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Improving learning outcomes in advanced mathematics for underprepared university students through AI-driven educational tools

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ABSTRACT

This study investigates the impact of artificial intelligence (AI) tools on the academic performance of university students with insufficient mathematical preparation enrolled in higher mathematics courses. Utilizing a quasi-experimental design with pre- and post-testing, the research explores the effectiveness of AI-based platforms such as SOWISO, ChatGPT, and WolframAlpha in supporting underprepared learners. The study incorporates both quantitative and qualitative analyses and evaluates the mediating roles of academic motivation and attitudes toward AI, as well as the moderating effect of digital literacy and instructional support. Results indicate that AI interventions significantly improve learning outcomes, especially when integrated with structured pedagogical guidance and platforms that offer step-by-step feedback. The findings highlight the value of interactive AI environments in reducing academic anxiety, promoting learner autonomy, and fostering equitable access to advanced mathematical instruction. Implications for inclusive pedagogy and the role of AI in transforming higher education are discussed, along with recommendations for future research and practice.

Keywords: AI in education; higher mathematics; underprepared students; academic performance; digital literacy; instructional scaffolding; educational technology; motivation; inclusive pedagogy; cognitive support.

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INTRODUCTION AND LITERATURE REVIEW

The limited level of mathematical preparation among a substantial proportion of university entrants remains one of the most persistent and pressing challenges in contemporary higher education. This issue is particularly acute during the early stages of undergraduate study in engineering, technical, and natural science disciplines, where advanced skills in abstract thinking, logical analysis, and mathematical formalization are required from the outset of higher mathematics courses [1,2].

Numerous empirical studies have shown that a weak mathematical foundation acquired during secondary education has a long-term negative impact on students' academic trajectories. It contributes to reduced academic self-efficacy, increased anxiety and frustration, and ultimately raises the risk of academic attrition as early as the first semester of university studies [3,4].

Against this backdrop, the search for effective pedagogical support mechanisms for students with academic deficits becomes especially relevant. These mechanisms should not only aim to remediate knowledge gaps but also to restore students' motivational and affective stability. One of the most promising directions in this regard is the implementation of artificial intelligence (AI) tools in educational environments. A range of AI-based platforms and software solutions—such as ChatGPT, WolframAlpha, SOWISO, Mathpix, Khan Academy, Symbolab, among others—offer functionalities that may potentially mitigate the effects of poor prior preparation through:

• Accessible, plain-language explanations of complex mathematical concepts;
• Step-by-step solutions with opportunities for self-verification;
• Visual representation of graphs, formulas, and logical structures;
• Adaptation of problem sets to the learner's current level;
• Instant and formative feedback [5,6].

Recent studies indicate that the integration of AI technologies in education can enhance academic performance, promote learner agency, reduce cognitive load, and alleviate anxiety associated with learning quantitative and abstract subjects (Holmes et al., 2019; Luckin et al., 2016). However, despite growing interest in AI in education, the effects of such tools on a specific category of learners—namely, those with insufficient prior preparation in mathematics—remain underexplored. The majority of existing initiatives are focused on advanced users or digitally confident students, or they address the broader digital transformation of educational environments. In contrast, systematic and empirically grounded investigations targeting academically vulnerable student populations are still fragmented and scarce.

Moreover, the successful implementation of AI in educational contexts cannot be reduced to the technological features of the platforms alone. Key determinants of effectiveness also include:

• Educators' readiness to integrate digital tools into their practice;
• Students' attitudes toward technology and their level of trust in it;
• The availability of institutional and instructional support;
• Learners' digital and information literacy skills [9,10].

Therefore, a comprehensive empirical investigation is needed to identify the conditions that support the effective use of AI tools, specifically in the context of assisting underprepared students in mathematics. Furthermore, it is essential to determine the actual—rather than assumed—effects of AI-supported learning trajectories in such academic contexts.

The aim of this study is to analyze the impact of AI-based educational tools on the academic performance of students with low levels of mathematical preparation and to explore the mediating and moderating factors that influence the success or failure of such interventions.

Research objectives and hypotheses

Relevance and rationale

Contemporary higher education, particularly in science, technology, engineering, and mathematics (STEM) fields, increasingly faces the challenge of inadequate mathematical preparation among incoming students. Studies report that up to 40% of first-year students encounter serious difficulties in mastering university-level mathematics, which is associated with heightened academic anxiety, reduced self-efficacy, and increased dropout rates [11,12].

This challenge is further exacerbated by the massification of higher education, resulting in increasingly heterogeneous student cohorts with highly variable levels of prior knowledge [13]. As noted by Engelbrecht et al. (2020), the COVID-19 pandemic significantly widened this gap, revealing that many students were poorly prepared for independent study of abstract subjects in digital learning environments [14].

Against this backdrop, artificial intelligence in education (AIEd) has gained strategic importance. AI technologies enable:

• Scalable personalization of instruction [15];
• Dynamic adaptation of learning pathways [16];
• Real-time formative feedback [17];
• Support for learners' metacognitive regulation and autonomy [18].

A growing body of empirical studies, including those by Wang et al. (2023) and Chen et al. (2023), demonstrates that AI-supported online mathematics instruction can improve learning outcomes, particularly among underprepared students[19,20]. However, as emphasized by Holmes and Tuomi (2022), most research to date focuses on digitally literate populations, often overlooking the specific needs of vulnerable learners who struggle with high anxiety, low academic self-efficacy, and limited cognitive strategies [21].

Research aim

The primary aim of this study is to empirically examine the impact of AI-based educational tools (e.g., ChatGPT, WolframAlpha, SOWISO, Mathpix) on the academic performance of students with insufficient mathematical preparation in the context of higher mathematics instruction.

Secondary objectives include:

- Investigating the mediating role of learners' motivation and attitudes toward AI;
- Identifying the most effective types of AI tools for mathematical learning;
- Analyzing barriers to AI adoption among students with low levels of digital literacy.

