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META messenger AI tutoring for developing graphical reasoning in rotational kinematics and science process skills

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Graphical reasoning in rotational kinematics remains a persistent challenge for secondary students, largely due to difficulties in interpreting and connecting angular displacement, velocity, and acceleration graphs. Similarly, the integration of science process skills (SPS) in physics instruction is often underemphasized. This study examined the effectiveness of META Messenger–based AI tutoring in improving students' graphical reasoning and SPS in the context of rotational motion. A clustered quasi-experimental design was employed with 120 Grade 12 students from a public secondary school in the Philippines, assigned to an experimental group (artificial intelligence [AI] tutoring, n = 60) and a control group (traditional instruction, n = 60). Students completed validated assessments of graphical reasoning, basic SPS, and integrated SPS before and after the 4-week intervention. Results indicated statistically significant learning gains in both groups, with the experimental group demonstrating substantially greater improvements. Posttest scores for the experimental group were significantly higher than those of the control group across all measures, with large adjusted effect sizes and confidence intervals consistently excluding zero. These findings suggest that conversational AI tutoring delivered via accessible platforms can provide effective scaffolding for complex, graph-based physics concepts while simultaneously fostering scientific inquiry skills. The study contributes to emerging evidence on AI-enhanced science education and illustrates a practical model for integrating adaptive technologies in resource-constrained contexts.

Keywords: AI tutoring; graphical reasoning; physics education; rotational kinematics science process skills

Introduction

Graphical reasoning in physics, especially in the context of rotational kinematics, represents a critical component of conceptual understanding and scientific literacy (Beichner, 1994; Klein et al., 2017). Students often struggle to decode and interpret motion graphs, such as angular displacement–time and angular velocity–time graphs, due to their abstract and multidimensional nature (Testa et al., 2002). These challenges

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impede not only their grasp of rotational dynamics but also hinder the development of higher-order scientific process skills (SPS), which are crucial for inquiry-based learning and problem-solving in Science, Technology, Engineering, and Mathematics (STEM) education (Conchas et al., 2023; Agustinin &Suyatna, 2018).

The advent of AI in education presents an opportunity to personalize and scaffold science instruction through adaptive, data-driven tutoring systems (Rizvi, 2023; Strielkowski et al., 2024). Messenger-based AI tutoring – using chat-driven agents integrated within familiar messaging platforms – offers a novel, student-centered learning environment that can reinforce conceptual understanding while fostering SPS. These platforms can guide learners in real time as they analyze motion graphs, interpret data patterns, formulate hypotheses, and communicate findings, all integral to scientific reasoning (Wenger, 1987; Tabuenca et al., 2024).

Despite growing evidence of AI-enhanced learning effectiveness in physics (Papakostas et al., 2024; Xu, 2024), few studies have specifically explored how meta-messenger AI tutoring impacts learners' graphical reasoning in rotational motion and their engagement with both basic and integrated SPS. This study addresses this gap by evaluating students' performance on key graphical interpretation tasks and SPS development through targeted interventions delivered via AI tutoring on Meta Messenger.

Literature review

Challenges in graphical reasoning in rotational kinematics

Graphical representations are central to understanding kinematic relationships. However, multiple studies highlight that students often misinterpret the slope and area under curves in motion graphs (Beichner, 1994; Planinic et al., 2012). These difficulties are compounded in rotational contexts, where angular displacement, velocity, and acceleration involve cyclical patterns and trigonometric interpretations (Mashood & Singh, 2012; Chen et al., 2023). For example, determining angular velocity from a displacement–time graph requires distinguishing between constant and variable rates, which students frequently conflate (Beichner, 1994; Mergner et al., 1996; Testa et al., 2002; Bollen et al., 2016). From a cognitive load perspective, such errors can be understood as the result of intrinsic task complexity and the working memory demands of coordinating multiple representations simultaneously. This suggests that effective instructional strategies must include scaffolds that externalize reasoning steps and reduce unnecessary cognitive demands, thereby supporting students' development of representational fluency.

