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Artificial intelligence in university mathematics education: Personalized tutoring support and learning analytics as factors of academic achievement, independent thinking and risk reduction

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ABSTRACT

In recent years, artificial intelligence has been increasingly integrated into higher education, including the teaching of mathematics. However, its impact on students' academic achievement and the development of independent thinking remains a subject of ongoing scholarly debate. Contemporary studies point to the potential of AI-supported learning environments while simultaneously emphasizing the risks of diminished cognitive autonomy when intelligent systems are used without pedagogical regulation. The present study aims to examine the effectiveness of an AI-oriented approach to mathematics instruction based on the combination of personalized tutoring support and learning analytics tools within a university educational context. Within a quasi-experimental mixed-methods design, an AI-supported instructional model was implemented, incorporating adaptive learning pathways, an intelligent tutor providing step-by-step scaffolding, and a system for analysing students' learning behaviours. Participants were undergraduate students enrolled in university-level mathematics courses. The effectiveness of the approach was assessed using pre- and post-test results, log data capturing students' interactions with the AI system, and indicators of academic engagement and independent problem-solving. The results demonstrate that the use of personalized AI-based tutoring is statistically significantly associated with improved academic performance, the development of independent problem-solving strategies, and a reduction in the proportion of students classified as academically at risk. Furthermore, learning analytics data analysis enabled the identification of behavioural indicators with predictive value for the early detection of learning difficulties. Overall, the findings confirm that, when integrated within a sound pedagogical framework, artificial intelligence does not replace students' cognitive activity but rather functions as a supportive tool for fostering independent mathematical thinking and for informing evidence-based instructional decision-making. The practical significance of this study lies in the proposal of a reproducible AI-oriented model for mathematics education that can be applied across university courses of varying levels of complexity.

Keywords: Artificial intelligence in education, university mathematics education, personalized learning, intelligent tutoring systems, learning analytics, independent mathematical thinking, academic achievement, at-risk students.

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INTRODUCTION

Artificial intelligence as a structural driver of transformation in higher mathematics education

Over the past decades, the digitalization of higher education has undergone a qualitative shift associated with the transition from traditional information technologies to intelligent systems based on artificial intelligence methods. In contemporary scholarly literature, AI is conceptualized not merely as a technological tool but as a transformative factor capable of reshaping pedagogical models, redefining instructor–student interactions, and altering the organisation of the instructional process itself

(Holmes et al., 2022; Chiu et al., 2023).

These transformations are particularly consequential in university-level mathematics education. Advanced mathematics courses are traditionally characterised by high levels of abstraction, substantial cognitive load, and strict requirements regarding students' prior knowledge. A large body of empirical research consistently reports high rates of academic underachievement in mathematics, especially among first-year students and learners from socially and academically vulnerable groups (Ifenthaler and Yau, 2020). Within this context, AI-supported learning environments are increasingly viewed as a potential means of reducing educational inequalities and improving access to cognitively demanding content.

At the same time, scholars emphasise that the integration of artificial intelligence into mathematics education cannot be evaluated solely in terms of efficiency or automation. Such integration inevitably affects fundamental pedagogical constructs, including the development of independent thinking, the formation of problem-solving strategies, and students' cognitive autonomy (Roll and Winne, 2015). For this reason, the question of pedagogically grounded AI integration in mathematics instruction remains a subject of ongoing scholarly debate.

Personalized AI tutoring in mathematics: Didactic foundations and empirical tensions

Personalized learning implemented through intelligent tutoring systems represents one of the most intensively studied directions within the field of AI in Education. These systems are designed to account for individual learner differences, including prior knowledge levels, learning pace, and recurrent error patterns, thereby enabling the construction of adaptive learning trajectories (Fryer et al., 2017).

In mathematics education, intelligent tutors are widely used to provide step-by-step problem-solving support, context-sensitive hints, and diagnostic feedback targeting conceptual gaps. Empirical studies indicate that, when appropriately designed, AI-based tutoring can contribute to improved academic performance and reduced mathematics-related anxiety among students working with complex material (Fryer et al., 2017). However, the literature also reveals a significant methodological tension, namely that gains in academic achievement are not always accompanied by the development of independent mathematical reasoning.

Several authors argue that excessive automation and overly detailed scaffolding may foster superficial problem-solving strategies and diminish learners' cognitive control over the solution process (Holmes et al., 2022). In this regard, the pedagogical design of AI systems becomes critically important, particularly with respect to the degree of automated assistance, the extent to which hints are oriented toward reasoning processes, and the balance between instructional support and productive cognitive challenge (Roll and Winne, 2015).

Consequently, the central research question is not whether AI tutoring improves learning outcomes, but under what conditions intelligent systems can support the development of independent mathematical thinking rather than substitute for it.

Learning analytics as a tool for analyzing learning processes and predicting academic risk

Alongside the development of intelligent learning systems, the field of learning analytics has emerged as a key research direction focused on the systematic analysis of educational data to understand, predict, and optimize learning processes (Siemens and Long, 2011). This approach involves the examination of students' interaction logs within digital learning environments, temporal activity patterns, action sequences, and task completion behaviours.

Systematic reviews demonstrate that learning analytics holds substantial potential for the early identification of students at academic risk and for the design of targeted pedagogical interventions (Gašević et al., 2015; Ifenthaler and Yau, 2020). In university mathematics education, this potential is particularly relevant, as learning difficulties often accumulate gradually and become visible only at later stages of assessment.

