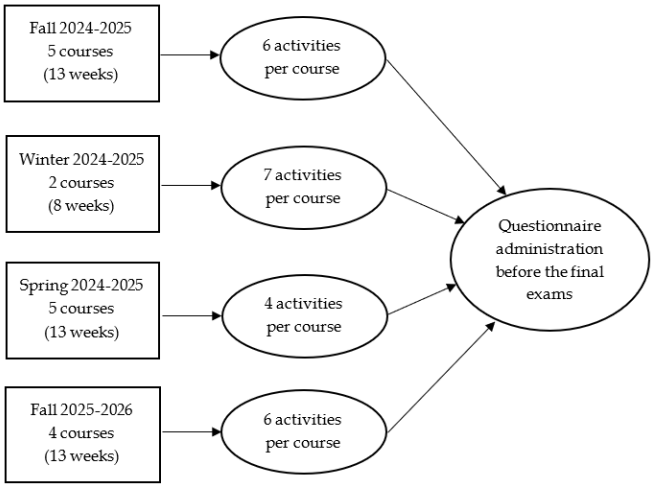


Figure 1. Graph-based visualization of the research design (the authors' own elaboration)

RESEARCH METHODOLOGY

Research Design

This study employed a correlational survey design to examine the relationship between AI-generated active learning interventions and STEM students' perceived course success in higher education mathematics and statistics courses. Since the research study did not include control and experimental group comparisons, random assignment, or pre-/post-test measurement, the correlational survey design is considered to be appropriate. The data were collected through a structured questionnaire administered after exposing students to AI-designed active learning activities in their courses, the data were analyzed to identify the direction and strength of associations between the variables. The data were collected over four academic semesters, and the respective courses included 16 courses of mathematics and statistics which were offered by Abu Dhabi University in United Arab Emirates (UAE). The active learning activities that were created by AI were integrated on a case-by-case basis.

The implementation is shown in **Figure 1** in the following semesters: Fall 2024-2025, Winter 2024-2025, Spring 2024-2025, and Fall 2025-2026. At the end of each semester, which was before the final examinations, a structured questionnaire was administered to elicit the quantitative information on the learning experience of students and the AI-designed active learning activities. The software of SPSS 26.0 was used to conduct the quantitative analyses.

Participants

The sample of the study included 330 undergraduate STEM students enrolled at Abu Dhabi University in UAE (**Table 2**). The data were gathered over four academic semesters from students enrolling in 16 courses of mathematics and statistics. These courses included foundational and quantitatively intensive learning contexts in STEM education. Five hundred and forty-six students enrolled in the 16 courses, with 330 respondents filling their questionnaires, thus producing an overall response rate of 60%. The non-participant comprised those students who exited courses or did not respond to the survey questionnaire. The sample includes both male and female students, and the majority of participated were in the early years of their undergraduate degrees.

Table 2. Summary of participating students

Semester	Number of courses	Total number of students	Number of participated students	Response rate
Fall 2024-2025	5	191	169	88%
Winter 2024-2025	2	54	31	57%
Spring 2024-25	5	154	31	20%
Fall 2025-26	4	147	99	67%
Total	16	546	330	60%

Instructional Context

All courses of mathematics and statistics adopted a lecture-based instructional mode accompanied by AI-designed active-learning activities. The conventional assessment tools which are homework assignments, exam 1, exam 2, and final exam were also left unaltered in order to maintain consistency of instruction.

AI-Designed Active Learning Activities

In lectures, the instructors presented the objectives of learning and then continued with the organized activities that lasted 20 to 30 minutes with at least five questions for each activity. The students worked in teams of three or four students selected per team. In some activities, students were given the opportunity to form their own teams by themselves. In other activities, the teams were formed by the course instructor. The implementation of these activities happened within standard classroom teaching rather than under experimentally controlled conditions.

The instructional framework integrated course-based active learning activities with AI-enhanced tools, specifically Pearson's AI-driven learning system to facilitate structured practice, deliver formative feedback, and promote interactive participation. In this way, the research investigated students' perceptions of AI-designed active learning as experienced in real mathematics and statistics classroom environments.

The teams appointed an individual that submitted their answers through the class digital channel. The questions were given out in order and feedback given on the same questions and the assessment evaluated instantly which followed up with the next question and ensured constant formative assessment (Black & Wiliam, 2009).

Gamified scoring system was included in the activities where points were earned on accuracy and speed of submission. Each session had final scores which were computed at the end of the session and the winning teams were declared and captured.

Table 3 depicts the workflow of the activities with records on team formation, sample of multiple-choice and essay questions, submission of answers, feedback of the instructor, and final results. These processes contributed to teamwork, quick feedback and lifelong interaction during the learning process.

Table 3 were obtained from a course of intermediate statistics and research methods which was selected as a sample from the broader set of 16 courses of mathematics and statistics.