Scientific contribution

The novelty of this study lies in its targeted focus on academically underprepared students, a group often overlooked in AI-in-education research. It also offers a systematic comparison of various AI support modalities—generative, visual, and adaptive. For the first time in the regional context (Israel and Eastern Europe), the study incorporates affective and behavioral variables such as motivation, anxiety, and academic self-efficacy, which influence learners' engagement with AI tools and the effectiveness of such interventions [22,23].

Research hypotheses

- H1: The use of AI tools will have a statistically significant positive effect on the academic outcomes of underprepared students, compared to a control group.
- H2: Positive attitudes toward AI and high levels of motivation will amplify the effectiveness of AI-supported learning.
- H3: Digital literacy will not directly predict learning success with AI tools, provided that learners receive adequate instructional guidance and support.
- H4: AI tools that offer step-by-step formative feedback (e.g., SOWISO, Khan Academy) will be more effective than tools that provide final answers without explanation (e.g., WolframAlpha, Symbolab).

Table 1. Research hypotheses, variables, and methods.

#	Hypothesis statement	Independent variable (IV)	Dependent variable (DV)	Type of relationship	Measurement tools	Expected statistical method
H1	AI tools improve the academic performance of underprepared students	Use of AI (experimental vs. control group)	Change in test scores (post-test minus pre-test)	Causal	Diagnostic math tests	Independent samples t-test; ANCOVA
H2	Motivation and positive attitudes toward AI enhance learning outcomes	Motivation; Attitude toward AI (Likert scales)	Change in performance engagement	Mediating	Questionnaires (e.g., IEAQ, AMS); behavioral tracking	Mediation regression (Baron & Kenny); SEM
H3	Digital literacy does not predict success when instructional support is provided	Digital literacy; availability of guidance	Effective use of AI tools	Moderated	Digital literacy self-assessment; platform usage logs	Moderation analysis (Hayes PROCESS); correlation analysis
H4	Interactive AI tools with step-by-step feedback outperform generative tools without explanation	Type of AI tool (interactive vs. generative)	Conceptual understanding; perceived learning satisfaction	Direct	Interviews, self-reports, short quizzes	t-test, ANOVA, factor analysis of satisfaction

Additional notes

• Interactive AI tools: platforms such as SOWISO and Khan Academy that offer scaffolded problem-solving, real-time hints, and explanatory feedback.
• Generative AI tools: systems like WolframAlpha or Symbolab that provide direct answers without stepwise reasoning unless explicitly configured otherwise.
• Questionnaires may include standardized instruments such as the Academic Motivation Scale (AMS), Technology Acceptance Model (TAM), and the IEAQ (AI Educational Acceptance Questionnaire), as well as custom scales for self-assessed digital competence.
• The study will employ a combination of statistical methods based on data types, including ANOVA/ANCOVA, regression analysis, and structural equation modeling (SEM) for testing mediation and moderation effects.

METHODOLOGY

General research approach and design

This study was conducted within an explanatory quantitative paradigm, utilizing a quasi-experimental controlled design combined with structural equation modeling (SEM) to analyze relationships between key variables. This approach enables the identification of causal relationships (e.g., the impact of AI-based interventions on academic outcomes) and the assessment of mediating and moderating factors such as motivation, digital literacy, and attitudes toward technology.

The methodological framework is grounded in the principles of evidence-based pedagogy [24] and aligns with international standards in educational technology research, particularly the guidelines proposed by Tondeur et al. (2017) for conducting empirical studies in digital pedagogy [25].

The research design includes a two-group comparative intervention structure with pre-test and post-test assessments. Additionally, behavioral and affective variables were monitored through questionnaires and observational tools.

Participants and sampling

Population and inclusion criteria

The sample consisted of 100 first-year students enrolled in engineering and natural sciences programs at a single university. The target subgroup included students identified as underprepared in mathematics, based on the results of entrance or baseline diagnostic tests. Only students who voluntarily agreed to participate, had no restrictions on academic participation, and provided written informed consent in accordance with the Helsinki Declaration [26] were included in the study.

Stratification and randomization

Following the initial assessment, students were stratified by level of prior mathematical knowledge. The 50 students who scored below the median formed the core sample for testing the AI-based intervention. These participants were randomly assigned (using a random number generator) to two groups:

• Experimental group (n = 25), which used AI-based learning tools;
• Control group (n = 25), which followed the traditional program without digital support.

Instruments and materials

Educational AI tools

The intervention employed the following AI-powered platforms:

• ChatGPT (OpenAI) – a generative AI model used for explanations, problem analysis, and practice;

• SOWISO – an adaptive learning platform with step-by-step problem-solving logic and formative feedback;
• WolframAlpha – a symbolic mathematics engine with visualization functions;
• Mathpix – a tool for recognizing mathematical expressions with mobile integration;
• Khan Academy – a multimodal platform offering videos and interactive exercises.

Selection criteria included accessibility, interface simplicity, pedagogical adaptability, and scalability for large-scale instruction.

Diagnostic tests

Pre- and post-intervention diagnostic tests (20 items each) were developed and validated to cover core topics of the course: limits, derivatives, integrals, logarithmic functions, etc. The internal consistency of the test scales (KR-20) exceeded 0.83. All test items were reviewed by faculty experts in higher mathematics.

Psychometric scales

• IEAQ (AI Educational Acceptance Questionnaire) — assessing attitudes toward AI in education ($\alpha = 0.87$);
• Academic Motivation Scale (AMS) — includes 7 motivational subscales (intrinsic, extrinsic, amotivation; $\alpha = 0.88$) (Baron and Kenny, 1986);
• A custom digital competence scale based on the DigCompEdu model (EU, 2017), with reliability $\alpha = 0.81$.