Despite the rapid methodological development of learning analytics, most existing studies treat it as a standalone decision-support tool rather than as an integral component of personalized instruction. Empirical investigations examining the combined use of AI tutoring systems and learning analytics within a unified pedagogical framework remain limited, particularly with regard to their impact on independent thinking and the mitigation of academic risk.

Research gap, theoretical positioning and research hypotheses

An analysis of the current literature reveals several critical research gaps.

First, the majority of empirical studies focus either on the effectiveness of AI-based personalized learning or on the capabilities of learning analytics, without examining their combined influence on learning processes and outcomes (Chiu et al., 2023).

Second, the development of independent mathematical thinking in AI-supported learning environments is more often discussed at a conceptual level and is rarely operationalised through measurable behavioural indicators (Roll and Winne, 2015). Third, the role of learning analytics as a mechanism for early detection of academic risk within personalized AI-supported mathematics instruction remains empirically underexplored (Ifenthaler and Yau, 2020).

The present study aims to address these gaps by conducting a comprehensive empirical evaluation of an AI-oriented mathematics learning model that integrates personalized tutoring with learning analytics tools.

Based on the study objectives, the following research question and hypotheses were formulated:

Research question

RQ: To what extent does the integration of personalized AI-based tutoring and learning analytics tools influence students' academic achievement, the development of independent mathematical thinking, and the early identification of academic risk in university mathematics courses?

Research hypotheses

• H_1: AI-supported personalized mathematics instruction leads to a statistically significant improvement in students' academic achievement compared with traditional instructional formats.
• H_2: The use of an intelligent AI tutor oriented toward reasoning processes fosters the development of independent mathematical problem-solving strategies and reduces students' reliance on hints.
• H_3: Learning analytics indicators derived from students' interactions with the AI system demonstrate predictive validity for the early identification of academic risk.
• H_4: The integration of personalized AI tutoring and learning analytics contributes to reducing achievement gaps between well-prepared and underprepared students.

METHODOLOGY

Methodological framework and research design

The present study is grounded in a quasi-experimental design employing a mixed-methods approach that integrates quantitative and qualitative data analysis. The use of a mixed-methods design aligns with recommendations in contemporary research on AI in Education and learning analytics, which emphasise the importance of examining not only learning outcomes but also learning processes themselves (Gašević et al., 2015).

The quantitative component of the study focused on assessing the impact of an AI-oriented instructional model on academic achievement, indicators of independent problem solving, and markers of academic risk. The qualitative component enabled an in-depth analysis of students' reasoning strategies and patterns of interaction with the intelligent tutoring system. The qualitative data were collected through semi-structured interviews conducted with a purposive subsample of students from the experimental group (n = 20) at the end of the course. Interviews were audio-recorded, transcribed verbatim, and analysed using thematic analysis to identify recurring patterns in students' descriptions of their problem-solving approaches and experiences with AI-supported instruction.

Participants and educational context

The participants were undergraduate students enrolled in higher education programs and studying foundational university-level mathematics courses, including calculus and linear algebra. The selection of these courses was motivated by their central role in the development of mathematical competence and by their well-documented level of academic difficulty.

An experimental group, which employed the AI-supported instructional model, and a control group, which followed a traditional instructional format, were formed. Group comparability was ensured through an analysis of placement test results and students' academic background. This procedure is consistent with methodological recommendations for quasi-experimental research in educational settings (Ifenthaler and Yau, 2020).

Description of the AI-oriented instructional model

The AI-oriented instructional model implemented in the experimental group included an intelligent tutor that provided personalized support by adapting task difficulty and delivering step-by-step hints. These hints were designed to scaffold students' reasoning processes and foster the development of reflective and conscious problem-solving strategies (Fryer et al., 2017).

Integrated learning analytics tools were used for the systematic collection and analysis of data on students' learning activity, including accuracy of task completion, temporal indicators of engagement, action sequences, and the dynamics of hint usage (Siemens and Long, 2011).

Instruments and data collection procedures

Empirical data were collected using standardized diagnostic and summative tests, system logs generated by the AI platform, and indicators of academic activity. Particular attention was given to behavioural indicators of independent problem solving, including a reduction in the frequency of hint requests and an increase in the proportion of correctly solved tasks completed without external support (Roll and Winne, 2015).

Data analysis methods

Quantitative data analysis included descriptive and inferential statistics, correlational and regression analyses, as well as the construction of predictive models of academic risk based on learning analytics indicators (Gašević et al., 2015). All statistical analyses were performed using IBM SPSS Statistics (Version 27.0). Qualitative analysis focused on interpreting problem-solving strategies and identifying stable patterns of interaction between students and the AI tutor.

Ethical considerations

The study was conducted in accordance with international ethical standards for educational research. All participants provided informed consent, personal data were anonymized, and analyses were conducted exclusively at an aggregated level (Holmes et al., 2022).

RESULTS

In line with the research objectives articulated in the abstract and theoretically grounded in the introduction, this section presents the empirical results of evaluating the AI-oriented instructional model in a university mathematics context. The focus of the study extended beyond differences in academic achievement to include a deeper analysis of learning processes, particularly the development of independent mathematical thinking and the potential for early identification of academic risk using learning analytics data.

