Gradus Vol 13, No 1 (2026)
ISSN 2064-8014

Working With AI in Mathematics: A Small-Scale Exploration of Student Perceptions

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https://doi.org/10.47833/2026.1.CSC.002

Keywords:
higher education;
mathematics;
critical thinking

Article history:

Received	30 March 2026
Revised	2 April 2026
Accepted	8 April 2026

Abstract

The rapid integration of artificial intelligence into higher education is reshaping the demands of mathematics instruction, where traditional emphases on formal reasoning and procedural accuracy increasingly intersect with the need for critical thinking. This study investigates how the use of AI-based tools in a university mathematics course relates to shifts in students' attitudes, particularly those connected to critical awareness and reflective judgment.

In this empirical study students worked in pairs with generative AI systems throughout the semester, and their perceptions were measured at the beginning and end of the course. The results reveal a nuanced change: while intentions to use AI remained high, perceived risks increased, suggesting not rejection but a deepening of critical thinking toward technology. Slightly rising comfort levels also indicate growing digital confidence. Although limited by a small sample, the study suggests that AI supported mathematics learning environments may contribute to the development of critical thinking alongside disciplinary knowledge.

1 Introduction

In computer science studies at the university level, the fact that multiple mathematics classes are included reflects their role as foundational in character. The reason for this role should be immediately obvious to any student. The core areas of computer science—algorithms and data structures, complexity theory, cryptography, computer graphics, machine learning, and formal methods—each depend fundamentally upon mathematical ideas from discrete mathematics, linear algebra, probability, logic, and analysis. These topics cannot be understood or used without a mathematics background; in short, their importance to computer science is not just significant or valuable but critical.

Nonetheless, at the same time, the position and role of mathematics in computer science education go beyond its direct applicability. While it is plain to argue that some form of professional and domain-specific knowledge is definitely required in order to train skilled professionals in the field, mathematics education is ultimately meaningful in terms of a consequent, much broader and much deeper concern. Indeed, it is in mathematics that forms of abstract thinking find their most developed and most rigorous formulation: mathematical thinking indeed calls upon forms of thinking in terms of abstract objects, underlying structures, and forms of generalized thinking in relation to particular instances.

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Moreover, mathematics uniquely operates in a space where precision and strictness are not simply ideals but requirements. Thinking through definitions, proof development, and critical evaluation of assumptions helps to cultivate a strict methodology of thought. As students work through rigorous arguments and counterarguments with each other in a dialogue of sorts, they absorb a sense of what constitutes correctness and completeness in a thought process that can powerfully affect how they think about issues of complexity.

Finally, mathematics creates a singularly propitious environment for fostering critical thinking. By introducing students to problems that resist easy solutions, this approach fosters healthy skepticism toward unexamined claims and trains students to evaluate arguments based on logical validity rather than intuition. Mathematics education thus trains not only technically proficient professionals but equally reflective and analytically inclined ones.

For these reasons, the teaching of mathematics within computer science programs should be understood not simply as a means to support specific applications, but as a central component of intellectual training. It equips students with ways of thinking that are essential for both the theoretical foundations and the long-term evolution of the discipline.

Today’s models for pursuing a higher education increasingly place a strong emphasis on student involvement, flexibility, and incorporating pedagogical innovation effectively into the curriculum. The same is true of the mathematical component of computing science programs of study. Though mathematical complexity and abstractness are undeniably the hallmarks of mathematical studies, today’s educational approaches do their best to make such aspects engaging and interesting for the students to grasp.

Against this background, the value of a number of educational approaches has become particularly relevant. The use of problem-based learning, interactive lectures, and computational tools supports active engagement with mathematics, moving beyond a purely theoretical framework. Well-chosen examples from applications in computer science can be particularly valuable in reinforcing the sense that mathematics is relevant without relying on a resolutely instrumental approach.

On the other hand, modern education in mathematics more and more recognizes the diversity of students' pre-existing knowledge and learning styles [1]. Hence, adaptive methods of assessment are potentially beneficial to more effective knowledge acquisition as well as to persistent intellectual engagement. Such methods are not only helpful to the acquisition of knowledge, but they are also helpful to articulated understanding, difficulties, and improvements.