Table 3. Workflow of the activities

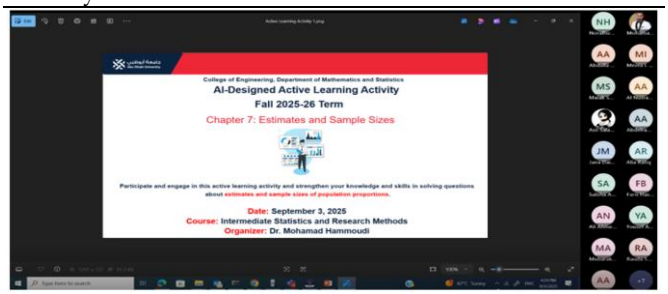
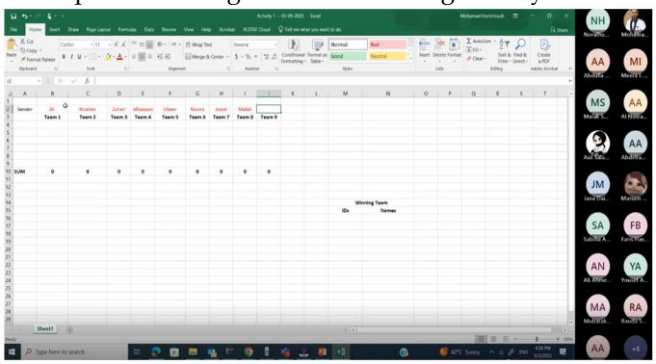
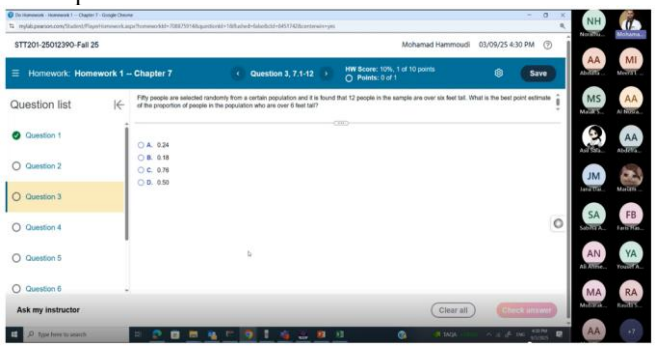
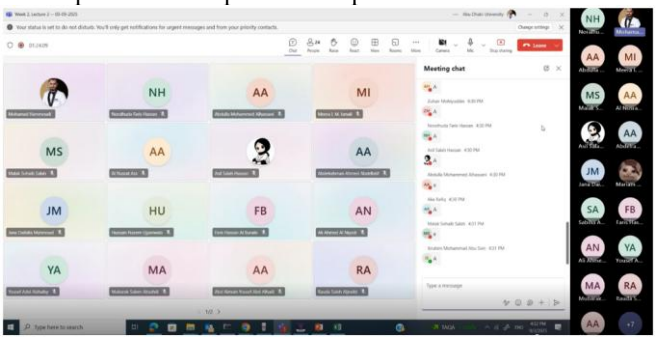
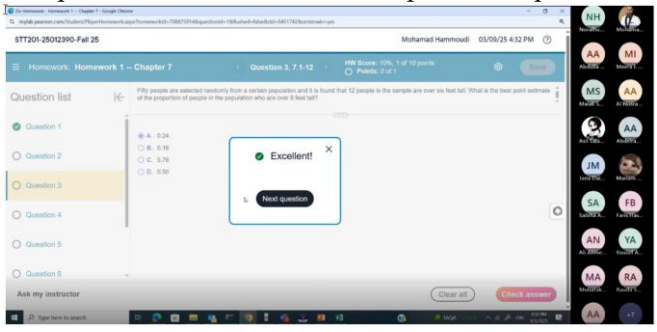
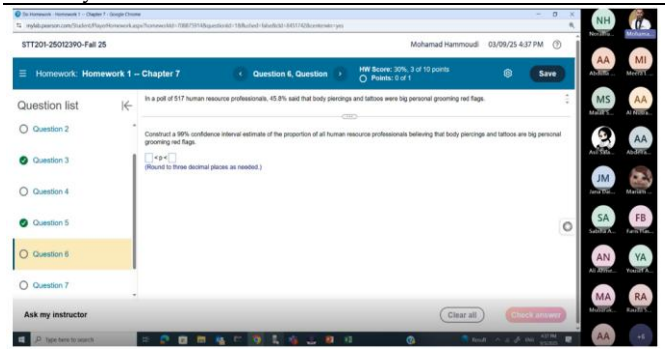
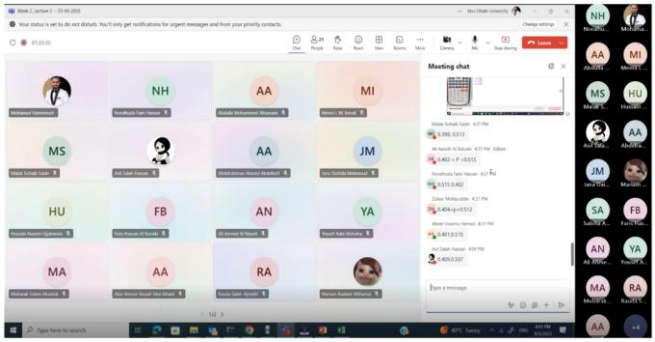
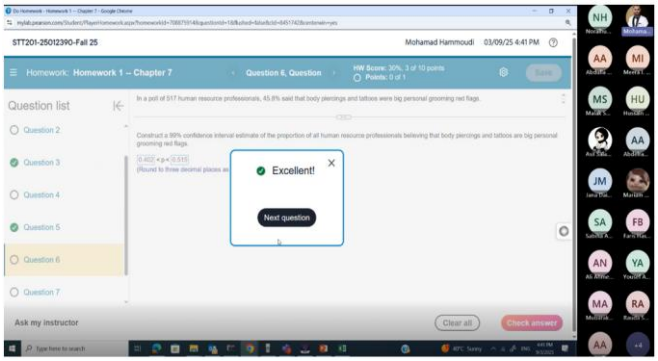
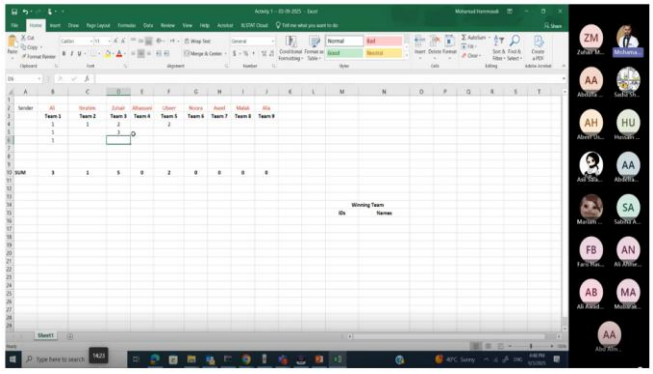
Activity
 1. Sample of AI-designed active learning activity
 2. Sample of the formation of teams on Microsoft Excel
 3. Sample of a multiple-choice question
 4. Representatives' answers to multiple-choice question
 5. Correct answer to the multiple-choice question

Table 3 (Continued).

Activity

6. Sample of an essay question

7. Representatives' answers to the essay question

8. Correct answer to the essay question

9. Final results of the AI-designed active learning activity

Pearson AI Learning System

The AI-powered study tools of Pearson aided the intervention (such as MyLab) and offered personalized practice, real-time feedback, and adaptivity in the learning processes. These systems have the purpose of improving the learning process by means of constant evaluation, dedicated support, and automatic scoring (Pearson, 2026). To solve this issue, the AI tools of Pearson served as an extension of in-class tasks in this research, enabling students to learn concepts further, get individual feedback, and work on it in accordance with the course goals. Analytics and auto-grading were also useful to instructors who could use them to make data-driven instructional decisions. It was also the combination of these tools which formed a unified AI-enriched learning environment that was not limited to classroom activities.

Instrumentation

The study employed a 47-item instrument constructed by adapting and synthesizing components from validated measures associated with mathematics education, achievement-related emotions, motivational orientations, attitudinal dispositions, and collaborative learning practice. The instrument's items were created from achievement emotions questionnaire-mathematics (AEQ-M), mathematics motivated strategies for learning questionnaire (MMSLQ), intrinsic motivation inventory (IMI), attitudes to technology in mathematics learning questionnaire (ATMLQ), attitude toward mathematics inventory (ATMI), and limited number of researcher-created items. The measurement tool was structured to assess six distinct dimensions of students' perceptions regarding AI-designed active learning: CO, IN, enjoyment, interest in the course, attitudes toward the course, and CL. All items were rated on a 5-point Likert scale of strongly disagree (1) to strongly agree (5). The dependent variable is conceptualized as perceived course success of STEM students. The complete 47-item survey questionnaire is included in **Appendix A**.

The AEQ-M is based on the control-value theory and it was developed to measure achievement emotions among students during learning mathematics. It identifies emotional structures including pleasure, anxiety, along with the boredom during classroom activities and homework. Psychometric properties of the AEQ and its mathematics version have been shown to be high in several research studies, and Cronbach's alpha coefficients are generally reported to be between 0.80 and 0.93, which proved high internal consistency (Pekrun et al., 2011). Its construct validity and high relationships with academic engagement and performance have been established in previous research, which has led to its application in the field of mathematics research at higher education.