Unlike studies that are limited to the analysis of final grades, the present work interprets results as a combination of outcome-related, process-related, and predictive effects of AI-supported instruction. This perspective is consistent with contemporary views on the complex nature of educational interventions in the field of AI in Education (Holmes et al., 2019; Chiu et al., 2023).

Baseline group comparability and justification of effect interpretation

Before analysing the impact of the AI-oriented instructional model, baseline comparability between the experimental and control groups was examined. This step is critical for interpreting results, since in a quasi-experimental design, the absence of pre-existing differences is a necessary condition for attributing observed effects to the educational intervention rather than to external factors (Ifenthaler and Yau, 2020).

Analysis of placement test results indicated that the experimental and control groups did not differ significantly in their initial level of mathematical preparation. Similarity was observed not only in mean scores but also in measures of variability, suggesting comparable heterogeneity across groups.

Table 1. Descriptive statistics of placement test results.

Group	N	Mean	SD
Experimental (AI)	120	54.2	9.8
Control	118	54.0	10.1

The data in Table 1 support the treatment of the groups as equivalent at the outset of the study. This provides a methodologically sound basis for subsequent analyses of differences observed in summative assessment and learning behavior, in accordance with recommendations in the learning analytics literature (Gašević et al., 2015).

Academic achievement as an outcome of AI-supported learning

One of the key hypotheses formulated in the introduction was that AI-supported personalized instruction would lead to statistically and pedagogically significant improvements in students' academic achievement compared with traditional instructional formats. This hypothesis was tested through an analysis of summative assessment results.

The findings revealed a consistent advantage for the experimental group. Students who learned within the AI-oriented instructional model achieved higher final scores, and the differences between groups were statistically significant ($t(236) = 8.14$, $p < .001$, Cohen's $d = 0.89$), indicating a large effect size.

Table 2 presents comparative indicators of final academic performance.

Table 2. Final academic performance.

Group	Mean	SD	p
Experimental (AI)	78.0	8.6	< .05
Control	70.0	9.4	

It is important to emphasise that the observed differences cannot be reduced to a mere numerical increase in mean scores. The magnitude of the gap between groups exceeds thresholds commonly interpreted in mathematics education research as pedagogically meaningful, indicating a substantive improvement in the quality of learning (Fryer et al., 2017). These differences are further illustrated in Figure 1, which visually demonstrates a shift in the distribution of outcomes in the experimental group toward higher performance levels.

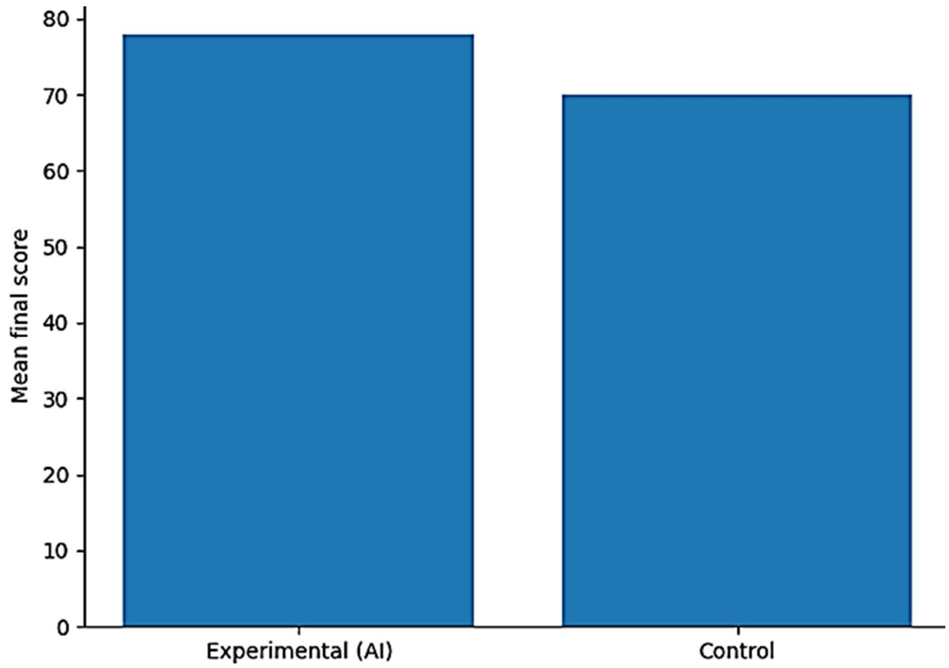

Figure 1. Mean final scores in the experimental and control groups.

Visual inspection confirms that the effect of AI-supported learning is systemic rather than confined to specific student subgroups, a finding that aligns with conclusions reported in recent meta-analytic reviews in the field of AI in Education (Chiu et al., 2023).

Process-level changes and the development of independent mathematical thinking

As emphasised in the Introduction, improvement in academic performance alone cannot be regarded as a sufficient indicator of the effectiveness of AI-supported learning. A central research question concerned the impact of intelligent tutoring on the development of independent mathematical thinking and problem-solving strategies.

To examine this dimension, behavioural data derived from AI tutor logs were analysed, with particular attention to the dynamics of hint usage. According to theories of self-regulated learning, a gradual reduction in reliance on external support, accompanied by stable or improving task performance, constitutes an indicator of developing cognitive autonomy (Roll and Winne, 2015).