Significantly, the introduction of contemporary pedagogical practices does not undermine the primacy of rigor and abstractness in mathematical thinking. Instead, it attempts to make such rigor and abstractness, which are mediated by the process of exploration, formalization, and proof, easier to grasp and understand, thus possibly demystifying and actively engaging students with abstract thought processes.

In such a manner, new forms of educational approach within mathematics serve a double objective. They become effective not only in sustaining student interest and curriculum interaction but also in supporting the fundamental intellectual objectives of mathematical education. Therefore, mathematics education is able to remain a foundation component of computer science programs, supporting both the pragmatic goals of the subject and well-defined cognitive capabilities.

From the point of view of student success, and specifically from the perspective with which they will be expected to perform in later professional and personal life, well-founded skills in critical thinking represent a key area of development. They will be expected to evaluate complex situations, make decisions based upon incomplete and even uncertain data, and successfully navigate dynamic environments. The ability to think critically and well is necessary not only to effectively apply the information that they have been given, but also to navigate new problems in a rapidly changing world.

2 Literature review

The significance of critical thinking and student success within higher level education has already been established within contemporary educational theory. In relation to the field of mathematics education and computer science, a number of prominent theoretical frameworks have been advanced which can facilitate a coherent understanding of the relationship between instruction design and the establishment of cognitive skill sets. These various theories, while having clear differences in terms of philosophical approach, have converged towards the notion that learning is an active and socially constructed phenomenon which is motivationally driven.

Bandura’s social learning theory [2] identifies the importance of observation and modeling in the teaching and learning process. According to social learning theory, critical thinking development correlates with student perceptions of their own ability. In a mathematically demanding domain, the teacher not only transfers information to the student but also models critical thinking and problem-solving ability. When students observe the teacher’s thinking made explicit through examples and discussion, they can more readily absorb a powerful cognitive strategy.

Kolb's Experiential Learning Theory [3] is another perspective that sheds additional light on mathematics education. The cyclical movement between concrete experience, reflective observation, abstract conceptualization, and active experimentation is similar to the process that mathematics is often applied, viewed, or conceived. This model supports the construction of learning designs that emphasize exploration, theory, and application, thus supporting the idea that critical reflective thinking is a vital element of the learning process.

Lastly, self-determination theory, as expounded by Deci and Ryan [4], highlights the motivating context which allows in-depth learning and critical thinking to emerge. The context includes an encouraging learning environment, the freedom to express competence, and intellectual challenge. In a mathematically challenging program, this is important so that students can continue learning in the face of difficulty and are encouraged to engage in a reflective mode of study.

These perspectives promise a rich conceptual model in relation to an investigation of the potential contribution of mathematics education towards facilitating success within computer science studies. They imply that, in fact, the refinement of critical thinking skills in mathematics does not depend merely on the substance that one learns, but rather on a learning context that combines rigor, social context, experience, and intrinsic motivation.

Recent empirical work refines and extends these theoretical perspectives by considering the ways in which information technology and artificial intelligence reshape learning environments in higher education. Contemporary studies consistently show that, while technological innovation offers considerable pedagogical potential, new structural, ethical, and institutional challenges arise to directly touch on student success.

While [5] [6] do stress that contemporary educational technologies, especially AI-driven systems, allow for increasing personalization of learning pathways and more sophisticated analytical approaches toward student performance, their contributions also bring forth concerns with regard to digital equity and the disparate development in teachers' technological competencies. These results imply that pedagogical benefits of advanced technologies can materialize only if institutions are able to ensure suitable infrastructure, continuous professional development for educators, and ethical and data protection considerations [7]. In this sense, technology-enhanced learning should be considered a socio-technical system rather than merely a technical upgrade.

Similarly, [8] posits that artificial intelligence has the potential of transforming higher education institutions by providing personalized learning supports and automating administrative tasks. Additionally, the study points out that artificial intelligence can be applied in the training of students in response to future workforce requirements, enabling an adaptive mindset and information technology competency. Nonetheless, the author highlights that education can have significant outcomes if AI integration is comprehensive and includes consideration of its ethical dimensions—a concept that resonates with both the self-determination and sociocultural theories as a mediating variable within a structured learning context, without replacing humans.