The MMSLQ is based on the mathematics motivated strategies of learning questionnaire paradigm, which was created to assess motivational belief and self-regulated learning strategies in students (Pintrich et al., 1991). The mathematics specific adaptation measures the constructs of self-efficacy, intrinsic value, and self-regulation in mathematics learning. Empirical research has shown a high level of reliability and there is an

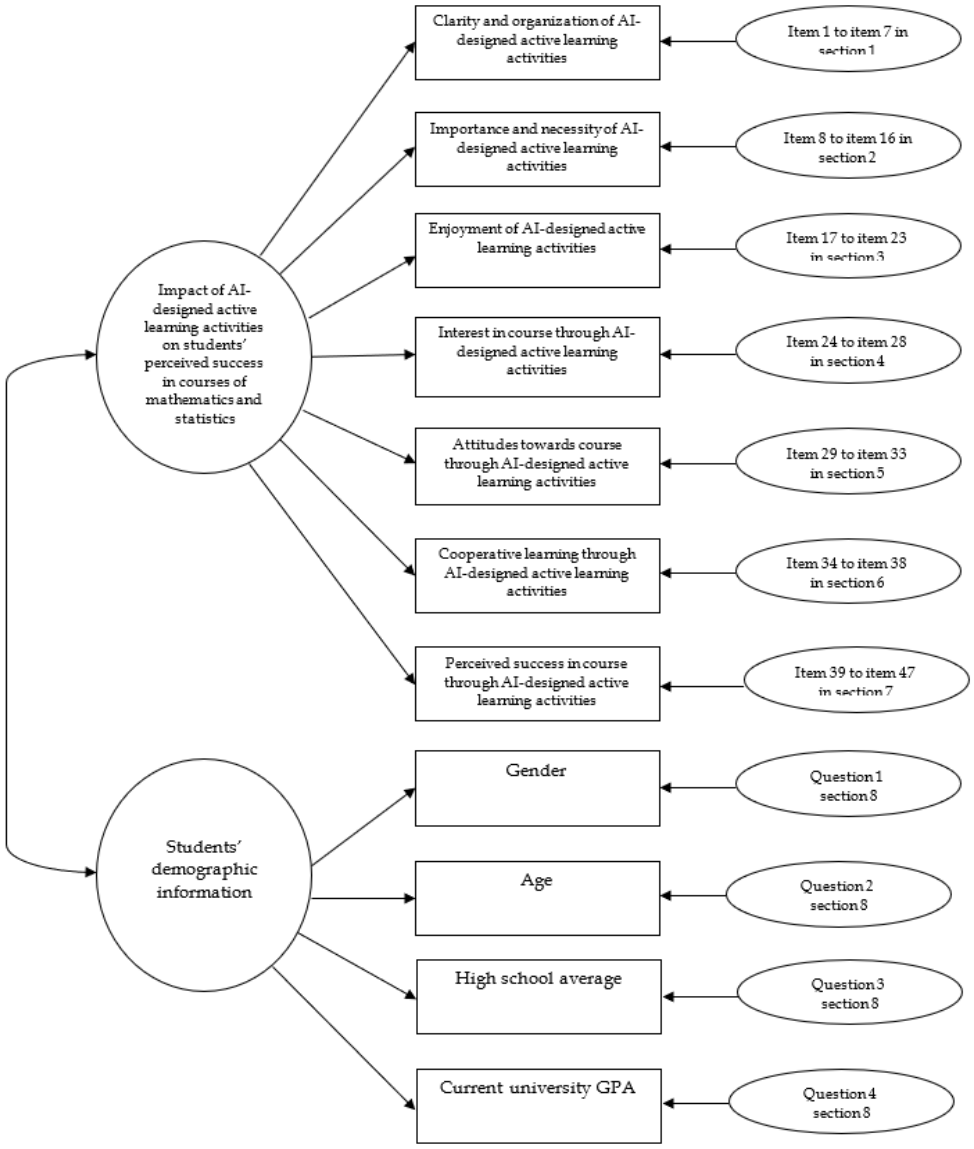


Figure 2. Questionnaire's items distributions on subscales (the authors' own elaboration)

average of Cronbach's alpha values between 0.74 and 0.92 between subscales (Pintrich & De Groot, 1990). The validity of its factorial and predictive associations with academic achievement is supported using evidence of its applicability in an academic context of higher education.

The IMI was created within the context of self-determination theory to help estimate the subjective experiences of participants about their target activity, that is, concern, interest, enjoyment, perceived competence, effort, value, and pressure (Deci et al., 1994). The IMI is prevalent in the academic studies and has been proven to be highly reliable with the majority of subscales having alpha coefficients greater than 0.80 (McAuley et al., 1989; Tsigilis & Theodosiou, 2003). Construct validity and multidimensional form cross-context confirmatory factor analysis (CFA) have supported its multidimensional structure and construct validity.

The ATMLQ is used to determine the perception held by students regarding the use of technology in learning mathematics, in terms of perceived usefulness, engagement and assistance in conceptual learning. Similar technology-attitude instruments have been found to have high internal consistency, generally more than 0.80, and indicated factorial validity in technology-boosted learning settings (Palacios et al., 2013). These results justify its validity in assessing the perceptions of AI-designed active learning activities.

The ATMI is a test that is able to evaluate students with regards to their attitude towards mathematics along the dimensions of value, enjoyment, motivation and self-confidence (Tapia & Marsh, 2002). Excellent reliability of the validation studies has been documented with the Cronbach's alpha value usually being between 0.85 and 0.95. The tool has shown good con validity and a significant level of correlation with mathematics success, ascertaining its appropriateness in gauging attitudes towards course (ATC) and PS.

Figure 2 shows the questionnaire's items distributions on subscales.

Table 4. KMO, Bartlett's test, and reliability analysis

Variables' scales	KMO values	Bartlett's test of sphericity p-values	Cronbach's alpha coefficient
CO of AI-designed active learning activities	.892	.000	.875
IN of AI-designed active learning activities	.902	.000	.848
EJ of AI-designed active learning activities	.885	.000	.812
IC through AI-designed active learning activities	.886	.000	.907
ATC through AI-designed active learning activities	.888	.000	.895
CL through AI-designed active learning activities	.843	.000	.862
PS in course through AI-designed active learning activities	.931	.000	.927

All items dealing with questions were coded and variables were formed in relation to each of the constructs: CO of activities about active learning provided by AI, IN of active learning activities provided by AI, enjoyment of active learning activities provided by AI, interest in course (IC), attitudes to course, CL, and success in course. Each construct was operationalized by aggregating the mean scores of its corresponding items. Negatively formulated questions were reverse coded before the analysis as a way of ensuring consistency in the interpretation of the scales. Two negatively phrased attention-check items were included to identify inattentive responses.

Figure 2 illustrates the alignment of questionnaire items with the study constructs. **Figure 2** shows how the items of the questionnaire were distributed over the study variables. Section 1-section 3 (items 1-23) assess perceptions of AI-designed active learning activities, namely CO, IN, and enjoyment. Section 4 (items 24-28) identifies IC, section 5 (items 29-33) identifies attitudes toward course, section 6 (items 34-38) identifies CL and section 7 (items 39-47) identifies PS in course. Section 8 consists of demographic factors (gender, age, high school average, and current university GPA), which were not included in the 47 scale items. The structure provides extensive measures of perceptual and outcome constructs.

EXPLORATORY FACTOR ANALYSIS

An exploratory factor analysis was performed to examine the underlying dimensional structure of the 47-item instrument. Principal axis factoring with Promax (oblique) rotation was used to examine the natural structure of the variables and determine the relationships between the items. The adequacy of the sample for this analysis was evaluated through the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. The factor loading matrix, eigenvalues, and variance explained by each retained factor are reported in tabular format to enhance the transparency and comprehensiveness of the validity evidence supporting the instrument's multidimensional framework.

The 47-item survey questionnaire included items that were used to develop the research variables. The constructs, i.e., CO of AI-designed active learning activities, IN of AI-designed active learning activities, enjoyment of AI-designed active learning activities (EJ), IC, attitudes toward course, CL, and PS in course through AI-designed active learning activities, were operationalized as a sum of the mean scores of the items associated with them.