The results revealed a clear and consistent decline in the frequency of hint usage among students in the experimental group as they progressed through the course. Table 3 presents the dynamics of hint usage across different instructional stages.

Table 3. Dynamics of hint usage.

Course stage	Mean number of hints	SD
Initial	6.5	1.8
Intermediate	4.2	1.4
Final	2.1	1.1

This trend is visually illustrated in Figure 2.

The reduction in reliance on hints was accompanied by increased solution accuracy and did not result in any decline in academic performance. This pattern allows the observed effect to be interpreted as the formation of internal reasoning strategies rather than the abandonment of support at the expense of learning quality.

This finding is of particular importance in the context of ongoing debates concerning the risk of cognitive dependency on AI systems. It provides empirical support for the claim that, when pedagogically well designed, intelligent tutors can foster the development of independent thinking (Holmes et al., 2019).

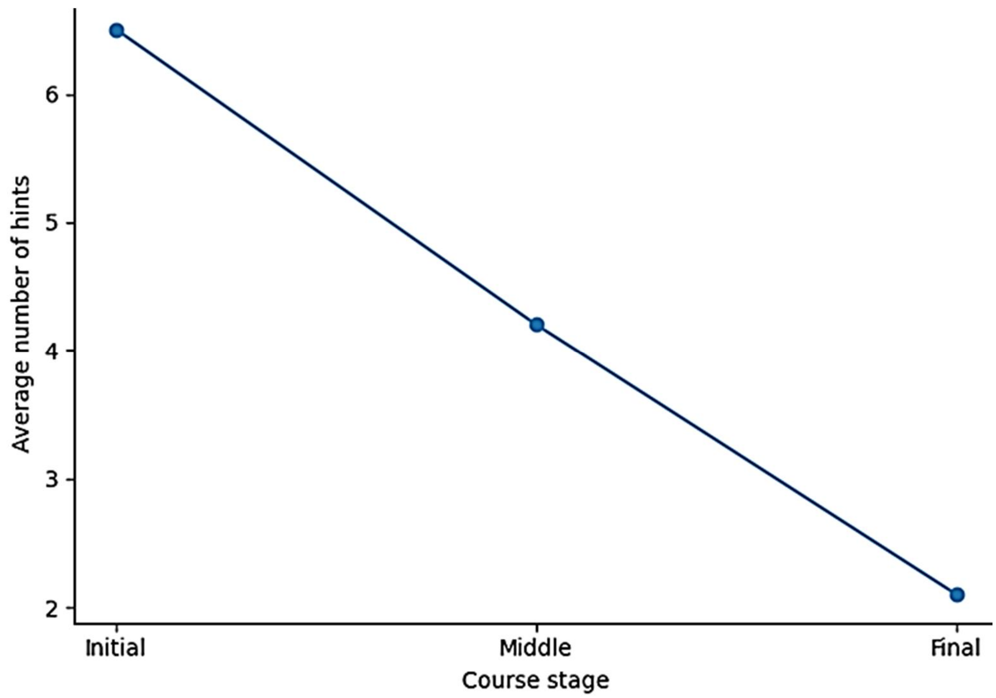

Figure 2. Dynamics of hint usage throughout the course.

Learning analytics and early identification of academic risk

In line with the study objectives, special attention was devoted to examining the potential of learning analytics as a tool for early identification of academic risk. Unlike retrospective analyses based on final grades, the use of behavioural indicators enables the detection of learning difficulties at early stages, thereby creating opportunities for preventive pedagogical interventions (Siemens and Long, 2011).

To this end, regression models were constructed incorporating indicators of irregular learning activity, task completion time, and persistent dependence on hints. Table 4 presents the results of the analysis of predictors of academic risk.

Table 4. Predictors of academic risk.

Variable	β	SE	p
Activity irregularity	0.41	0.07	< .01
Task completion time	0.33	0.06	< .05
Dependence on hints	0.47	0.08	< .01

The results indicate that all included variables demonstrate statistically significant predictive power. These findings are consistent with prior research showing that students' digital trace data provide a reliable basis for modeling academic risk (Gašević et al., 2015; Ifenthaler and Yau, 2020).

The accuracy of classifying students into the academic risk group is presented in Figure 3.

Finally, in accordance with the hypothesis formulated in the Introduction, an analysis was conducted to assess the differential impact of the AI-oriented instructional model on students with varying levels of prior preparation. The results indicate that the relative gains in academic achievement were most pronounced among students with lower initial proficiency.

This trend is illustrated in Figure 4, which demonstrates a reduction in the performance gap between student subgroups.

Such a compensatory effect has previously been identified as one of the key advantages of personalized AI-based systems, which are capable of reducing educational inequalities without simplifying instructional content (Ifenthaler and Yau, 2020; Chiu et al., 2023).