The opportunities and challenges of AI-based adaptive learning have been explained in the research article by [9]. Based on data-driven personalization, the article ensures to prove the advantages of using these adaptive learning systems. For this, it uses SWOT analysis and Force Field Analysis. The advantages of using an adaptive learning system are increased efficiency and automated assessments. However, it also faces challenges like increased costs of implementation and reduced personal engagement. Nevertheless, the article also offers resolutions to these challenges.

Moving beyond the level of personalization, [10] also seeks to understand the role that crowdsourcing and collective intelligence can play in the process of examining and using big data in the field of education. Indeed, this study demonstrates the ways in which digital technologies have allowed us to rethink the way in which knowledge is created and shared, specifically through a model that understands theories of collective intelligence and the "wisdom of crowds."

Empirical evidence from institutional experimentation supports the findings of this study. A 2024 study conducted at a prominent Hungarian university reports on a pilot project examining the implementation of an AI-based tutoring system designed to support students' preparation for a master's-level entrance examination in statistics and data analytics [11]. The system provided textbook-level responses with a high degree of accuracy and was primarily used by students as a time-efficient support tool for active learning, conceptual comparison, and self-directed study. These results support the conclusion that AI tutors can effectively complement traditional instruction while reinforcing autonomous and reflective learning behaviors.

Finally, insights from Technology Acceptance research also bring an important motivational factor to the table. In fact, [12] undertakes a comparative research critically examining the key models of Technology acceptance and revealed that only the Value-Based Adoption Model is most likely to account for intellectual user intentions towards AI-related Intelligent Products. Indeed, there are clear indications that enjoyment and social factors are decisive over other skills like utility. As it pertains to Education Settings, it is implied that enjoyment and social value would play an important role for Technology Acceptance.

Furthermore, the effectiveness of pedagogy facilitated by technology is also shown in the work of [13], where it is demonstrated that such pedagogy can be effective within the constraints of practicality, particularly in the use of cost-effective technology to assist in the processes of planning, collaboration, and student production, in relation to the concept of limited resources. Metacognition and lifelong learning also supports the above perspective. Firstly, the concept of secondary school student metacognitive awareness in relation to lifelong learning is shown in a survey [14]. Secondly, attitudes to lifelong learning in relation to language learning in vocational education are shown in the findings [15].

Evidence on self-regulated learning also supports the above findings. In vocational secondary education, large individual differences in goal-setting, persistence, and feedback utilization have been observed, and scaffolding of instruction may be necessary to facilitate the stabilization of effective self-regulation [16]. These studies collectively highlight the importance of a comprehensive approach in technology-rich learning environments.

These studies substantiate the preceding theories by demonstrating, again, that when it comes to the development of critical thinking skills and student achievement in technologically enriched environments, an integrated approach is needed, balancing characteristics such as personalization, innovation, responsibility, and autonomy with support.

3 Methods

3.1 Learning Environment

The study was carried out within the framework of one semester of a mathematics course at a university, with the participating students making use of various artificial intelligence-based tools to assist their learning processes. The various artificial intelligence-based learning and studying tools that were made use of included ChatGPT, Microsoft Copilot, and Gemini [17] [18] [19].

The integration of AI-based tools was implemented across a range of learning scenarios. In some cases, their use was embedded in relatively structured instructional settings aligned with clearly defined learning objectives and tasks. In other cases, students engaged with these tools in more open-ended learning situations, in which they had the autonomy to determine both how and to what extent the tools would be employed. This dual approach afforded students multiple opportunities to reflect on the role and implications of AI use across varying learning contexts. During the entire course, students were required to work in pairs, with the basic unit of learning being collaborative problem-solving. Each pair was required to find a mutually agreed solution to a given problem in mathematics. Though the use of AI-based tools was supported during the task completion, the final solution was always a result of a shared process of interpretation, evaluation, and decision-making.