Data adequacy was assessed using the KMO index of sampling adequacy and Bartlett's test of sphericity before factor analysis was undertaken. The KMO statistic is used to measure the percentage of variation between variables which can be common variance and thus can be analyzed using factor analysis. KMO values range between 0 and 1, with values above 0.60, above 0.80, and above 0.90 considered acceptable, meritorious, and excellent, respectively (Kaiser, 1974). To test whether the correlation matrix is significantly different than an identity matrix, Bartlett's test of sphericity is used. A statistically significant result indicates that the variables are sufficiently correlated to warrant factor analysis (Bartlett, 1954). The appropriateness of factor analysis is proved by a statistically significant p-value ($p < 0.05$).

As shown in **Table 4**, all subscales had KMO values above 0.80 between 0.843 and 0.931 with meritorious to excellent sampling adequacy. In particular, CO (0.892), IN (0.902), enjoyment (0.885), IC (0.886), attitudes toward course (0.888), CL (0.843), and PS in course (0.931) were above the recommended mark. In addition, Bartlett's test of sphericity was statistically significant in all subscales ($p < 0.001$), which justified the fact that the inter-item correlations were high to continue with the factor analysis. All these results suggest that the data were appropriate in terms of factor analysis and that the factors derived are adequate to represent the constructs of interest.

After the factor analysis, a reliability test was carried out to test the cohesion and homogeneity of the items in each subscale. The main aim of the reliability analysis was to determine the internal consistency of the individual constructs by analyzing the extent to which the items of the individual subscale measure the same underlying construct. Cronbach's alpha coefficient was used to determine internal consistency reliability as it is one of the most acceptable measures of scale reliability (Cronbach, 1951).

All the alpha coefficients of Cronbach were above 0.80 which means that the internal consistency and reliability were good. As shown in **Table 4**, the alpha coefficients of CO, IN, enjoyment, IC, attitudes toward course, CL, and PS in course were 0.875, 0.848, 0.812, 0.907, 0.895, 0.862, and 0.927, respectively. The alpha values greater than 0.80 are regarded as the signs of the good reliability and high level of internal validity of the scales (Nunnally & Bernstein, 1994). These findings show that the items used in each of the subscales are highly consistent and coherent and thus confirm the reliability of the measurement tool used in this study.

Principal axis factoring of 47 items produced six components with Eigenvalues greater than 1. The first factor accounted for 48.7% of variance, as in **Table 5**, and the combined six components accounted for 61.8% of the total variance—a test of strong factor structure. The components were extracted according to the Eigenvalues > 1 rule (Kaiser's criterion), and the cumulative variance provides meaningful groupings of STEM students' PS in higher education courses of mathematics and statistics.

Table 5. PCA loading of items

Component	Initial Eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings[a]
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total
1	23.289	49.551	49.551	22.911	48.747	48.747	17.935
2	2.261	4.811	54.362	1.897	4.037	52.784	18.705
3	1.724	3.667	58.029	1.382	2.940	55.724	13.860
4	1.432	3.047	61.077	1.092	2.324	58.048	17.314
5	1.320	2.808	63.885	.972	2.067	60.115	14.978
6	1.168	2.485	66.370	.781	1.662	61.777	2.770
7	.995	2.117	68.486				
8	.879	1.870	70.356				
9	.847	1.801	72.157				
10	.733	1.559	73.717				
11	.668	1.422	75.139				
12	.632	1.344	76.483				
13	.625	1.330	77.813				
14	.586	1.247	79.060				
15	.572	1.217	80.277				
16	.540	1.149	81.427				
17	.509	1.083	82.510				
18	.504	1.073	83.583				
19	.487	1.037	84.620				
20	.442	.941	85.561				
21	.434	.924	86.485				
22	.406	.863	87.349				
23	.404	.859	88.207				
24	.374	.797	89.004				
25	.359	.765	89.769				
26	.349	.743	90.512				
27	.343	.731	91.242				
28	.318	.676	91.918				
29	.316	.673	92.591				
30	.293	.624	93.215				
31	.272	.579	93.793				
32	.266	.567	94.360				
33	.257	.548	94.908				
34	.243	.518	95.425				
35	.231	.492	95.918				
36	.223	.474	96.392				
37	.208	.442	96.834				
38	.191	.406	97.240				
39	.180	.382	97.623				
40	.172	.366	97.989				
41	.161	.343	98.332				
42	.155	.329	98.661				

Table 5 (Continued).

Component	Initial Eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings[a]
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total
43	.144	.306	98.967				
44	.134	.285	99.253				
45	.132	.282	99.534				
46	.119	.252	99.787				
47	.100	.213	100				

Note. Extraction method: PCA; [a]When components are correlated, sums of squared loadings cannot be added to obtain a total variance

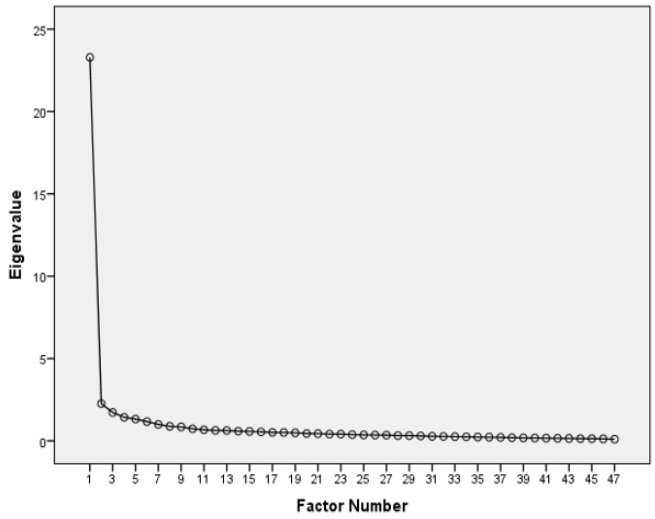


Figure 3. Scree plot of 47 items by principle component analysis (the authors' own elaboration using SPSS)

The scree plot in **Figure 3** supports the principle component analysis (PCA) result, where the "elbow" occurs after the sixth component. The graphical method, used to visually identify the optimal number of components, also confirms the retention of six informative factors. The rapid drop from factor 1-factor 3 followed by stabilization supports the factor retention based on Eigenvalue magnitude.

Finally, the conclusion of the principal axis factor analysis and Promax rotation based on the high KMO values and significant Bartlett's test results shows that the factor structure is acceptable. Besides this, the Cronbach's alpha coefficients indicate a high level of internal consistency of the items in the constructs. All these results indicate construct validity and reliability of the scales that were used to measure the perception of students regarding AI-designed active learning activities and the corresponding academic outcomes.

Table 6. Measurement model goodness-of-fit indices

Fit statistics	χ^2 / *df* (CMIN/df)	SRMR	RMSEA	CFI
Model value	2.825 (1,333.40/472)	0.048	0.074 (90% CI [0.069, 0.079])	0.897

CONFIRMATORY FACTOR ANALYSIS

A CFA was held on six latent factors using SPSS AMOS indirect effect plugin tool to rigorously examine the internal measurement model and establish structural construct validity (Gaskin et al., 2022). The latent factors included EJ, interest and attitudes (IA), CO, PS, CL, and IN.

As shown in **Table 6**, the model fit matrices demonstrated acceptable to good global fit across multiple indices X^2 = 1333.400 (df = 472), CMIN/df = 2.825 (1333.40/472.00, $p < 0.001$), SRMR = 0.048, and RMSEA = 0.074 (90% confidence interval [0.069, 0.079]). The values of CMIN/df and SRMR met conventional criteria with an acceptable RMSEA range. The comparative fit index (CFI) stood at 0.897, which was marginally below the 0.90 benchmark (Kenny & McCoach, 2003).