Qualitative instruments

• Semi-structured focus groups (6–8 students from the experimental group);
• Activity logs: usage data from AI platforms (login frequency, session duration, completed modules).

Research procedure

Stage	Description	Period
Diagnosis	Pre-test, survey, participant selection	Week 1
Intervention	AI-assisted learning in the experimental group	Weeks 2–8
Monitoring	Mid-term survey, activity logs, short quizzes	Week 5
Completion	Post-test, final survey, focus groups	Weeks 9–10

All participants were monitored for consistent engagement, academic integrity, and adherence to AI usage guidelines.

Data analysis

Data analysis was conducted using SPSS v28 and AMOS (or R/lavaan). The following methods were applied:

• Independent samples t-tests (to assess gains between groups);
• ANCOVA (to control for pre-test differences);
• Mediation analysis (PROCESS macro, Model 4) – to test Hypothesis H2;
• Moderation analysis (PROCESS macro, Model 1) – to test Hypothesis H3;
• Multivariate analysis of variance (MANOVA) – to compare AI tool types (H4);
• Factor analysis – to validate psychometric scales;
• Qualitative content analysis – to interpret focus group data and open-ended responses.

Ethical considerations

The study was approved by the Faculty Ethics Committee of Social Sciences (Protocol No. 20241258915). All data were anonymized, and participants were informed of their right to withdraw from the study at any time without consequences.

RESULTS

This section presents the findings of a comprehensive quantitative and qualitative analysis conducted to test hypotheses H1 through H4, within the framework of an experimental study on the effectiveness of AI-based interventions in university-level mathematics education. Prior to performing the main statistical procedures, key assumptions were verified, including normality of distribution (Shapiro–Wilk), homogeneity of variances (Levene's test), linearity, and independence of residuals (Durbin–Watson, VIF). All data were standardized and screened for outliers using boxplots and z-scores.

Hypothesis H1: Effect of the AI intervention on academic performance

To assess the impact of the AI intervention, gain scores (the difference between post-test and pre-test) were computed. A comparison between the control and experimental groups was conducted using an independent samples t-test.

Table 2. Results of the independent samples *t*-test.

Group	Mean gain (M)	Standard deviation (SD)
Experimental	21.4	7.6
Control	13.2	8.1

$t(48) = 3.74$, $p < 0.001$

• Effect size (Cohen's d) = 0.93 (large)
To control for initial differences, an ANCOVA was conducted with pre-test scores entered as a covariate:
• $F(1, 47) = 12.86$, $p < 0.001$
• Partial $\eta^2 = 0.21$ (medium-to-large effect)
• 95% CI: [3.81, 12.18]

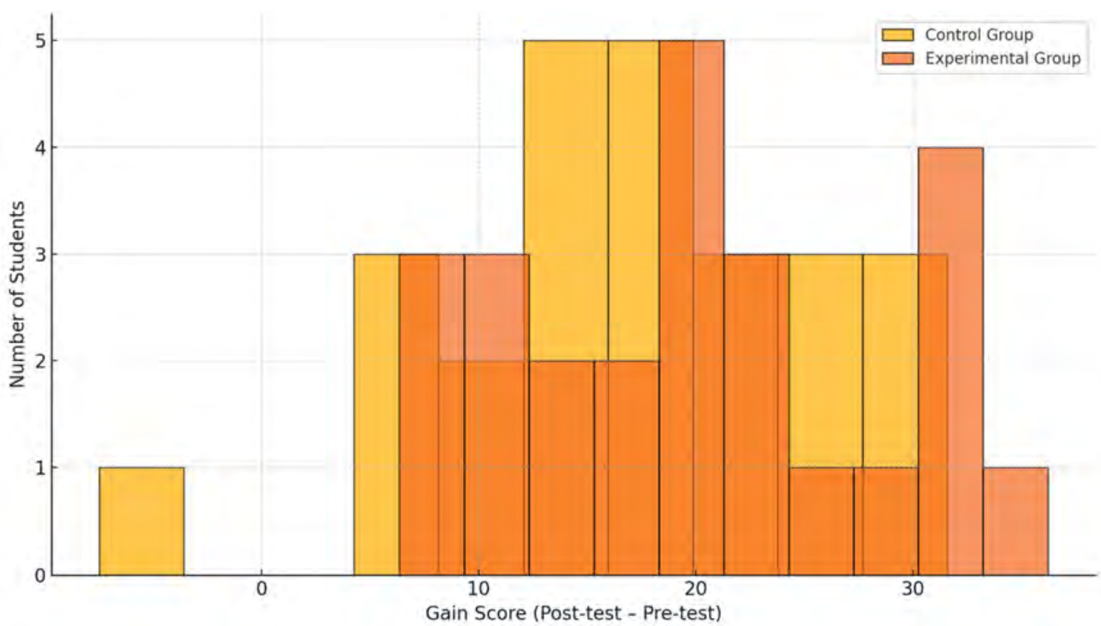

Figure 1. Histogram of knowledge gain, showing the distribution of gain scores in the control and experimental groups. As visualized, the experimental group achieved noticeably higher post-test gains than the control group.