Such an integration of collaborative work and AI-supported inquiry created a learning environment where "critical thinking" was a crucial factor. In problem-solving, students collectively developed questions for the AI systems, discussed the process of their solution strategy, and collectively interpreted and judged the answers provided by the AI systems themselves. Special attention was given to judging the correctness, relevance, and applicability of the provided information by the AI systems, comparing it with the already formulated mathematical principles and the specific context of the problem.

The processing of AI-generated outputs was therefore not mechanical, but reflective in nature. Students systematically compared the suggestions offered by the AI with their prior knowledge, the mathematical methods covered in the course, and formal solution requirements. In computational tasks, the application of AI-provided information was subject to verification and justification, reinforcing habits of analytical scrutiny and reasoned judgment. This approach supported the development of critical thinking by requiring students to continuously evaluate assumptions, detect potential errors, and justify their conclusions.

Overall, the instructional design of the course provided a complex learning environment in which AI-based tools functioned not as end points of problem-solving, but as cognitive resources embedded within a broader pedagogical framework. Within this environment, the use of artificial intelligence supported the activation and development of students' critical thinking by foregrounding evaluation, reflection, and responsible decision-making as integral components of mathematical problem-solving.

3.2 Questionnaire Design

The methodological framework of the study was built around a structured questionnaire administered both at the beginning and at the end of the semester. The instrument was a self-developed questionnaire based on the Artificial Intelligence Attitude Scale proposed by [20]. The original scale was primarily designed to explore general attitudes, perceptions, and acceptance patterns related to artificial intelligence, with particular emphasis on perceived usefulness, reliability, and societal impact of the technology.

The items of the Grassini scale were adapted to the aims of the present study and complemented with additional questions. These supplementary items focused on the perceived benefits and risks of AI in educational contexts, students' self-assessed understanding of basic AI concepts, and their level of comfort with using AI-based tools. Together, these questions enabled the examination of the extent to which students were able to interpret the role of AI in the learning process in a reflective manner, recognize its limitations, and make informed decisions regarding its use.

Questions addressing potential future applications of AI—such as personalized learning, automated assessment, and chatbot-based instructional support—were interpreted as indicators of technological openness and adaptability. Responses to these items reflect students' receptiveness to innovation and their willingness to engage with emerging forms of learning organization.

In the present study, critical thinking was not treated as a directly measurable competency. Instead, it was operationalized through students' reflective, critical, and adaptive attitudes toward the use of artificial intelligence, as captured by their responses to the questionnaire items related to AI-supported learning.

3.3 Data Collection

Data collection was conducted through an online questionnaire. Prior to completing the questionnaire, students received detailed information about the purpose of the study, the research procedures, and the intended use of the collected data. Participation was entirely voluntary, the questionnaire was completed anonymously, and no personally identifiable information was collected at any stage of the research.

The data collection process adhered to the ethical standards applicable to educational research. Participants were informed of their right to withdraw from the study at any time, and it was ensured that their responses would be used exclusively for research purposes.

The questionnaire was administered at two time points: at the beginning of the semester and at the end of the semester, allowing for the examination of changes in attitudes over time. Data collection took place in the spring of 2025 among students enrolled at a foundation-maintained regional university.

During the first data collection phase, a total of 18 valid questionnaires were obtained, while 16 students completed the questionnaire at the second measurement point. The difference in sample size between the two administrations resulted from the voluntary nature of participation and was taken into account in the interpretation of the findings.

The sample size of the study was limited by the educational context and organizational framework of the course. The research was linked to a specific, one-semester university course with a relatively small total enrollment. Consequently, it was not possible to expand the sample without altering the pedagogical context and interpretive framework of the study.

The aim of the research was not to draw representative conclusions or to develop generalizable statistical models, but rather to conduct an exploratory investigation of an educational practice implemented within a specific learning environment. In this sense, the small sample size should not be interpreted as a methodological limitation, but as a consequence of a context-sensitive research design that enables deeper pedagogical interpretation.