The discriminant validity was assessed with the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the heterotrait-monotrait (HTMT) ratio (Henseler et al., 2015). As shown in **Table 7**, all six constructs demonstrated acceptable composite reliability (CR) (> 0.78) and average variance extracted (AVE) (> 0.54).

Furthermore, all HTMT values remained safely below both the strict (0.850) and liberal (0.900) thresholds, ranging from 0.132 to 0.804 as shown in **Table 8**. It worthy to note that zero HTMT warnings were observed confirming that all constructs possess adequate discriminants validity despite observed inter-variable correlations.

Table 7. Scale reliability and convergent validity summary

Scale	CR	AVE	Maximal reliability (H)	Convergent validity established
IA	0.933	0.634	0.934	Yes (AVE > 0.50)
PS	0.925	0.639	0.928	Yes (AVE > 0.50)
EJ	0.921	0.593	0.922	Yes (AVE > 0.50)
CO	0.876	0.586	0.879	Yes (AVE > 0.50)
CL	0.784	0.547	0.786	Yes (AVE > 0.50)
IN	0.813	0.685	0.826	Yes (AVE > 0.50)

Table 8. Discriminant Validity – HTMT ratio matrix

	IA	PS	EJ	CO	CL	IN
IA	-					
PS	0.769	-				
EJ	0.804	0.761	-			
CO	0.683	0.625	0.622	-		
CL	0.784	0.693	0.740	0.668	-	
IN	0.195	0.251	0.312	0.132	0.188	-

Table 9. Demographic information

Variables	Categories	Frequency	Percentage (%)
Gender	Male	190	57.6
	Female	140	42.4
Age	17-20	248	75.2
	21-24	66	20.0
	25-28	11	3.3
	29-32	4	1.2
	33-36	1	0.3

As shown in **Table 8**, the highest HTMT ratio is 0.804 (EJ → IA), which is strictly below the 0.850 conservative threshold. HTMT analysis confirmed satisfactory discriminant validity across all pairs:

- PS → IA: 0.769
- PS → EJ: 0.761
- CO → IA: 0.683
- CL → IA: 0.784
- IN → IA: 0.195

QUANTITATIVE ANALYSIS

Demographic Information

Table 9 shows the demographic properties of respondents. The number of students involved in the study was 330. In terms of gender distribution, there were 190 male and 140 female respondents who were 57.6 and 42.4 percent, respectively. The participants were aged between 17 and 20 years with majority of 248 students (75.2%) representing this age group. The 21-24 years old group of students became 66 respondents (20%). A reduced sample percentage was in the 25-28 years age (11 respondents, 3.3%). The respondents who fell in the age bracket of 29-32 years only numbered four (1.2%) with the rest (1) falling in the age bracket of 33-36 years. These results suggest that the sample mostly represented students in their early years of higher education, which is expected in introductory STEM classes.

Correlation Analysis

The Pearson correlation analysis was conducted to investigate the strength and direction of the relationship that existed between the variables that were included in the study. The most popular statistical methods in the measure of linear relationships of continuous variables are Pearson correlation coefficient (r). The approach allows researchers to establish the extent as well as the direction of the relationship between variables and it is widely applied in educational and behavioral studies as a pre-calculation to regression analysis (Field, 2018; Pallant, 2020).

The present study included a correlation analysis of seven variables: the PS of students in courses of mathematics and statistics, CO of AI-designed active learning activities, IN of AI-designed active learning activities, EJ, IC through AI-designed active learning activities, attitudes toward course through AI-designed active learning activities, and CL through AI-designed active learning activities.

The software of SPSS 26.0 was used to define and create each variable based on the average scores of the items that represented the construct in the survey questionnaire. Indicatively, the CO of AI-designed active learning activities variable was developed using seven items of the questionnaire with the rest of the constructs also being calculated using the corresponding items sets as outlined in **Figure 2** within the instrumentation section.

Table 10 represents the findings of the Pearson correlation analysis. The results show that the PS of students in mathematics and statistics courses is positively and significantly associated with all six independent variables at the 0.01 level of significance. To be more precise, course success exhibits high levels of correlation with CL ($r = 0.809$, $p < 0.01$), course attitudes ($r = 0.800$, $p < 0.01$), course interest ($r = 0.776$, $p < 0.01$), EJ ($r = 0.749$, $p < 0.01$), IN of AI-designed active learning activities ($r = 0.749$, $p < 0.01$), and CO of AI-designed active learning activities ($r = 0.659$, $p < 0.01$).

These findings indicate that learners who record greater rates of positive perceptions towards AI-designed active learning exercises also are more likely to be observed to have greater rates of PS in mathematics and statistics courses. Besides, the relationships within the independent variables are even positive and significant. It means that the constructs, even though being interconnected, reflect specific yet complementary aspects of the learning process among students in AI-assisted active learning settings. The correlation analysis revealed positive associations among the study variables, indicating that students expressing more favorable perceptions of AI-designed active learning also generally reported greater perceived course success. However, several variables exhibited relatively strong intercorrelations, implying conceptual overlap among certain dimensions. Consequently, the regression findings should be interpreted with caution, as substantial shared variance among predictors may impact the stability and unique explanatory power of individual regression coefficients. This concern is supported by the CFA, where latent inter-factor

Table 10. Correlations analysis

		SPS	CO	IN	EJ	IC	ATC	CL
SPS	Pearson correlation	1						
	Sig. (2-tailed)							
	N	330						
CO	Pearson correlation	.659**	1					
	Sig. (2-tailed)	.000						
	N	330	330					
IN	Pearson correlation	.749**	.703**	1				
	Sig. (2-tailed)	.000	.000					
	N	330	330	330				
EJ	Pearson correlation	.749**	.610**	.858**	1			
	Sig. (2-tailed)	.000	.000	.000				
	N	330	330	330	330			
IC	Pearson correlation	.776**	.672**	.730**	.725**	1		
	Sig. (2-tailed)	.000	.000	.000	.000			
	N	330	330	330	330	330		
ATC	Pearson correlation	.800**	.681**	.774**	.750**	.842**	1	
	Sig. (2-tailed)	.000	.000	.000	.000	.000		
	N	330	330	330	330	330	330	
CL	Pearson correlation	.809**	.658**	.774**	.761**	.781**	.808**	1
	Sig. (2-tailed)	.000	.000	.000	.000	.000	.000	
	N	330	330	330	330	330	330	330

Note. SPS: Students' perceived success in courses of mathematics; **Correlation is significant at the 0.01 level (2-tailed)

correlations among constructs ranged from 0.69 to 0.92 and such overlap indicates that these dimensions are not fully independent.

Regression Analysis

The multiple regression analysis was used to test the combined effect of a number of independent variables on one dependent variable. Regression analysis is a significant statistical tool that allows researchers to approximate how many fluctuations of independent variables describe changes in a dependent variable. Regression models have become commonly applied in educational studies to test the impacts of instructional strategies, psychological variables, and learning conditions on academic achievement and learning outcomes (Cohen et al., 2018; Tabachnick & Fidell, 2019).

Within the framework of the present research, the regression analysis was conducted to examine the extent to which six dimensions of AI that predetermined active learning activities are associated with the PS of students in mathematics and statistics courses. There were six independent variables namely: CO of AI-designed active learning activities, IN of AI-designed active learning activities, EJ, IC through AI-designed active learning activities, attitudes toward course through AI-designed active learning activities, and CL through AI-designed active learning activities. The dependent variable was the PS of students in courses of mathematics and statistics through AI-designed active learning activities.