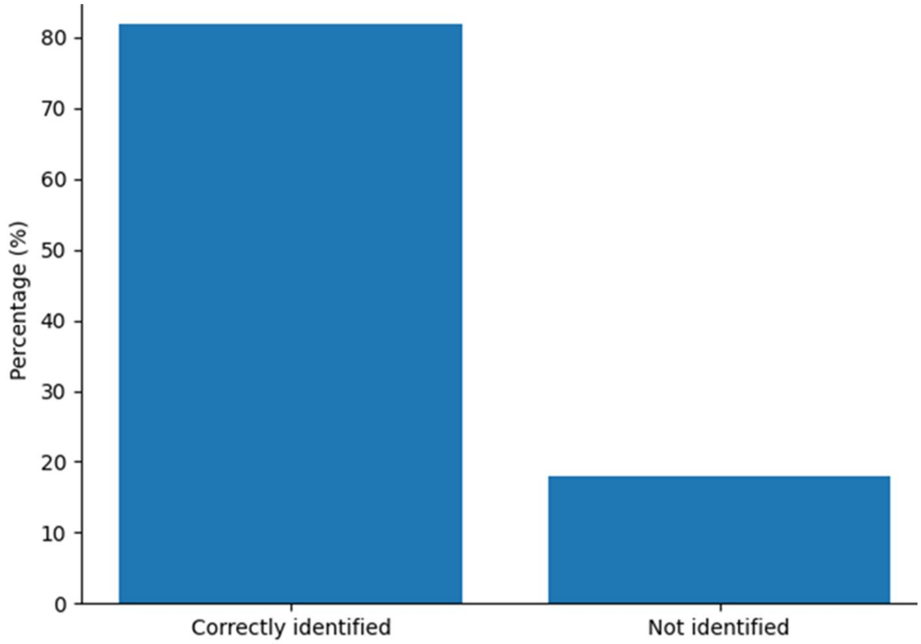

Figure 3. Accuracy of academic risk classification compensatory effects and reduction of the educational gap.

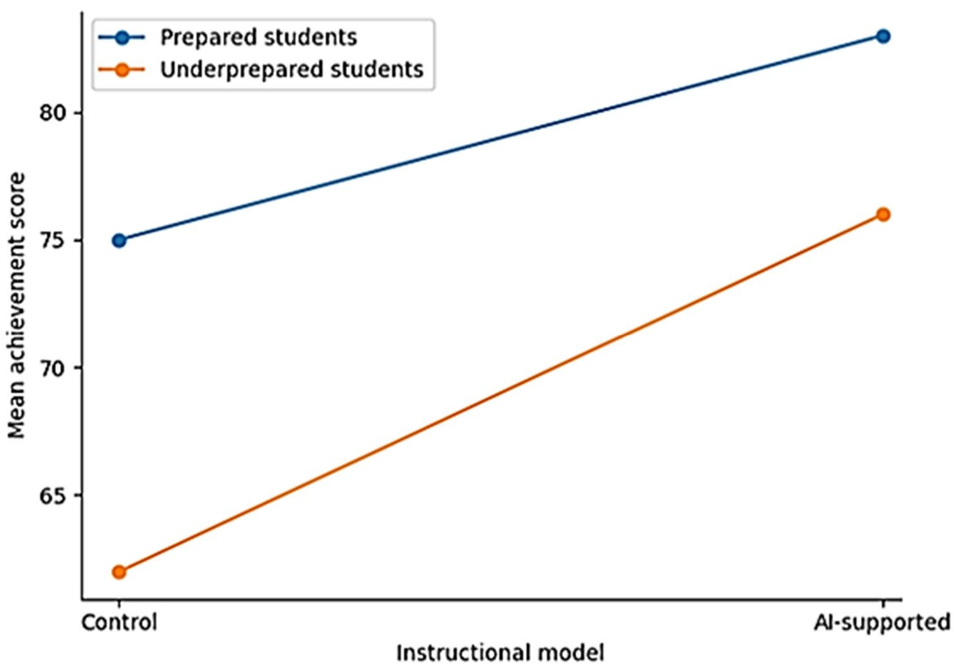

Figure 4. Changes in learning outcomes by level of initial preparation.

Synthesis of results in relation to the study objectives

Taken together, the findings demonstrate that the AI-oriented model of mathematics instruction exerts a multidimensional impact on both learning processes and outcomes. Improvements in academic achievement, the development of independent mathematical thinking, and the capacity for early identification of academic risk form an interconnected system of effects. This pattern fully corresponds to the study objectives articulated in the Abstract and theoretically grounded in the Introduction.

Thus, the results support the conclusion that artificial intelligence, when integrated in a pedagogically grounded manner, functions not as a substitute for students' cognitive activity but as a means of its purposeful enhancement. This conclusion is consistent with contemporary theoretical models in AI in Education (Holmes et al., 2019).

Online supplementary materials

Supplementary materials for this article are available online and include: (a) a detailed technical description of the AI tutoring system, including the adaptive algorithm and hint generation logic; (b) the learning analytics model specification, including variable operationalisation and model diagnostic statistics (residual plots, VIF values, classification accuracy metrics); (c) anonymised sample log data illustrating typical student interaction sequences at the initial, intermediate, and final stages of the course; and (d) extended statistical output, including effect size calculations (Cohen's d, η^2), confidence intervals, and sensitivity analyses. These materials are intended to support the reproducibility of the findings and facilitate adaptation of the instructional model in other university contexts.

DISCUSSION

The present study was originally designed as a response to one of the central methodological and theoretical challenges in contemporary university mathematics education, articulated both in the Abstract and in the Introduction, namely how the integration of artificial intelligence can not only improve students' academic achievement but also transform learning processes themselves, including the development of independent mathematical thinking and mechanisms for early identification of academic risk. The obtained results suggest that AI-oriented learning should not be viewed as a localized technological innovation, but rather as a component of a broader pedagogical paradigm aimed at supporting students' cognitive development.