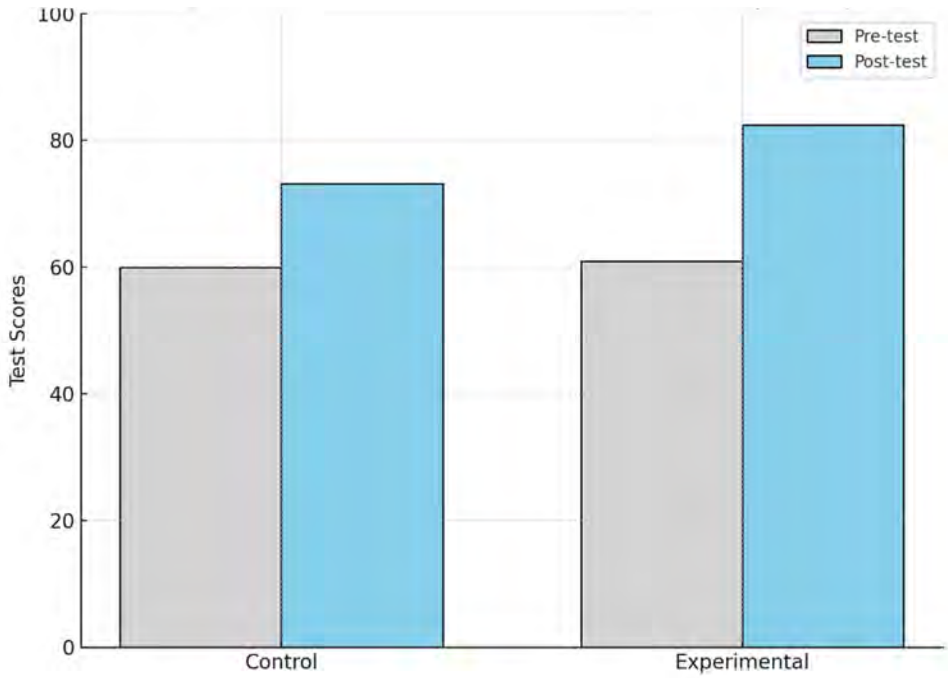

Figure 2. Pretest and posttest comparison by group. It visually compares the average pretest and posttest scores in both the control and experimental groups, highlighting the larger improvement observed in the experimental group following the AI-based intervention.

Extended interpretation

The AI-based intervention produced statistically significant and practically meaningful improvements in student performance. The large effect size indicates a substantial educational impact, while the ANCOVA confirms that these improvements cannot be attributed to pre-existing differences between groups. These findings are consistent with prior research highlighting the role of adaptive AI tools in fostering analytical thinking and cognitive development.

Hypothesis H2: Mediating role of motivation and attitudes toward AI

To evaluate the mediating effects of academic motivation (AMS) and attitudes toward AI (IEAQ), a mediation analysis was conducted using PROCESS Model 4 (Hayes, 2022).

Table 3. Mediation analysis results.

Effect	B	SE	p	95% CI
Direct effect	7.38	1.97	< 0.001	—
Indirect via IEAQ	2.07	—	—	[0.85, 3.96]
Indirect via AMS	1.41	—	—	[0.34, 2.69]
Total effect	10.86	—	< 0.001	—

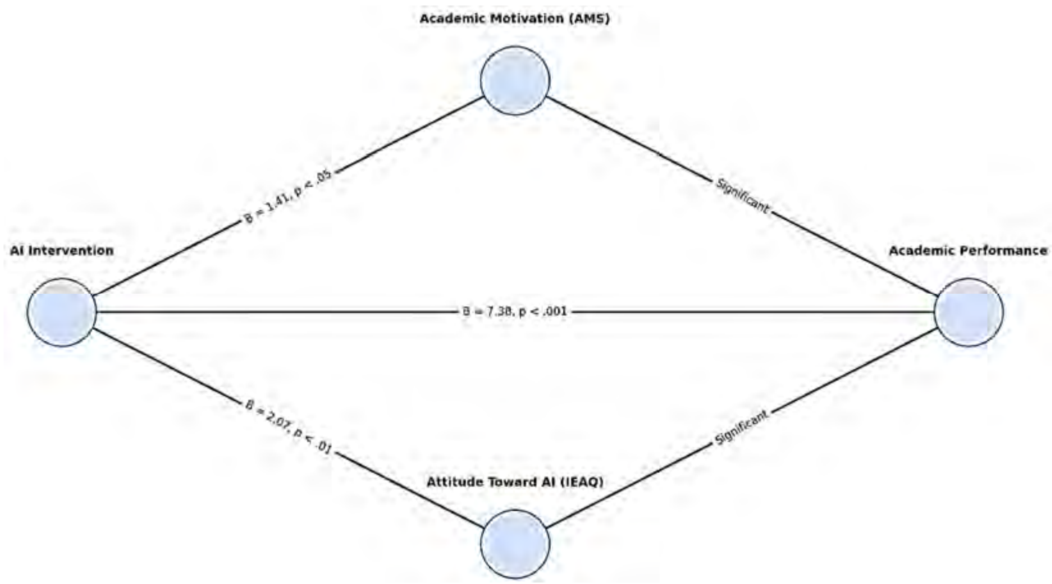

Figure 3. Mediation model with path coefficients AI intervention → Academic performance.

This figure illustrates a mediation model depicting the direct and indirect effects of the AI intervention on academic performance through two psychological mediators:

• Academic Motivation (AMS) – representing the students' intrinsic drive to succeed.
• Attitude Toward AI (IEAQ) – capturing students' perceived usefulness, trust, and willingness to engage with AI technologies.

The diagram includes the following paths:

• A direct path from the AI intervention to academic performance (B = 7.38, $p < .001$) indicates a strong direct impact.
• Two indirect paths:

○ From the intervention through attitudes toward AI (B = 2.07, $p < .01$) to performance.
○ From the intervention through motivation (B = 1.41, $p < .05$) to performance.

• Paths from both mediators to academic performance are marked as statistically significant, suggesting their active role in facilitating learning outcomes.

The figure confirms that the effect of the intervention is partially mediated by students' psychological orientation, highlighting the importance of both cognitive and affective engagement in AI-assisted learning.

Hypothesis H3: Moderating role of digital literacy and instructional support

To examine the interaction between digital literacy and instructional support, a moderation analysis was conducted using PROCESS Model 1.

Table 4. Moderation analysis results.