According to recent research on STEM education, AI-based active learning classrooms are potentially highly effective at increasing engagement, conceptual learning, and academic performance of students. Intelligent technologies promote active learning and engagement among students, more profound cognitive thinking, and knowledge sharing (Freeman et al., 2014; Zawacki-Richter et al., 2019). Correspondingly, the coherence and systematic nature of instructional processes will also be critical to enable efficient learning as well as enhance the understanding of complicated mathematical ideas among the students (Prince, 2004).

Students' beliefs about the value and need of learning activities are also known to play significant roles in declaring their motivation and persistence in their academic activities (Deci & Ryan, 2000). Personal and motivational variables like fun and desire to engage in learning activities have been proposed to be good predictors of academic engagement and achievement (Pekrun, 2006). In addition, the academic commitment and the enhancement of academic outcomes are usually facilitated by positive attitudes towards learning activities (Pintrich, 2003).

Another most popular potential pedagogical tool in STEM education is also CL. Group learning facilitates students to share ideas, train their critical thinking skills as well as enhance their problem-solving skills, which is the ultimate result of improving academic performance (Johnson & Johnson, 2009).

Out of these theoretical and empirical concerns, there are six research hypotheses developed in the study to examine the relationship between the independent variables and the PS of students in mathematics and statistics courses.

Table 11. Model I summary

Model	R	R^2	Adjusted R^2	Standard error of the estimate
I	.862[a]	.743	.739	2.93396

Note. [a] Predictors: (Constant); CO of AI-designed active learning activities, IN of AI-designed active learning activities, EJ, IC through AI-designed active learning activities, ATC through AI-designed active learning activities, CL through AI-designed active learning activities

Table 12. Model I ANOVA[a]

Model		Sum of squares	df	Mean square	F	Significance
I	Regression	8,059.304	6	1,343.217	156.041	.000[b]
	Residual	2,780.421	323	8.608		
	Total	10,839.724	329			

Note. [a] Dependent variable: PSC through AI-designed active learning activities; [b] Predictors: (Constant); CO of AI-designed active learning activities, IN of AI-designed active learning activities, EJ, IC through AI-designed active learning activities, ATC through AI-designed active learning activities, CL through AI-designed active learning activities

Ho_1: There is no relationship between the CO of AI-designed active learning activities and students' PS in courses of mathematics and statistics ($b_1 = 0$).

Ho_2: There is no relationship between the IN of AI-designed active learning activities and students' PS in courses of mathematics and statistics ($b_2 = 0$).

Ho_3: There is no relationship between students' EJ and their PS in courses of mathematics and statistics ($b_3 = 0$).

Ho_4: There is no relationship between the IC through AI-designed active learning activities and students' PS in courses of mathematics and statistics ($b_4 = 0$).

Ho_5: There is no relationship between students' attitudes toward AI-designed active learning activities and their PS in courses of mathematics and statistics ($b_5 = 0$).

Ho_6: There is no relationship between the CL through AI-designed active learning activities and students' PS in courses of mathematics and statistics ($b_6 = 0$).

Regression Model

The regression model used in this study can be expressed mathematically as follows: $Y' = a + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_5X_5 + b_6X_6 + u$. Y' in this model represents the PS of students in courses of mathematics and statistics through the use of AI intended active learning processes. Where X_1 implies CO of AI-designed active learning activities, X_2 represents IN of AI-designed active learning activities, X_3 implies enjoyment of course through AI-designed active learning activities, X_4 represents interests in course through AI-designed active learning activities, X_5 implies ATC through AI-designed active learning activities, and X_6 represents CL through AI-designed active learning activities. The constant value a is the intercept of the regression model, the b_1 to b_6 values indicate the association of each independent variable with the dependent variable, holding the others constant.

According to the regression findings, a linear regression model can be estimated as follows: $Y' = 0.120 + 0.133X_1 + 0.035X_2 + 0.198X_3 + 0.291X_4 + 0.402X_5 + 0.571X_6 + u$.

Model Summary

Table 11 gives the summary of model I. The multiple correlation coefficient (R) is 0.862 which shows the existence of a strong relationship between the independent variables and the PS of students in mathematics and statistics courses. The coefficient of determination (R^2) is 0.743 which indicates that almost 74.3 percent of the variance in the PS of students in mathematics and statistics courses can be attributed to the six independent variables used in the regression model. The value of adjusted R^2 of 0.739 also attests to the strength of the model once the numbers of predictors are adjusted. The standard error of the estimate is 2.93396 which indicates the average difference between the observed values and the predicted values of the dependent variable.

Overall, the model summary indicates that the regression model effectively explains students' PS in mathematics and statistics courses through AI-designed active learning activities.

ANOVA Results

Table 12 presents the results of the analysis of variance (ANOVA). The ANOVA test is used to determine whether or not the entire regression model explains the dependent variable with statistical significance. The findings show that the regression equation is very significant as the F value is 156.041 and the p value is below 0.001.

The regression sum of squares equals 8,059.304 with a residual sum of squares equals 2,780.421 resulting in a total sum of squares of 10,839.724. The F value computed is significant thus showing that the six independent variables as a whole have a considerable influence on the PS of students in mathematics and statistics courses. Thus, the statistical validity of the regression model is acceptable to describe the correlation between the AI-designed active learning activities and the perceived academic success of students.

Table 13. Model I coefficients[a]

Model	Unstandardized coefficients		Standard coefficients	T	Sig.	Collinearity statistics	
	B	Standard error	Beta			Tolerance	VIF
I (Constant)	.120	1.516		.079	.937		
CO of AI-designed active learning activities	.133	.069	.082	1.930	.054	.437	2.289
IN of AI-designed active learning activities	.035	.064	.034	.536	.592	.196	5.098
EJ of AI-designed active learning activities	.198	.075	.155	2.650	.008	.231	4.331
IC through AI-designed active learning activities	.291	.106	.156	2.751	.006	.248	4.038
ATC through AI-designed active learning activities	.402	.115	.215	3.503	.001	.211	4.734
CL through AI-designed active learning activities	.571	.100	.315	5.736	.000	.263	3.796

Note. [a] Dependent variable: PSC through AI-designed active learning activities

Regression Coefficients and Testing Hypotheses

Table 13 gives regression coefficients of the independent variables. The unstandardized beta coefficients show the proportion that each variable makes to the PS of students in mathematics and statistics courses.

Active learning activities designed by means of CL realized through AI showed the strongest association with PS (b = 0.571, p < 0.00), indicating that students who report more cooperative experiences also report higher PS. As such, the null hypothesis $\mathbf{Ho_6}$ is rejected. The attitudes toward course through AI-designed active learning activities also significantly positively relate with the PS of the students (b = 0.402, p = 0.001). This indicates that students with more positive attitudes towards AI assisted learning processes are more likely to attain a greater degree of academic success. Thus, $\mathbf{Ho_5}$ is rejected. The fun of the AI based active learning exercises is also significantly associated with students' PS in a positive manner (b = 0.198, p = 0.008) in a statistically significant way. Learners who report more enjoyment in AI mediated learning processes also tend to report greater perceived academic success. Consequently, $\mathbf{Ho_3}$ is rejected. The IC through AI-designed active learning activities showed the same effect on the PS of students by showing a significant positive risk (b = 0.291, p = 0.006). This suggests that the higher interest is associated with higher PS. Therefore, $\mathbf{Ho_4}$ is rejected.