Scientific process skills in physics learning

Scientific process skills comprise a spectrum of cognitive and procedural abilities, including observation, classification, measuring, hypothesizing, experimenting, and interpreting data (Padilla et al., 1983). In physics, the integration of these skills fosters a deeper conceptual understanding and scientific inquiry competence. Basic SPS such as measuring and classifying are foundational for interpreting motion graphs, while integrated SPS such as forming hypotheses and drawing conclusions support experimental reasoning (Padilla et al., 1983; Beaumont-Walters & Soyibo, 2001). Studies show that explicit instruction and practice in these skills enhance problem-solving in physics (Larkin & Reif, 1979; Huffman, 1997). Instead, scaffolding SPS within instruction is essential. A socio-constructivist perspective highlights how collaborative dialogue, guided questioning, and teacher or AI-mediated scaffolding can make implicit reasoning strategies explicit, enabling learners to appropriate scientific practices as their own.

Role of AI in supporting SPS and graphical reasoning

AI tutoring systems offer adaptive feedback and scaffolding that can support both conceptual and procedural learning (Walker et al., 2013; Lin et al., 2023). Intelligent tutoring systems (ITS) like AutoTutor and ALEKS have demonstrated gains in learners' ability to reason with graphs and solve physics problems (Oueini, 2019; Khine, 2024). More recently, AI-enhanced messenger platforms have enabled real-time, interactive learning experiences outside the traditional classroom, especially in underserved or remote contexts (Ahmed et al., 2024). These systems can dynamically adapt tasks based on students' responses, provide guided questions, and simulate inquiry-based dialogue – all conducive to SPS development (Ahmed et al., 2024). These affordances suggest that AI can function not merely as a delivery tool but as a scaffold that supports both conceptual reasoning and the enactment of scientific practices.

META-Messenger AI for contextualized learning

The use of messaging platforms like META Messenger for educational AI introduces familiar, low-barrier environments for students to engage in physics tasks. These platforms can incorporate visual graph interpretation tasks and prompt SPS activities such as prediction, experimentation, and data interpretation (Sun et al., 2023; Chen et al., 2024). Research shows that conversational agents in messenger apps can increase engagement, retention, and conceptual accuracy, especially when the content is personalized and scaffolded (Kocaballi et al., 2019; Yusuf et al., 2025). Viewed through the lens of scaffolding theory, messenger-based AI can be seen as a distributed tutor, gradually transferring responsibility for reasoning to the learner while maintaining cognitive support. This dual capacity to reduce cognitive overload and promote socially mediated learning underscores the promise of AI-powered messaging platforms in advancing both conceptual and procedural competencies in physics.

Synthesis and research gap

Although a substantial body of research has examined graphical reasoning in physics and the development of science process skills (SPS), these domains are frequently treated in isolation, with minimal integration in the context of rotational kinematics – a domain where students consistently face persistent misconceptions in interpreting angular motion graphs. Prior studies on AI tutoring systems demonstrate their effectiveness in fostering conceptual learning and SPS, yet their potential has primarily been explored within structured ITSs rather than in widely accessible, low-bandwidth environments. Moreover, few investigations have explicitly addressed how AI can simultaneously scaffold both basic and integrated SPS while supporting students' representational fluency in rotational kinematics. Research seldom considers messenger-based platforms like META Messenger as vehicles for inquiry-oriented learning, despite their familiarity and ubiquity among students. This study addresses these gaps by examining the dual role of META Messenger AI tutoring in enhancing students' graphical reasoning and developing SPS within the challenging domain of rotational motion, thereby extending theoretical and practical insights into how conversational AI can be leveraged for equitable, scalable science education.

Research aim

This study aimed to investigate the effectiveness of META Messenger AI tutoring in enhancing students' learning of rotational kinematics. Specifically, it sought to:

- Determine the effect of META Messenger AI tutoring on students' graphical reasoning in rotational kinematics compared to traditional instruction.
- Examine the impact of META Messenger AI tutoring on students' basic and integrated SPSs relative to traditional instruction.
- Assess the extent of learning gains in both the experimental and control groups by comparing pretest and posttest performance.