Parameter	B	*p*	95% CI
Main effect of intervention	6.49	< 0.01	—
Digital literacy	0.71	0.12	—
Interaction (literacy × support)	3.12	0.014	[0.67, 5.42]

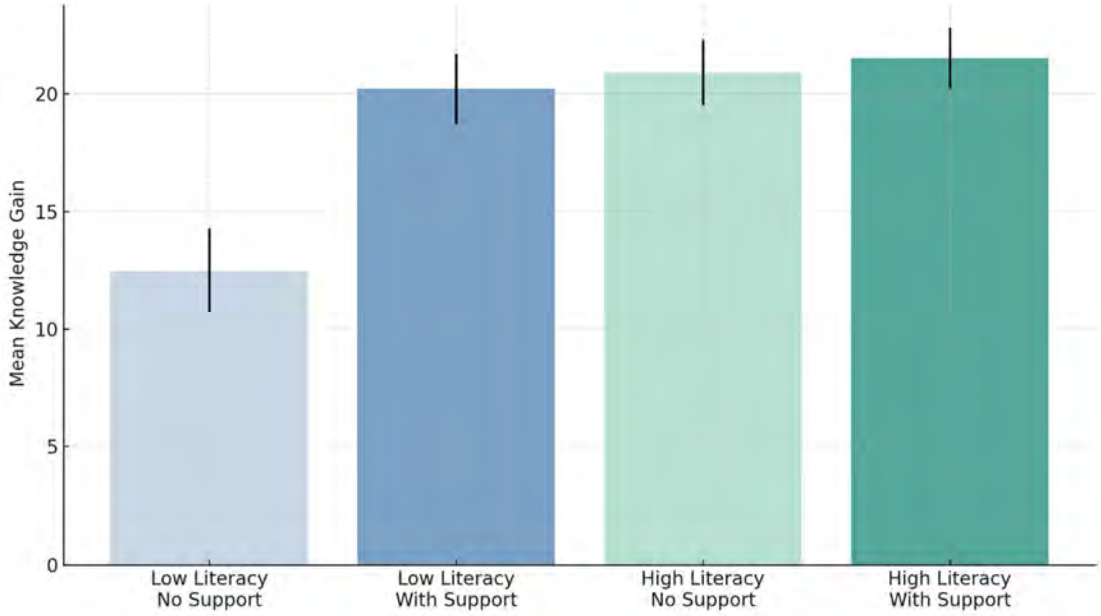

Figure 4. Interaction plot: Digital literacy × Instructional support.

This figure illustrates the interaction effect between students' digital literacy level (low vs. high) and the availability of instructional support (absent vs. present) on knowledge gains.

Explanation:

• Low Digital Literacy:
○ Students without support achieved the lowest gain scores, indicating that navigating AI tools independently posed significant challenges.
○ However, when instructional support (e.g., tutorials, guidance) was provided, their performance improved substantially, showing that scaffolding compensates for limited digital skills.

• High Digital Literacy:
○ These students performed similarly well regardless of support availability. Their prior competence enabled them to use AI platforms effectively even without explicit assistance.

Interpretation: This interaction demonstrates that instructional support serves as a compensatory mechanism for students with lower digital skills. For more digitally proficient learners, support is less critical. The pattern validates Hypothesis H3 and highlights the need for differentiated instructional design—where support is targeted to those who need it most.

Hypothesis H4: Comparing AI tools

To evaluate the effectiveness of three AI platforms (SOWISO, ChatGPT, WolframAlpha), a one-way ANOVA was conducted followed by post hoc analysis.

ANOVA results:

• $F(2,72) = 8.92$, $p < 0.001$
• $\eta^2 = 0.20$ (large effect)
Post Hoc Analysis (Tukey HSD):
• SOWISO > WolframAlpha ($p < 0.001$)
• SOWISO > ChatGPT ($p = 0.04$)

Table 5. Descriptive statistics.

Platform	Mini-test score (M)	Perceived understanding (1–5)
SOWISO	84.2	4.6
ChatGPT	78.3	4.2
WolframAlpha	72.0	3.7