Conversely, AI implemented active learning activities with a clear structure and organization (b = 0.133, p = 0.054) has no statistically significant effect at the traditional 0.05 level of significance. In turn, $\mathbf{Ho_1}$ cannot be rejected. In the same fashion, the significance and need of AI that facilitates active learning activities (b = 0.035, p = 0.592) is not an indication of a statistically significant correlation with students' PS. $\mathbf{Ho_2}$, thus, cannot be rejected. The interpretation of these non-significant findings is addressed within the discussion section.

In order to examine if the research variables are collinear or are dependent on each other, a diagnostic test is held to check for multicollinearity. As shown in **Table 13**, collinearity was examined using tolerance and variance inflation factor (VIF). All were within the lenient limits (tolerance > 0.1 and VIF < 10). Together with the high inter-factor correlations from the CFA (up to 0.92), this indicates that is no strong evidence of multicollinearity among the studied variables.

Graphical Visualization of the Model

A graphical representation of the regression model is given in **Figure 4**. **Figure 4** gives the standardized beta coefficients of the six independent variables and how they correlate with the PS of students in mathematics and statistics courses. The strength of each predictor in the model is brought out clearly in the graphical representation.

Figure 4 does confirm that CL has the most influence on predicting the PS of students, then there are the attitudes to course, IC, and EJ. These results highlight the relevance of group and encouraging learning contexts to enhancing the performance of students in mathematics and statistics courses with the aid of AI-based active learning tasks.

DISCUSSION

The findings show a positive association between students' more favorable perceptions of AI-designed active learning and their PS in courses of mathematics and statistics. From the final regression model, CL, along with students' attitudes toward the course, level of interest, and enjoyment, were identified as the most significant predictors. The results highlight the critical role of affective and social dimensions of learning when AI-designed active learning is integrated in higher education STEM contexts.

The findings confirm that AI-designed active learning dimensions are strongly associated with the PS of mathematics and statistics classes. The regression model has good explanatory power of the variables (R^2 = 0.743) which indicates that nearly three-quarters of the variance of students' PS is shared with the six predictors. The most indicative (b = 0.571) was the cooperation of learning followed by ATC, interest and enjoyment (b = 0.402, b = 0.291, b = 0.198, respectively). These results may also be supported with strong positive associations

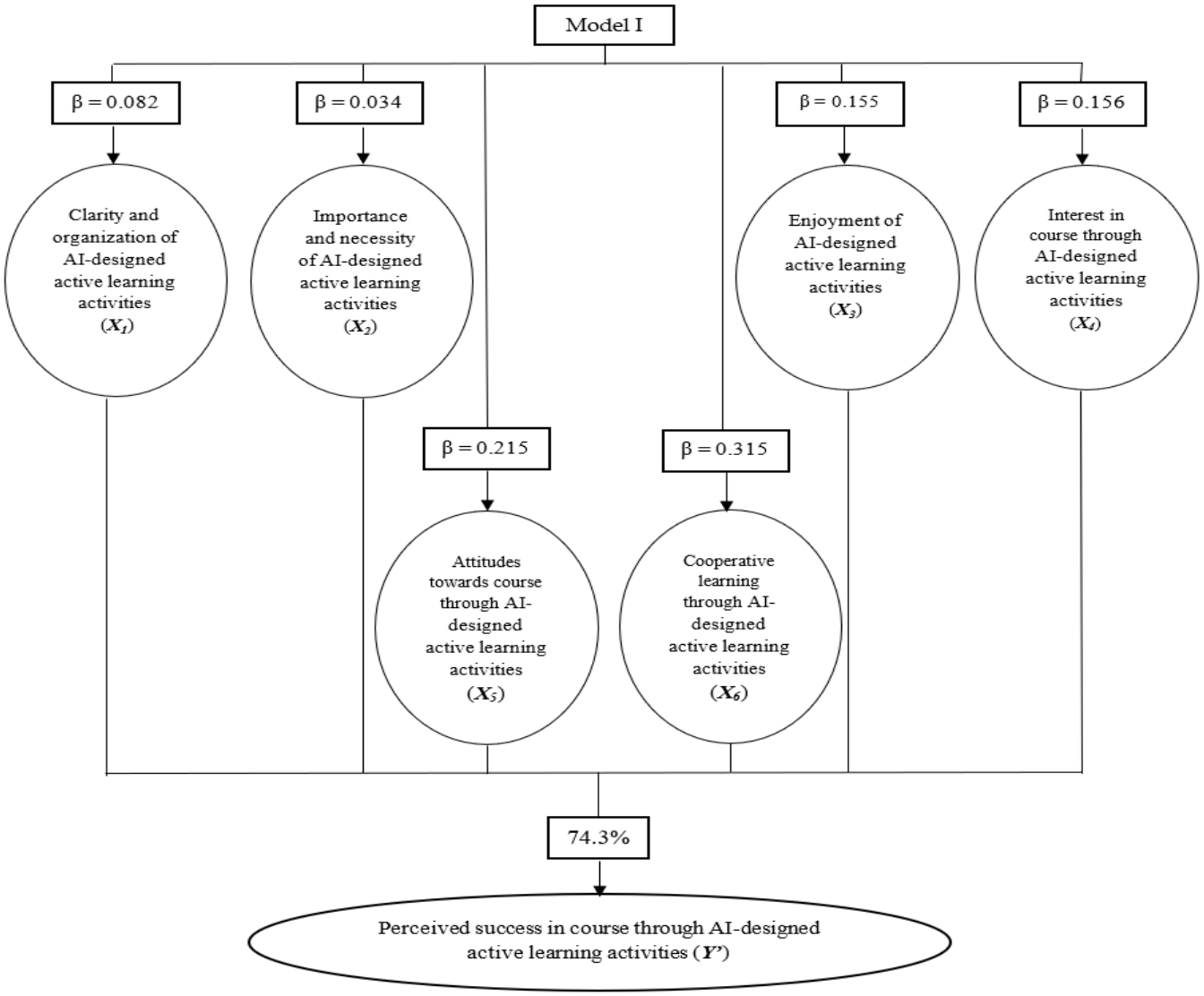


Figure 4. Model I graphical visualization (the authors' own elaboration)

(r = 0.809) between CL and the PS. The CO as well as the IN variables were not significant predictors since these factors may not be directly related to students and are more related to instructors of mathematics and statistics. According to the data found in **Figure 4**, the following connections might be defined and the most obvious ones are collaborative and affective aspects, as the frontier of the present research and its key contribution to the literature. The clusters of information have demonstrated a definite sign that the learner groups which are engaged participants of the AI-assisted CL environments and whose attitude towards the phenomenon of learning is positive are more likely to report higher PS.

A key outcome of the analysis is that CO, along with IN did not emerge as statistically significant independent predictors within the full regression model, in spite of the fact that both variables were positively related to the perceived course success at the correlational level. One plausible interpretation is that these dimensions serve as baseline instructional prerequisites rather than direct drivers of PS. While students may expect well-structured course design and acknowledge the relevance of AI-designed learning, such conditions alone may be insufficient to shape their perceptions of success once more immediate experiential elements such as CL, enjoyment, interest, and positive course attitudes are taken into consideration. Alternatively, the diminished predictive uniqueness of these dimensions may stem from substantial conceptual overlap among conceptually related predictors, thereby attenuating their individual explanatory power in multivariate analysis. This explanation is supported by the CFA, in which Fornell-Larcker criteria were not fully met and interest and attitudes loaded in a single factor, although HTMT values indicated the constructs remain distinguishable. From a pedagogical perspective, this implies that successful implementation of AI-designed active learning must move beyond mere structural coherence and perceived utility, emphasizing instead dynamic students' engagement, interactive processes, and meaningful participation.