Accordingly, the results are presented in a cautious, descriptive, and interpretive manner. Observed attitude changes and relationships are discussed not as generalizable claims, but as experiences situated within a particular course and student cohort. At the same time, the limited sample size allows for a close alignment between the interpretation of quantitative data and the pedagogical practices of the course, as well as the phenomena observed during the learning process.

The findings of the present study should therefore be regarded primarily as hypothesis-generating. They may serve as a foundation for future research conducted with larger samples, which would allow for the application of more extensive statistical analyses.

Quantitative data were analyzed using descriptive statistical procedures. Responses to individual items were summarized using frequencies, means, and standard deviations, in accordance with the exploratory nature of the study and the size of the sample. The purpose of the analysis was not to draw inferential conclusions, but to illustrate response patterns and changes in attitudes between the two measurement points.

4 Results and discussion

The students participating in the study were drawn from a homogeneous educational context. All were enrolled in the third year of a fulltime undergraduate university program, sharing a comparable level of academic progression and similar age characteristics. The course was conducted in English and brought together an international student cohort, with participants originating from different regions of the world.

The questionnaire did not include demographic items. This decision was based on two considerations. First, within the examined student group, key demographic variables such as age, program type, and year of study were largely uniform, and therefore unlikely to provide meaningful differentiation for the purposes of the study. Second, given the small size and international composition of the cohort, the collection of more detailed demographic data—such as country or region of origin—would have increased the risk of compromising participant anonymity.

The deliberate omission of demographic variables was thus primarily motivated by ethical considerations related to data protection and confidentiality. Accordingly, the focus of the study was not on demographic differences, but on how attitudes toward artificial intelligence and patterns related to critical thinking emerged within a clearly defined learning environment.

The homogeneity of the sample allowed the analysis to concentrate on the learning process itself, the pedagogical role of AI-based tools, and associated changes in student attitudes, without the confounding influence of demographic variability.

The administration of the questionnaire at two time points enabled the examination of how sustained, learning-oriented use of artificial intelligence was associated with changes in students' attitudes and perceptions over the course of the semester. The results reveal several interrelated patterns that can be interpreted through the lens of critical thinking.

The most pronounced change was observed in students' assessment of the potential risks posed by artificial intelligence to humans. The mean score for this item increased substantially to 3.81 (with standard deviation 0.98) from 2.83 (with standard deviation 1.15) by the end of the semester. This shift suggests that regular, guided engagement with AI tools supported not only familiarity with their functionality, but also heightened students' critical sensitivity toward the technology. Within this interpretive framework, the increased perception of risk does not indicate rejection of AI, but rather the emergence of a more nuanced and reflective stance, characteristic of developed critical thinking and responsible evaluation of technological tools.

At the same time, students' intention to use artificial intelligence in the future remained consistently high and showed virtually no change between the two measurement points (mean 4.55 and 4.56, both standard deviations are 0.51). This stability indicates that students continued to perceive AI as a relevant and useful support for learning, even as they became more aware of its potential limitations and risks. The coexistence of sustained use intention and increased risk awareness reflects an ambivalent yet informed attitude, in which acceptance is accompanied by critical judgment.

Perceptions of AI's impact on individual quality of life and academic or work-related effectiveness showed a slight decline (to 4.06 from 4.22); however, these changes were not statistically significant. This trend may indicate that, as a result of their experiences during the semester, students developed a more realistic and less idealized understanding of AI's role in supporting their own performance. Such recalibration is consistent with critical selfreflection, in which technology is viewed as a supportive instrument rather than a universal solution.

In contrast, perceptions of AI's usefulness at the level of society as a whole showed a slight positive shift, although this change did not reach statistical significance. This tendency suggests that students were able to distinguish between individual level uncertainties and broader societal opportunities, reflecting the capacity for multi-perspective reasoning and complex evaluation, both central components of critical thinking.

Students' assessment of the reliability of AI-generated information remained largely unchanged, while their level of comfort in using AI tools increased modestly over the semester. This combination indicates growing confidence in interacting with AI systems alongside the maintenance of a cautious and evaluative stance. Increased comfort coupled with stable reliability judgments suggests that students became more proficient users without relinquishing critical scrutiny.