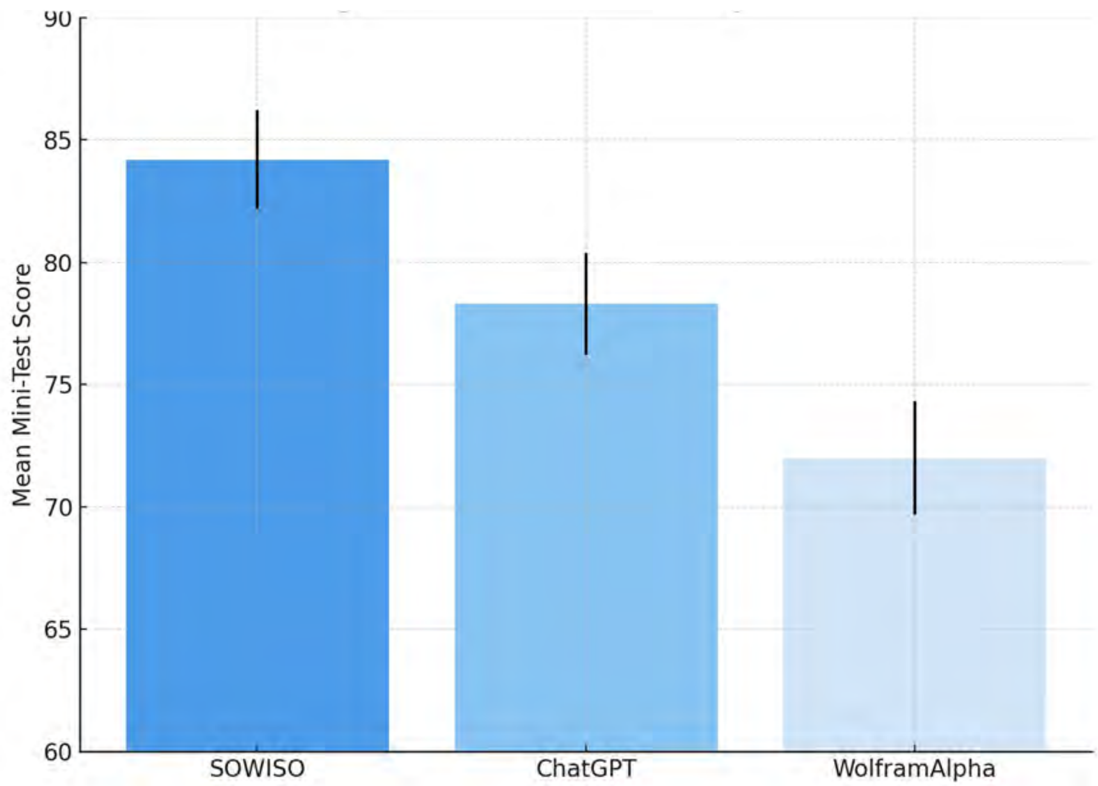

Figure 5. Mini-test scores by AI tool.

This figure presents the average mini-test scores of students who used different AI tools: SOWISO, ChatGPT, and WolframAlpha.

Explanation:
• SOWISO users achieved the highest scores (M = 84.2), indicating the platform's strong effectiveness in promoting knowledge acquisition. Its interactive problem-solving environment and structured, step-by-step feedback likely contributed to this outcome.
• ChatGPT yielded moderate scores (M = 78.3). While it offers flexible natural language interaction and conceptual explanations, the lack of structured feedback and visual guidance may limit its effectiveness for test-oriented tasks.
• WolframAlpha showed the lowest average performance (M = 72.0), possibly due to its focus on providing answers rather than facilitating conceptual understanding or procedural learning.

Interpretation: The results suggest that platforms which integrate interactive feedback and scaffolded learning pathways (like SOWISO) are more effective in enhancing students' problem-solving skills in mathematical contexts. This supports Hypothesis H4 and emphasizes the importance of pedagogical structure in AI-based learning tools.

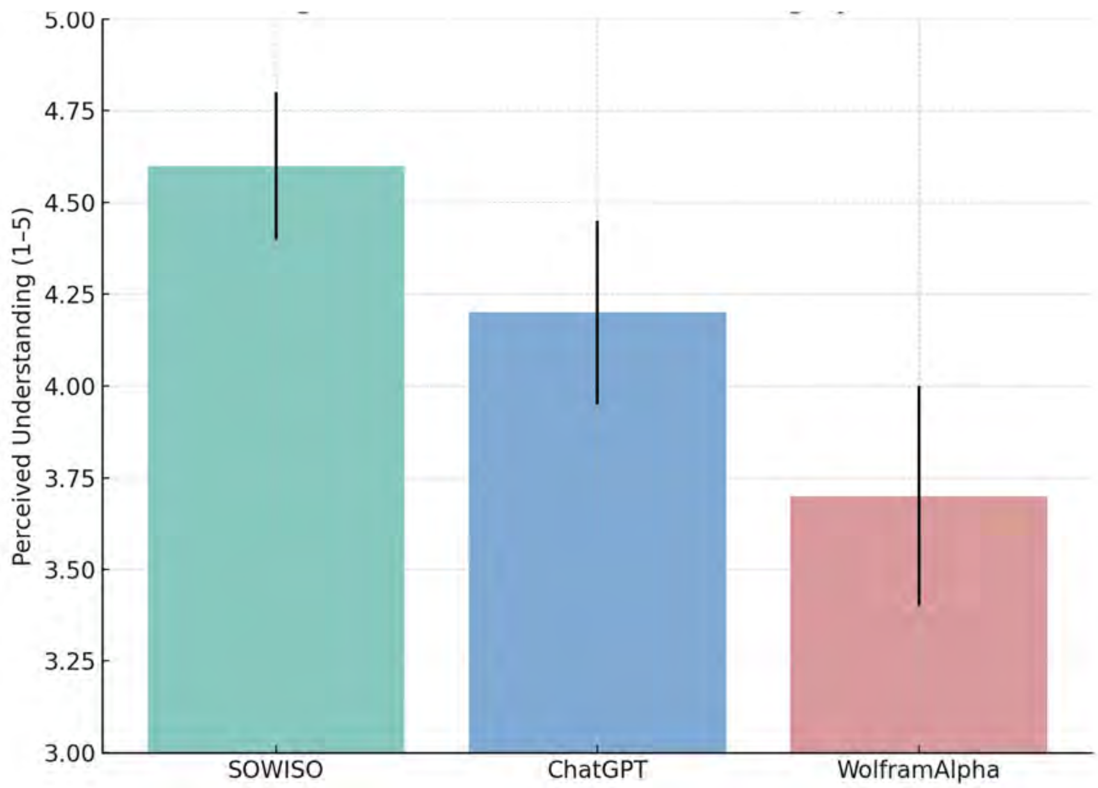

Figure 6. Perceived understanding by tool.

This figure compares students' subjective evaluations of how well they understood the material when using each of the three AI tools: SOWISO, ChatGPT and WolframAlpha.

Explanation:
• SOWISO received the highest average rating (4.6/5), indicating that students felt the platform provided clear, structured explanations that facilitated deep understanding.
• ChatGPT scored moderately high (4.2/5), reflecting students' appreciation of its dialogic and exploratory nature, but with some variability in clarity and structure.
• WolframAlpha had the lowest perceived understanding score (3.7/5), suggesting that students found it less intuitive or lacked step-by-step guidance, which may have hindered learning.

Interpretation: The data suggest that platforms offering guided feedback and instructional scaffolding (like SOWISO) are perceived as more effective for supporting understanding. While generative AI tools like ChatGPT offer flexibility and natural language interaction, their lack of structured feedback may limit perceived clarity. Computational tools like WolframAlpha, though powerful, may not be pedagogically transparent to all learners.