Research methodology

Research design

This study employed a quasi-experimental pretest–posttest control group design to evaluate the effectiveness of Meta Messenger AI tutoring on students' graphical reasoning in rotational kinematics and their SPSs (Creswell, 2014). The design allowed for both within-group comparisons (pretest to posttest) and between-group comparisons (experimental vs. control), enabling the assessment of learning gains attributable to the intervention.

Study context and participants

The study was conducted in a public secondary school in Nueva Vizcaya, Philippines, during the Academic Year 2024–2025. Participants were 120 Grade 12 students enrolled in science classes. Sixty students were assigned to the experimental group, which received AI-based instruction through Meta Messenger, while another 60 students formed the control group, receiving traditional teacher-led instruction. Assignment was conducted at the class level to prevent contamination between groups. Informed consent was obtained from all participants and their guardians, and ethical clearance was secured from the school division research committee prior to data collection.

Data collection

Data collection was conducted over a 6-week period, beginning with the administration of pretests during the first week. All participants completed three instruments: the Graphical Reasoning Assessment, the Basic SPS Test, and the Integrated SPS

Test. These instruments were administered under standardized classroom conditions and were proctored by the respective science teachers. Prior to implementation, each instrument underwent expert validation and reliability analysis using the present sample.

The Graphical Reasoning Assessment consisted of 20 multiple-choice items assessing interpretation of position–time, velocity–time, and acceleration–time graphs, with a total possible score of 20. Internal consistency for this sample was acceptable (KR-20 = 0.84), with item–total correlations ranging from 0.42 to 0.71. The Basic SPS Test contained 15 items measuring observing, classifying, inferring, and predicting skills (score range: 0–15), demonstrating good reliability (Cronbach's $\alpha = 0.86$). The Integrated SPS Test, composed of 18 problem-based items requiring variable control, hypothesizing, and experiment interpretation (score range: 0–18), also showed strong reliability (Cronbach's $\alpha = 0.88$). To ensure temporal stability, a subset of participants ($n = 32$) completed a 2-week test–retest pilot prior to the main study, yielding intraclass correlation coefficients (ICCs) ranging from 0.79 to 0.83 across the three measures, indicating good reliability.

Scoring procedures and test form equivalence

All instruments were scored dichotomously (1 = correct, 0 = incorrect), and total scores were computed by summing correct responses per test. Higher scores indicated greater proficiency in graphical reasoning or SPSs. Pretest and posttest forms were identical, as the study aimed to measure learning gains using repeated-measures comparisons; however, item order was shuffled in the posttest to reduce recall bias. Data from all assessments were encoded, anonymized, and subjected to quality checks before statistical analysis. The entire testing process adhered to ethical standards for educational research, including informed consent, voluntary participation, and data confidentiality.

Intervention procedure

The intervention was implemented over a 4-week period and consisted of eight 45-min sessions integrated into the Grade 12 science curriculum, specifically during the unit on motion and kinematics, as outlined in the Department of Education's K to 12 Science Curriculum Guide. Both the experimental and control groups studied the same content, competencies, and performance tasks. To ensure experimental integrity, both groups received equivalent instructional time and were monitored to confirm comparable time-on-task across all eight sessions. The key distinction between the groups was in the mode of scaffolding: the experimental group received traditional teacher-led instruction supplemented with AI-powered tutoring via the Meta Messenger platform, while the control group received the same instruction but without digital or AI support. Thus, students in the experimental group did not rely exclusively on AI; instead, the AI tutor was an additional feature designed to extend and reinforce teacher-delivered lessons. This clarification avoids the misconception that the study claims AI agents alone outperform human instructors in teaching graphical reasoning or SPS.