To conclude on such outcomes, it is possible to say that the results can be linked to the previous research studies which have revealed the effectiveness of active learning and the implementation of AI in STEM learning and its further argumentation. In the aspects of engagement, the amount of feedback, academic outcome, and AI-based learning proves to be superior as found in several research studies (Holmes et al., 2019; Kestin et al., 2025; Zhai & Krajcik, 2024). Meanwhile, CL has continuously been linked to higher problem solving and success (Barefield, 2013; Slavin, 2019). Recent researchers (e.g., Awang et al., 2025; Létourneau et al., 2025; Nguyen & Pham, 2025) also show that the synergetic effect of active learning and AI can be achieved. However, in research, it is only the one that demonstrates the pivotal intervening position of the affective factors such as enjoyment and attitudes in the AI-mediated context. From an instructional perspective, the findings suggest that the pedagogical value of AI-facilitated active learning appears to depend less on AI integration per se than on how these tools support collaboration, enjoyment, intrinsic motivation, and positive attitudes toward the course. Therefore, instructors of mathematics and statistics courses may benefit from developing AI-designed activities that emphasize participatory design, social engagement, and meaningful alignment with students' learning experiences rather than relying solely on automated delivery or individualized practice.

CONCLUSION

This study examined the relationship between AI-designed active learning and STEM students' PS in higher education mathematics and statistics courses. Employing a correlational survey methodology, the study found several dimensions of AI-designed active learning were positively associated with perceived course success. In the final regression model, CL, attitudes toward the course, interest, and enjoyment emerged as the dimensions most strongly associated with PS. However, the results should be interpreted within the limits of self-reported data and correlational analysis. A CFA supported the measurement model, though with marginal CFI and overlapping constructs. Future research should cross-validate the model in independent samples, test measurement invariance, and incorporate objective academic performance indicators.

Some recommendations based on the research findings are possible. To begin with, the implementation of AI-based learning systems at institutions of higher education should support the interactive and adaptive approach to the CL process. Second, mathematics and statistics instructors should improve the learning and interaction, with the help of introduction of guided group work and real time feedback systems. Third, the findings are expected to enlighten mathematics and statistics educators on how to apply AI to the teaching process and hence, they will receive professional development programs. The policy makers should also fund the digitization of transformation needs on the current trends of STEM education.

The research also has its fair share of disadvantages though it has also made its contribution. It has a small sample size that is adequate but limited to a single institution and has a potential of reducing external validity. In addition to this, it may be biased during response due to self-reported information in questionnaires. The findings will be confirmed and extended in future studies by using bigger and more diverse samples as well as longitudinal research and designs.

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Ethical statement: This research study was held according to the ethical standards established within higher education. The permission to conduct the study was granted by the department concerned and instructors of mathematics and statistics who embed AI-designed active learning in their courses were approached. Additionally, participating students provided digital informed consent via an online form and were informed that their participation was voluntary and they had the right to withdraw at any time. The responses provided by students were treated with utmost confidentiality and were used for research purposes only.

AI statement: Generative AI or AI-based tools were not used in this study.

Declaration of interest: No conflict of interest is declared by the authors.

Data sharing statement: Data supporting the findings and conclusions are available upon request from the corresponding author.

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APPENDIX A

This survey questionnaire is conducted as part of a research study which aims at examining students' perceptions and attitudes towards artificial intelligence (AI)-designed active learning activities in science, technology, engineering, and mathematics (STEM) courses.

AI-designed active learning occurs through the use of AI in creating activities during the lectures instead of lecturing from the instructors' side or notes taking from the students' side.

Your assistance in responding to all the questions is highly appreciated. Please note all your information provided will be treated with full confidentiality and the study will not include any information that will identify your identity.

Clarity and Organization of AI-Designed Active Learning Activities

The purpose of AI-designed active learning activities is clearly explained by the instructor.

The instructor clearly discusses how AI-designed active learning activities are related to the learning process.

The explanation on what I'm expected to do in the AI-designed active learning activities is clarified by my instructor.

The instructor gives sufficient amount of time to engage in AI-designed active learning activities.

The level of difficulty of AI-designed active learning activities is appropriate (neither very easy, nor very difficult).

The instructor motivates students to engage in AI-designed active learning activities.

The instructor encourages students to ask questions about AI-designed active learning activities.

Importance and Necessity of AI-Designed Active Learning Activities

I believe the time I invest in AI-designed active learning activities is beneficial.

I feel the value of AI-designed active learning activities.

I actively participate and attempt to engage in AI-designed active learning activities.

I believe the effort invested from my side to complete AI-designed active learning activities is worthwhile.

I feel positive towards the instructor because of AI-designed active learning activities.

The AI-designed active learning activities are not important and necessary at all.

I like AI-designed active learning activities more than the traditional lectures in my course.

I wish AI-designed active learning activities were used in all my courses.

I hope to see more AI-designed active learning activities in my future courses.

Enjoyment of AI-Designed Active Learning Activities

I enjoy AI-designed active learning activities.

I give my maximum effort to AI-designed active learning activities.

I feel excited when working with my classmates and instructor during the AI-designed active learning activities.

I request my instructor to increase the frequency of conducting AI-designed active learning activities.

I like engaging in AI-designed active learning activities.

I use the internet, check social media, or do other things instead of doing the AI-designed active learning activities.

I never complaint to my instructor about the AI-designed active learning activities.

Interest in Course Through AI-Designed Active Learning Activities

I find AI-designed active learning activities to be interesting.

The AI-designed active learning activities allow sharing ideas with my classmates and instructors.

The active participation during AI-designed active learning activities makes the class more interesting.

The AI-designed active learning activities make the topics of my course more interesting.

The AI-designed active learning activities make the overall course more interesting.

Attitudes Towards Course Through AI-Designed Active Learning Activities

The AI-designed active learning activities help me feel positive towards the course.

The AI-designed active learning activities make me more comfortable to participate in the class discussion.

The AI-designed active learning activities assist me to understand, expand, and relate my ideas.

The AI-designed active learning activities improve my opinion about the course contents.

The AI-designed active learning activities make me more actively engaged in the learning process of the course.

Cooperative Learning Through AI-Designed Active Learning Activities

I always collaborate with my classmates in AI-designed active learning activities.

My interaction with classmates in AI-designed active learning activities enhances my understanding of course materials.

I believe I'm a good team player in AI-designed active learning activities.

I function as a good team leader in AI-designed active learning activities when there is a need.

The cooperative learning skills in AI-designed active learning activities are needed in my future career.

Success in Course Through AI-Designed Active Learning Activities

I utilize what I learn from AI-designed active learning activities for exams.

The AI-designed active learning activities help in clarifying the most difficult contents of the subject by making them easier to understand.

The AI-designed active learning activities enhance my ability to study better.

The AI-designed active learning activities motivate me to work harder during the lectures.

The AI-designed active learning activities change my attitude in the way I study.

I believe AI-designed active learning activities enhance my preparation for exams.

The AI-designed active learning activities enhance my performance in exams.

I think AI-designed active learning activities enhanced my overall performance in the course.

One of the main contributors to my success in the course is the use of AI-designed active learning activities.

Demographic Information

Gender:

Age:

Course name:

Major:

College:

University name:

High school average:

Current university GPA (out of 4):