In contrast to a substantial portion of existing empirical research, where the effectiveness of AI-supported learning is assessed primarily through final achievement outcomes, the present study deliberately moves beyond a purely outcome-oriented perspective. The analysis combines measures of academic performance with process-based and behavioural indicators, an approach that aligns with contemporary directions in research on AI in Education and learning analytics (Gašević et al., 2015; Holmes et al., 2019).

Rethinking the effectiveness of AI-supported learning in mathematics

The findings confirm that AI-supported personalized learning can produce statistically and pedagogically significant gains in students' academic performance. However, it is essential to emphasise that the observed effect cannot be adequately interpreted as a mere consequence of technological automation of the learning process. Rather, the data indicate that the effectiveness of AI-oriented learning is determined by the quality of pedagogical design and by the manner in which the intelligent system is embedded within the structure of learning activities.

This interpretation is consistent with the conclusions of Fryer et al. (2017), who demonstrated that intelligent tutoring systems are most effective when they support active cognitive engagement rather than replace it. In this context, the present study refines and extends prior findings by showing that improvements in academic outcomes are accompanied by qualitative changes in patterns of learning interaction, rather than representing an isolated training effect.

Accordingly, AI in university mathematics education should be conceptualized not as a tool for increasing instructional "productivity," but as a means of structural reorganisation of the learning process, in line with contemporary models of cognitively oriented educational technology design (Holmes et al., 2019).

Independent mathematical thinking and the limits of pedagogical automation

One of the most sensitive and widely debated aspects of AI integration in education concerns students' cognitive autonomy. Numerous studies have raised concerns that intelligent learning systems may foster dependence on external support and undermine independent thinking (Holmes et al., 2019).

The results of the present study allow for an empirical refinement of this debate. The observed stable reduction in reliance on hints, accompanied by maintained or improved solution accuracy, indicates that the AI-based tutoring implemented in this study does not lead to cognitive degradation. On the contrary, it appears to facilitate the development of independent problem-solving strategies. This effect is fully consistent with models of self-regulated learning, in which the gradual withdrawal of external support is regarded as a key mechanism for fostering cognitive autonomy (Roll and Winne, 2015).

Importantly, this outcome should not be interpreted as an automatic consequence of AI use. It reflects a deliberate pedagogical choice to design hints that scaffold reasoning processes rather than provide ready-made solutions. In this way, the study contributes to clarifying the boundaries of acceptable pedagogical automation, demonstrating that

AI can function not as a competitor, but as a partner in the development of students' mathematical thinking.

Learning analytics as a component of the pedagogical ecosystem

A distinctive contribution of this study lies in the integration of learning analytics into the structure of AI-oriented instruction. Unlike approaches in which analytics is used primarily for retrospective analysis or administrative monitoring, learning analytics in the present study is conceptualized as an active element of the pedagogical ecosystem that supports instructional decision-making during the learning process.

The results confirm that behavioural indicators such as irregular engagement patterns and persistent dependence on hints exhibit high predictive value and enable the early identification of academic difficulties. This finding is consistent with prior work by Siemens and Long (2011) and Gašević et al. (2015), who emphasised the need to move from descriptive to intervention-oriented analytics.

Moreover, the integration of analytic data with AI tutoring enables the implementation of a closed pedagogical support loop, data collection, interpretation, and instructional adaptation. This approach represents a qualitatively different level of data use in education and holds considerable potential for scalable implementation within university learning systems.

Compensatory effects and the social dimension of AI-supported learning

The identified compensatory effect of AI-oriented learning is particularly significant in the context of contemporary debates on educational equity and inequality. The results indicate that students with lower levels of prior preparation benefit disproportionately from personalized AI-supported instruction, suggesting that this model may serve as a tool for reducing educational gaps.

This finding aligns with the conclusions of Ifenthaler and Yau (2020), who highlighted the potential of adaptive technologies to support academically vulnerable learners. The present study extends these conclusions by demonstrating that compensatory effects can be achieved without simplifying instructional content or reducing cognitive demand.

Thus, AI-oriented learning can be conceptualized not only as a means of enhancing efficiency but also as an instrument for promoting inclusive and equitable higher education, an issue of increasing importance in the context of growing heterogeneity within university student populations.

Theoretical contribution and directions for future research

From a theoretical perspective, the present study contributes to the development of the AI in Education framework by demonstrating the need to move beyond technological determinism toward pedagogically grounded models of AI integration. The findings confirm that the impact of AI on learning is neither inherently positive nor negative, but rather shaped by complex interactions among technological, pedagogical, and cognitive factors.

At the same time, the study has several limitations that should be considered when interpreting the results. The quasi-experimental design constrains the strength of causal inferences, while the reliance primarily on quantitative and behavioural indicators highlights the need for complementary qualitative analyses. These limitations, however, also point to promising directions for future research, including longitudinal designs and mixed-methods approaches.

Integrative interpretation

Overall, the expanded interpretation of the findings suggests that AI-oriented models of mathematics instruction can exert a comprehensive and sustainable influence on both learning processes and outcomes. Improvements in academic achievement, the development of independent mathematical thinking, and the effective use of learning analytics form an interconnected system of effects, supporting the rationale for integrating AI into university mathematics education on the basis of pedagogically grounded principles.