In the experimental group, students interacted with an AI chatbot embedded in Messenger, programmed to deliver structured modules on interpreting kinematic graphs. The chatbot was developed using a prompt–response framework with natural language processing (NLP) features to simulate conversational tutoring. It guided students through conceptual discussions, graph-matching tasks, and computational exercises involving position–time, velocity–time, and acceleration–time graphs. The AI tutor provided step-by-step support through Socratic questioning, offering hints, corrective feedback, and, when necessary, worked-out solutions. Rather than supplying immediate answers, the chatbot scaffolded learners' reasoning by presenting intermediate prompts. The tutoring bot operated using a vendor-provided closed-model NLP system accessible through Meta's Messenger API, enabling structured prompting and adaptive reply generation while ensuring data privacy within the platform.

Each AI session followed a structured flow: (1) warm-up questions to activate prior knowledge; (2) interactive dialogue on lesson content; (3) embedded formative checks in the form of short-answer and multiple-choice questions; and (4) reflective prompts encouraging predictions, hypothesis-making, data interpretation, and reasoning. Examples of anonymized student–AI exchanges have been included in the Appendix to illustrate the kinds of questions asked (e.g. 'What happens to the slope of a position–time graph if velocity increases?'), the types of hints given, and the range of responses students produced. These examples also show the extent to which student queries resembled or diverged from the pretest and posttest instruments.

The control group engaged in the same sequence of lessons but through conventional methods, including lecture discussions, teacher explanations, textbook-based activities, and printed worksheets. Scaffolding and feedback were exclusively teacher mediated. To maintain instructional consistency, both groups followed an identical lesson plan aligned with the same learning objectives, and the teacher-facilitator designed all materials but did not overlap roles during delivery.

At the start of the intervention, participants completed validated pretest assessments in graphical reasoning (KGIT) and SPS. After the 4-week period, the same instruments were re-administered as posttests. For the experimental group, anonymized conversation logs were collected for qualitative analysis of usage patterns, including message frequency, types of queries, and time-on-task. Students were monitored for attendance and active participation across both groups to minimize confounding variables.

All procedures were reviewed and approved by the Division Basic Education Research Committee, Division of Nueva Vizcaya, with parental consent and student assent obtained prior to participation. To address data protection, AI logs were anonymized, stored securely, and analyzed only at the aggregate level. Safeguards against misinformation or bias in chatbot responses were applied, and parents and students were informed about the intervention, including the option to withdraw at any time.

This design allows for a controlled and transparent comparison of teacher-led instruction with AI-supported scaffolding versus teacher-led instruction alone, with documentation of the AI system's mechanics, example dialogues, and alignment with assessment tasks.

Data analysis

Quantitative data were analyzed using IBM SPSS Statistics (Version 28). Within-group changes from pretest to posttest were examined using paired-samples t-tests, while independent-samples t-tests were employed to compare posttest performance between the experimental and control groups. To control for baseline differences, adjusted gain scores were calculated, and analysis of covariance (ANCOVA) was conducted with pretest scores entered as covariates, yielding adjusted mean differences. Effect sizes were calculated using Cohen's d to determine the magnitude of differences, with 95% confidence intervals reported for adjusted gains and mean differences (Fritz et al., 2012).

Given the clustered nature of the data (students nested within intact classes), ICC were computed to assess the extent of variance attributable to group-level clustering. Low ICC values (< 0.10) indicated minimal clustering effects, suggesting that the observed differences were primarily driven by individual-level rather than class-level variance. Statistical significance was set at $p < 0.05$. Assumptions of normality and homogeneity of variance were tested using Shapiro–Wilk and Levene's tests, respectively, with no substantial violations observed.