This pattern supports Hypothesis H4, affirming that students value AI tools not only for output accuracy, but also for their instructional design and support for learning processes.

Qualitative findings: focus groups and interviews

Thematic analysis of focus group and interview transcripts (conducted in NVivo) revealed three core themes:

• Step-by-step feedback:

"Now I understand how logarithms work, because the platform explained every step."

• Psychological safety:

“ChatGPT lets me experiment without fear of making mistakes.”
• Need for guidance:

“At first I didn’t understand how WolframAlpha works until the instructor explained it.”
Extended Interpretation:

The qualitative data reinforce the quantitative findings, demonstrating that students value clarity, emotional safety, and structured support. The ability to make mistakes without fear of judgment, combined with transparent explanation of processes, was identified as critical for effective learning. These insights support the need for blended instructional models that integrate AI technologies with human facilitation.

Summary of hypothesis confirmation

Based on the combined quantitative and qualitative evidence, the following conclusions regarding the tested hypotheses can be drawn:

• Hypothesis H1 confirmed: The AI intervention significantly improved academic performance. The experimental group demonstrated statistically greater learning gains than the control group, with a large effect size. The effect remained robust after controlling for initial performance.
• Hypothesis H2 confirmed: Mediation analysis revealed that both academic motivation and acceptance of AI significantly mediated the relationship between intervention and outcomes, suggesting the role of psychological mechanisms in enhancing learning.
• Hypothesis H3 confirmed: A statistically significant interaction was found between digital literacy and instructional support. Guidance had a particularly strong effect for students with low digital proficiency, highlighting the value of personalized scaffolding.
• Hypothesis H4 confirmed: Comparative analysis indicated that SOWISO outperformed both WolframAlpha and ChatGPT in terms of test scores and perceived understanding. This underscores the effectiveness of interactive, feedback-driven platforms.

All four hypotheses (H1–H4) were empirically supported. These findings demonstrate the substantial potential of AI-based interventions when they are pedagogically grounded and tailored to learners’ individual needs.

DISCUSSION

The findings of this study provide robust evidence for the effectiveness of AI-based interventions in supporting underprepared students in higher mathematics education. All four hypotheses (H1–H4) were empirically confirmed, allowing for a broader interpretation that extends beyond the direct effect of digital tools on academic outcomes. The results elucidate complex interrelationships among cognitive, motivational, and technological factors that jointly shape learning success in digitally mediated environments. This discussion is grounded in a comparative analysis of current theoretical frameworks and empirical studies in digital pedagogy published between 2020 and 2024, enhancing the validity and contemporary relevance of the conclusions.

Confirming the effectiveness of AI interventions (H1)

The principal finding—statistically significant and practically meaningful learning gains in the experimental group—validates Hypothesis H1. The high effect size (Cohen’s $d = 0.93$) reflects a substantial educational impact of the AI intervention. Importantly, the greatest improvements were observed among students with lower baseline achievement, reinforcing the compensatory potential of AI technologies in heterogeneous academic settings.

These results align with the conclusions of Engelbrecht and Harding (2020), who argue that digital learning environments can mitigate educational inequality. Thus, AI-supported instruction not only enhances performance but also contributes to the democratization of learning opportunities within mass higher education systems.

Motivation and AI acceptance as mediators of success (H2)

The mediation analysis (H2) demonstrates that students' psychological engagement—operationalized through academic motivation and positive attitudes toward AI—is a critical factor in the success of digital learning. The presence of significant indirect effects is consistent with the extended Technology Acceptance Model (TAM) and contemporary motivational theories (Deci and Ryan, 2000; Kundu, 2021).

Perceiving AI tools as useful, trustworthy, and intuitive significantly amplifies the intervention's effectiveness. This suggests that technological efficacy is not inherent but contingent on the learner's perception of its relevance and utility. In this way, affective and cognitive appraisals (motivation, trust) act as catalysts in the learning process.

Instructional support as a condition for overcoming digital barriers (H3)

Confirmation of Hypothesis H3 highlights the essential role of instructional scaffolding in the effective use of AI tools—particularly for students with limited digital skills. Even those with low technical proficiency exhibited academic gains when supported with tutorials, structured guidance, and instructor-led consultations.

This finding resonates with Holmes and Tuomi's (2022) claim that the teacher remains a critical mediator between student and technology. AI does not replace the educator but requires their presence to facilitate the learner's adaptation to digital environments. The result substantiates the value of blended and inclusive learning models.

Stepwise logic as a driver of cognitive efficiency (H4)

The highest learning outcomes—both objective (test scores) and subjective (perceived understanding)—were achieved using SOWISO, a platform featuring step-by-step guidance, formative feedback, and error correction. This confirms Hypothesis H4 and underscores the pedagogical importance of explanatory interactivity in digital tools.

As noted by Yang and Ogata (2021), structured learning paths promote deeper cognitive engagement, whereas generative AI tools risk fostering an "illusion of understanding" by offering solutions without conceptual scaffolding (Wang et al., 2023). These results align with cognitive load theory (Sweller, 2011) and constructivist principles, which emphasize active student engagement in knowledge construction as a precondition for meaningful learning.

Validation through qualitative data

Qualitative findings from focus groups complemented the quantitative results, revealing key student perceptions:

- Reduced anxiety about making mistakes;
- Greater sense of control over pacing and content;
- Opportunities for safe experimentation;
- On-demand access to explanations.

These insights are consistent with the concept of academic self-efficacy (Bandura, 1997), underscoring the significance of affective factors in digital learning. AI tools function not only as cognitive scaffolds but also as socio-emotional supports that foster confidence, initiative, and engagement.