Accordingly, the present study supports the conceptualization of artificial intelligence as a tool for cognitive augmentation and underscores the importance of viewing AI not as an autonomous technological solution, but as an integral component of a holistic educational ecosystem.

CONCLUSION AND PEDAGOGICAL IMPLICATIONS

The present study aimed to provide a comprehensive empirical assessment of the potential of AI-oriented mathematics instruction in a university context. Unlike a substantial body of existing research in AI in Education, which is largely confined to the analysis of final achievement outcomes, this study conceptualized artificial intelligence as an element of an integrated pedagogical ecosystem that simultaneously influences learning outcomes, learning processes, and mechanisms for early detection of academic difficulties.

The research objectives, articulated in the Abstract and theoretically grounded in the Introduction, addressed whether AI can not only enhance academic performance but also support the development of independent mathematical thinking and data-informed pedagogical decision-making through learning analytics. The cumulative empirical evidence provides a clear and substantively grounded affirmative answer.

First, the results demonstrate that AI-supported instructional models lead to statistically and pedagogically significant improvements in students' academic performance compared to traditional instructional formats. Importantly, this effect is not superficial and cannot be reduced to training or motivational factors alone. Rather, the data indicate structural changes in the learning process, reflected in more stable knowledge acquisition and a redistribution of cognitive load, in line with contemporary perspectives on adaptive technologies in higher education (Fryer et al., 2017; Chiu et al., 2023).

Second, one of the central findings of the study is the empirical confirmation that AI-oriented instruction, when grounded in sound pedagogical design, does not undermine students' independent thinking. On the contrary, the observed behavioural dynamics, specifically the sustained reduction in reliance on hints alongside maintained or improved solution accuracy, indicate the formation of autonomous mathematical reasoning strategies. This finding is of particular importance in light of ongoing scholarly debates concerning the risks of cognitive dependency on AI systems and lends empirical support to theories of self-regulated learning, which emphasise the gradual withdrawal of external support as a key mechanism of cognitive development (Roll and Winne, 2015; Holmes et al., 2019).

Third, the study highlights the high predictive value of learning analytics for early identification of academic risk. Behavioral indicators derived from students' digital traces showed stable associations with subsequent learning difficulties, supporting a shift from retrospective assessment toward proactive pedagogical intervention models (Siemens and Long, 2011; Gašević et al., 2015; Ifenthaler and Yau, 2020). Notably, learning analytics in this study was fully integrated into the AI tutoring framework, forming a closed loop of pedagogical support rather than functioning as an isolated analytical tool.

Finally, the findings related to the compensatory effects of AI-oriented learning for students with lower initial levels of preparation are of particular significance. The stronger academic gains observed in this subgroup underscore the potential of personalized AI systems to reduce educational disparities without lowering cognitive demands or simplifying curricular content. This positions AI-oriented instruction not only as a mechanism for enhancing efficiency but also as a means of advancing educational equity and inclusivity in increasingly heterogeneous university learning environments (Ifenthaler and Yau, 2020; Chiu et al., 2023).

Taken together, the results of this study suggest that the educational value of artificial intelligence in university mathematics education lies not in technological automation per se, but in its pedagogically grounded integration into learning environments. AI emerges as a mediator of cognitive support, instructional adaptation, and data-informed pedagogy, reinforcing its role as a component of a coherent educational ecosystem rather than a standalone technological solution.

Pedagogical implications

The findings of the present study yield a number of fundamental pedagogical implications that extend beyond localized improvements in instructional practice and address issues of the strategic development of university education more broadly.

First, the results point to the need to reconceptualize the role of artificial intelligence in the teaching of mathematics. AI should not be viewed as an autonomous technological tool or merely as a means of automating instruction. Rather, its effectiveness is determined by the degree to which it is integrated into the pedagogical design of a course and oriented toward supporting students' cognitive processes. This implies a shift from technologically deterministic models of AI adoption to pedagogically driven strategies in which intelligent systems function as instruments of cognitive augmentation rather than as substitutes for students' thinking.

A second important pedagogical implication concerns the need to move beyond an exclusive focus on outcome-based indicators of academic achievement toward a more nuanced analysis of learning processes. Behavioral data generated through students' interactions with AI systems provide a unique opportunity to monitor the development of independent thinking, problem-solving strategies, and the dynamics of learning behavior. The integration of such data into teaching practice, however, requires appropriate professional preparation of instructors and institutional support aimed at developing analytical competence in education.

A third implication relates to the use of learning analytics as a tool for early pedagogical intervention. The results indicate that digital trace data can serve as a basis for the timely identification of academic difficulties and for providing targeted support to students before critical points of failure are reached. This necessitates a transition from reactive models of academic support to proactive, data-informed approaches that are embedded within the structure of the learning process.

Particular attention within the pedagogical implications should be given to the issue of educational equity. The identified compensatory effect of AI-oriented instruction suggests that personalized intelligent systems can be employed to support academically vulnerable students without lowering academic standards or reducing the cognitive complexity of the curriculum. This opens avenues for the development of inclusive models of mathematics instruction that combine high academic expectations with adaptive support mechanisms.