Results

Table 1 presents the within-group comparisons of pretest and posttest scores in graphical reasoning and SPS for the experimental and control groups. Results revealed significant improvements across all measures although the magnitude of change varied substantially between groups. For the experimental group, students demonstrated large and statistically robust gains in graphical reasoning, $t(59) = 14.32$, $p < 0.001$, $d = 1.85$, with an adjusted gain of 4.32 (95% confidence interval, CI [3.68, 4.96], $g = 1.72$). Similarly, significant improvements were observed in basic SPS, $t(59) = 13.25$, $p < 0.001$, $d = 1.71$, with an adjusted gain of 3.81 (95% CI [3.22, 4.40], $g = 1.70$), and in integrated SPS, $t(59) = 14.97$, $p < 0.001$, $d = 1.92$, with an adjusted gain of 4.45 (95% CI [3.89, 5.01], $g = 1.88$). By contrast, although the control group also showed statistically significant improvements in all domains (ps < 0.001), the effect sizes were small to moderate, ranging from $d = 0.52$ to 0.59, and adjusted gains were not reported. These findings underscore that while both

Table 1. Comparison of pretest and posttest scores in graphical reasoning and science process skills between control and experimental groups

Measure	Group	Pretest M (SD)	Posttest M (SD)	*t*	df	*p*	Cohen's *d*	Adjusted gain (95% CI)	Adjusted G
Graphical reasoning	Experimental	12.45 (2.31)	18.67 (1.95)	14.32	59	< 0.001	1.85	4.32 [3.68, 4.96]	1.72
	Control	12.28 (2.17)	14.06 (2.13)	4.56	59	< 0.001	0.59		
Basic SPS	Experimental	11.02 (2.10)	16.40 (1.84)	13.25	59	< 0.001	1.71	3.81 [3.22, 4.40]	1.70
	Control	10.87 (2.04)	12.33 (2.08)	3.98	59	< 0.001	0.52		
Integrated SPS	Experimental	9.84 (2.25)	15.76 (2.01)	14.97	59	< 0.001	1.92	4.45 [3.89, 5.01]	1.88
	Control	9.71 (2.31)	11.04 (2.22)	4.11	59	< 0.001	0.53		

SD, standard deviation; CI, confidence interval; SPS, science process skills.

Table 2. Between-group comparison of posttest scores in graphical reasoning and SPS

Measure	Group	Posttest M (SD)	*t* (df)	*p*	Cohen's d	Adjusted mean difference	Adjusted g	ICC
Graphical reasoning (Total)	Experimental	18.67 (1.95)	10.78 (118)	< 0.001	1.97	4.32 [3.68, 4.96]	1.72	0.07
	Control	14.06 (2.13)						
Basic SPS	Experimental	16.40 (1.84)	10.33 (118)	< 0.001	1.89	3.81 [3.22, 4.40]	1.70	0.06
	Control	12.33 (2.08)						
Integrated SPS	Experimental	15.76 (2.01)	11.45 (118)	< 0.001	2.07	4.45 [3.89, 5.01]	1.88	0.09
	Control	11.04 (2.22)						

SD, standard deviation; ICC, intraclass correlation coefficient; SPS, science process skills.

traditional instruction and AI-assisted learning facilitated learning progress, the magnitude of learning was far greater in the AI-supported group.

Between-group comparisons of posttest performance (Table 2) further confirmed the superiority of AI tutoring over traditional instruction. The experimental group significantly outperformed the control group across all measures: graphical reasoning, $t(118) = 10.78$, $p < 0.001$, $d = 1.97$, adjusted mean difference = 4.32 (95% CI [3.68, 4.96], $g = 1.72$, ICC = 0.07); basic SPS, $t(118) = 10.33$, $p < 0.001$, $d = 1.89$, adjusted mean difference = 3.81 (95% CI [3.22, 4.40], $g = 1.70$, ICC = 0.06); and integrated SPS, $t(118) = 11.45$, $p < 0.001$, $d = 2.07$, adjusted mean difference = 4.45 (95% CI [3.89, 5.01], $g = 1.88$, ICC = 0.09). These very large effect sizes indicate that the experimental intervention had a profound impact on students' mastery of both graphical reasoning and SPS, beyond what would be expected from conventional methods.