Overall, the results do not point toward a uniformly positive or negative shift in attitudes, but rather toward the development of a more differentiated and ambivalent relationship with artificial intelligence. The simultaneous presence of high use intention, increasing user confidence, and heightened awareness of risks reflects a pattern of engagement in which critical thinking plays a central role. Within the examined educational context, this pattern suggests that sustained, pedagogically guided use of AI can support the development of reflective, evaluative, and context-sensitive approaches to technology.

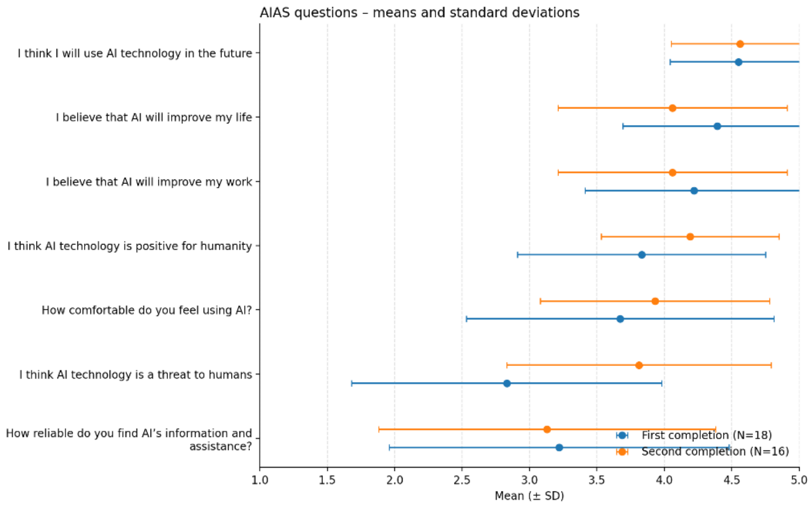

Figure 1. Comparison of AIAS item means (± SD) between the first (N=18) and second (N=16) completions. The plot displays mean responses with horizontal error bars indicating standard deviations. Items are ordered by the average of the two measurement points. The increase on the item "I think AI technology is a threat to humans" is the only change showing a statistically significant difference, while all other differences fall within overlapping variation ranges.

5 Conclusions

The purpose of this study was to examine how students' attitudes and critical thinking develop within an artificial intelligence–enhanced learning environment in a university level mathematics course. The findings indicate that the active, learning focused use of AI does not yield uniformly positive or negative shifts in attitudes; instead, it supports the formation of a more complex and ambivalent stance.

Students maintained a consistently high intention to use AI in the future, yet their awareness of the technology's potential risks to humans increased markedly. This dual pattern suggests that their engagement with AI fostered not only practical, function-oriented learning experiences but also deeper critical reflection. In this regard, the heightened sense of perceived threat should not be taken as a rejection of AI, but rather as evidence of strengthened soft skill dimensions related to critical thinking and the responsible use of technology.

Our findings confirm a fundamental duality in how people perceive artificial intelligence: trust shapes whether they emphasize its transformative benefits or its potential risks. Acceptance is largely determined by the level of trust, the breadth of perceived applications, and individuals' sense of vulnerability [21] [22].

These results are consistent with educational policy perspectives that highlight the growing significance of non-cognitive skills—such as adaptability, self reflection, and the ability to view complex issues from multiple perspectives—in technology rich environments. The ambivalence students expressed may signal the emergence of a mature technological mindset in which openness and critical sensitivity coexist [23].

From a pedagogical standpoint, the findings support the idea that emotional and cognitive engagement are closely intertwined with the quality of learning [24]. Interaction with AI created learning situations that required students to interpret, make decisions, and reflect—roles that align with theoretical frameworks emphasizing intrinsic motivation and deep learning.

Although the study's limitations—most notably the small sample size and the specific course context—restrict the generalizability of the conclusions, the identified trends offer hypothesis generating insights into how higher education may contribute to the development of soft skills in the era of emerging artificial intelligence. Future research could productively investigate similar learning settings with larger cohorts and integrate richer qualitative and longitudinal approaches.

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