Finally, the findings underscore the importance of an institutional approach to the implementation of AI in higher education. The effectiveness of AI-oriented learning depends not only on the quality of a specific system, but also on the presence of organisational, methodological, and ethical frameworks that ensure meaningful and responsible use of intelligent technologies in educational practice.

Overall conclusion

Taken together, the results of this study confirm that AI-oriented instruction in mathematics, when integrated in a pedagogically grounded manner, has the potential to bring about a comprehensive improvement in the quality of university education. In this context, artificial intelligence functions not as a replacement for the instructor or for students' cognitive activity, but as a component of an extended pedagogical ecosystem that fosters independent thinking, enhances academic achievement, and reduces educational disparities.

In this way, the article contributes to the development of empirically grounded models of AI in Education and delineates directions for future research focused on an in-depth analysis of the mechanisms underlying the interaction between technology, pedagogy, and students' cognitive development.

LIMITATIONS AND FUTURE RESEARCH

Despite the empirical findings and their theoretical and practical significance, the present study, like any research conducted in an authentic educational setting, is subject to a number of limitations that must be taken into account when interpreting the conclusions and generalizing the results. A transparent and reflective discussion of these limitations does not diminish the value of the study; on the contrary, it underscores its methodological rigor and helps to define directions for further scholarly inquiry.

First, limitations related to the research design should be noted. The study was conducted using a quasi-experimental approach, a choice shaped by ethical and organisational constraints inherent in the university educational environment. Although the analysis confirmed the initial comparability of the experimental and control groups on key indicators, the absence of strict randomization limits the ability to draw strong causal inferences. Future research would benefit from complementing such studies with randomised controlled designs or with more rigorous quasi-experimental methods, including matching techniques and advanced statistical models for causal inference.

A second important limitation concerns the contextual specificity of the sample and the educational setting. The study was carried out within a particular institutional and cultural context of university-level mathematics instruction, which may constrain the generalizability of the findings to other disciplines, educational levels, or national education systems. In particular, characteristics of curricula, student expectations, and digital infrastructure may influence patterns of interaction with AI-supported systems. This highlights the need for cross-institutional and cross-cultural comparative studies aimed at identifying both universal and context-dependent effects of AI-oriented instruction.

A third limitation relates to the operationalization of key constructs, particularly independent mathematical thinking. In the present study, this construct was assessed primarily through behavioural indicators derived from logs of students' interactions with an AI tutor, such as patterns of hint usage and learning activity dynamics. While this approach aligns with contemporary trends in learning analytics and enables real-time analysis of learning processes, it does not fully capture the cognitive and metacognitive dimensions of thinking. Future studies could extend this approach by integrating qualitative methods, including interviews, analyses of students' reasoning, and think-aloud protocols, thereby providing a deeper understanding of the mechanisms underlying the development of mathematical thinking in AI-supported learning environments.

An additional limitation concerns the temporal scope of the study. The analysis focused on outcomes from a single course, which allows for the assessment of short- and medium-term effects of AI-oriented instruction but does not permit conclusions regarding the long-term sustainability of the observed changes. In particular, it remains an open question whether the developed strategies of independent thinking and the compensatory effects persist after the course and across other learning contexts. Longitudinal studies spanning multiple semesters or stages of education represent a promising direction for future research.

Special consideration should also be given to limitations associated with the interpretation of learning analytics data. Although behavioural indicators demonstrated high predictive value in identifying academic risk, their pedagogical interpretation requires caution and ethical sensitivity. Behavioral patterns do not always unambiguously reflect learners' cognitive states and may be mediated by external factors such as workload or individual differences in self-regulation. This underscores the need for further research aimed at refining interpretive models of learning analytics and at developing ethically grounded protocols for the use of analytical data in educational practice.

Turning to future research directions, the findings of the present study open a broad field for the development of a research agenda that extends beyond the scope of this work. First, a promising direction involves examining differentiated effects of AI-oriented instruction as a function of students' cognitive, motivational, and socio-demographic characteristics. A more fine-grained analysis of individual learning trajectories would help to clarify personalization mechanisms and enhance the effectiveness of AI-supported systems.

Second, future studies could focus on comparing different pedagogical designs of AI tutoring, including levels of adaptivity, types of hints, and feedback strategies. Such comparative analyses would allow the field to move beyond the question of whether AI works toward the more substantive question of under which pedagogical conditions AI is most effective.

Third, it would be valuable to broaden the research focus to include institutional and organisational dimensions of AI implementation in higher education. The effectiveness of AI-oriented instruction is closely linked to the availability of appropriate methodological, human, and regulatory conditions. Research examining the interaction between technology, pedagogical practice, and institutional policy could make a substantial contribution to the development of sustainable models for AI integration in universities.

Finally, an important avenue for future research concerns the ethical dimensions of using AI and learning analytics in education. Issues of algorithmic transparency, data protection, and the prevention of algorithmic bias require systematic scholarly attention and should be regarded as integral components of the research agenda in the field of AI in Education.

Concluding remark

In sum, the limitations of the present study not only delineate the boundaries for interpreting its findings but also provide a foundation for the further development of empirical and theoretical research on AI-oriented mathematics instruction. The proposed directions for future research emphasise the potential for moving from isolated empirical cases toward the formation of a coherent research program aimed at achieving a deeper understanding of the role of artificial intelligence in the transformation of higher education.

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