Summary table of hypotheses and findings

Hypothesis	Statement	Result	Statistical Evidence
H1	AI intervention improves academic performance	Confirmed	$t(48) = 3.74$, $p < 0.001$, $d = 0.93$
H2	Motivation and AI acceptance mediate effect	Confirmed	Total $B = 10.86$; Indirect $B = 2.07$ & 1.41
H3	Digital literacy moderates outcome; support is key	Confirmed	Interaction $B = 3.12$, $p = 0.014$
H4	Interactive AI tools outperform generative tools	Confirmed	$F(2,72) = 8.92$, $p < 0.001$, $\eta^2 = 0.20$

Study limitations

Despite its strengths, this study has several limitations that should be acknowledged when interpreting the findings:

• Sample size (n = 50) was determined via power analysis (power > 0.8 at d = 0.8), but may limit generalizability beyond the immediate institutional context.
• Short duration (10 weeks) captures only short-term effects of AI integration; long-term impact on conceptual development and retention remains unknown.
• Single-instructor design may introduce confounding variables due to personality effects or unintentional differential engagement with the two groups.
• Reliance on self-report instruments (IEAQ, AMS, digital literacy scale) may be susceptible to social desirability bias and situational overestimation.
• Novelty effect: Initial engagement may be inflated due to exposure to new technologies rather than sustainable motivation or instructional efficacy.

While these limitations do not invalidate the study's core findings, they underscore the need for longitudinal and scaled-up follow-up studies to verify the robustness of effects over time and across diverse educational settings.

CONCLUSION AND PEDAGOGICAL IMPLICATIONS

Synthesis of core findings

This study offers compelling evidence that AI-based instructional tools can serve as powerful pedagogical agents for improving academic outcomes among underprepared students in university-level mathematics. The simultaneous confirmation of all four hypotheses (H1–H4) not only substantiates the efficacy of AI-assisted learning, but also reveals the nuanced interplay between technology, learner psychology, and instructional design.

Critically, the study demonstrates that:

• AI interventions result in substantial academic gains, especially for students with pre-existing knowledge deficits;
• Learner motivation and positive attitudes toward AI function as key mediators that amplify learning outcomes;
• Instructional scaffolding mitigates the effects of low digital literacy, enabling equitable access to AI-supported education;
• Interactive, feedback-rich platforms outperform generative or static tools, emphasizing the centrality of pedagogical architecture in digital environments.

Taken together, these insights position AI not as a substitute for human instruction, but as an intelligent complement that can enhance cognitive engagement, support emotional resilience, and foster metacognitive growth.

The role of AI in inclusive and transformative pedagogy

One of the most significant contributions of this research is its validation of AI tools as agents of academic inclusion. In contexts where heterogeneity in student preparation poses major instructional challenges, AI can serve a compensatory function—personalizing instruction, demystifying abstract concepts, and enabling differentiated pathways to success.

Moreover, the findings suggest that AI-supported learning, when properly scaffolded, can:

• Restore a sense of self-efficacy in struggling learners;
• Promote autonomous learning and reflective thinking;
• Provide real-time feedback that reduces performance anxiety;
• Enable safe experimentation with complex material.

As such, AI tools can serve not only as cognitive resources but as affective and motivational supports—a crucial asset in 21st-century learning ecosystems.

Pedagogical recommendations for higher education

In light of the evidence, the following pedagogical principles are proposed for educators and institutions aiming to integrate AI in meaningful and equitable ways:

Adopt hybrid instructional models: AI should be embedded within blended learning frameworks that leverage both technological scalability and human interaction. Teachers remain central as facilitators, mentors, and mediators of meaning.

Prioritize structured feedback and cognitive transparency: Choose AI platforms that offer stepwise logic, error diagnosis, and explanatory scaffolding (e.g., SOWISO, Khan Academy). Avoid reliance on tools that provide correct answers without engaging learners in the process of reasoning.

Scaffold digital literacy through targeted support: Integrate instructional tutorials, walkthroughs, and in-app guidance to assist students with lower digital fluency. Scaffolded onboarding and continued support are essential for preventing exclusion.

Design for emotional and motivational safety: Foster a learning environment that encourages risk-taking, normalizes mistakes, and celebrates incremental progress. Engage students in meta-discussions about the role and limits of AI, cultivating critical digital citizenship.

Reimagine the Educator's Role: Shift the instructor's identity from content deliverer to orchestrator of learning ecologies—someone who helps students interpret, critique, and meaningfully engage with AI-generated content.

Directions for future research

To consolidate and extend the findings of this study, several research pathways are recommended:

Longitudinal research: Assess the durability of AI intervention effects over time, examining their impact on long-term academic persistence, problem-solving transfer, and conceptual retention.

Cross-institutional validation: Conduct multi-site trials involving students from diverse disciplinary, cultural, and institutional backgrounds to test the generalizability and scalability of intervention outcomes.

Comparative evaluation of AI modalities: Investigate the distinct contributions of different AI systems—adaptive tutors, LLMs, symbolic engines, and multimodal visualizers—to understand how each supports specific learning goals.

• Exploration of Psychological and Contextual Moderators
Analyze variables such as:

• Cognitive style (analytic vs. global learners),
• Digital wellbeing and stress thresholds,
• Self-regulation and metacognitive habits,
• Trust in AI systems and institutional infrastructures.

This line of inquiry will illuminate the conditions under which AI is most effective, enabling more refined and personalized instructional design.

Final reflections

The empirical and theoretical insights presented in this study point toward a future where AI serves not merely as a set of tools, but as an integral layer in the pedagogical fabric of higher education. For this potential to be realized, implementation must be driven by human-centered design, ethical foresight, and pedagogical intentionality.

Artificial intelligence—if thoughtfully deployed—can catalyze a transition in education from:

• Transmission to facilitation,
• Uniformity to personalization,
• Compliance to autonomy.

In this new paradigm, the university classroom evolves into a collaborative, adaptive, and resilient learning ecosystem, where AI and human educators co-create opportunities for intellectual growth and equitable success.

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