Taken together, the results demonstrate that META Messenger-based AI tutoring is an effective pedagogical tool for strengthening students' capacity to interpret and reason with physics graphs while simultaneously fostering both basic and integrated SPSs. The consistent pattern of large effect sizes, substantial adjusted gains, and narrow confidence intervals across domains suggests that conversational AI, when delivered via accessible platforms, can serve as a powerful scaffold for conceptual and inquiry-based learning in physics, particularly in low-resource educational contexts.

Discussion

The results of this study indicate that Meta Messenger–based AI tutoring was associated with substantial improvements in students' graphical reasoning in rotational kinematics, as well as significant gains in both basic and integrated SPS, compared to traditional instruction. These findings suggest that AI-supported dialogue and feedback may have provided effective scaffolding for interpreting and connecting graphical representations of angular displacement, velocity, and acceleration. Nevertheless, the results should be interpreted cautiously, as several alternative explanations may account for the observed differences. For example, the novelty of engaging with an AI system, heightened teacher expectancy effects, or differences in time-on-task between groups may have contributed to performance gains, rather than the tutoring mechanism alone (Clark & Mayer, 2016; Kulik & Fletcher, 2019).

One plausible explanation for the observed improvements is that the AI tutor delivered targeted, immediate feedback and embedded formative checks that supported students' conceptual understanding and procedural accuracy. Prior work on ITSs has shown that frequent low-stake assessments, adaptive questioning, and dialogic scaffolds enhance both conceptual mastery and inquiry-oriented skills (Graesser et al., 2018; Walker et al., 2013). In the present study, students engaged in Socratic-style questioning through the AI interface, which may have promoted deeper engagement with graph interpretation tasks and facilitated the integration of SPS such as predicting trends, analyzing data, and formulating evidence-based conclusions. This mechanism resonates with research demonstrating the effectiveness of guided inquiry and feedback in promoting higher-order scientific thinking (Agustinin & Suyatna, 2018; Conchas et al., 2023).

The consistently large effect sizes observed across domains suggest a meaningful pedagogical impact; however, these results should not be generalized without consideration of contextual factors. The study was conducted in a Philippine secondary school where physics instruction aligns with the K–12 science curriculum standards and where English served as the primary language of instruction. Furthermore, students' access to devices and connectivity, though adequate for participation, may not reflect conditions in more rural or resource-constrained environments. As noted in recent studies, disparities in bandwidth, device ownership, and digital literacy can significantly mediate the effectiveness of mobile learning interventions (Ahmed et al., 2024; Strielkowski et al., 2024).

The use of Meta Messenger, a widely available communication platform, presents both opportunities and challenges. Its accessibility and low-bandwidth requirements make it a promising tool for integrating conversational AI into everyday learning, particularly in underserved contexts. At the same time, clarity is needed regarding the underlying AI engine and APIs that support such tutoring, as platform-specific features may influence both scalability and transferability. This raises important questions about sustainability, data privacy, and long-term implementation that future research should address (Kocaballi et al., 2019; Sun et al., 2023).

Finally, this study contributes to the growing body of evidence that embedding SPS activities within digital learning environments strengthens both conceptual and inquiry-based outcomes. While conventional physics instruction often emphasizes either procedural drills or abstract theory, the AI tutoring sessions integrated these dimensions by guiding students through authentic tasks such as identifying graphical trends, hypothesizing relationships, and drawing conclusions based on evidence. This approach mirrors the core of scientific literacy as defined in prior work (Padilla et al., 1983; Beaumont-Walters & Soyibo, 2001) and highlights how messenger-based platforms, when designed with inquiry in mind, can support higher-order reasoning and problem solving (Tabuenca et al., 2024; Yusuf et al., 2025).

In sum, the findings suggest that Meta Messenger–based AI tutoring has the potential to enhance both graphical reasoning and SPS in physics, but further studies are warranted to disentangle instructional effects from possible novelty or expectancy biases, to test longer-term retention, and to evaluate feasibility in varied educational contexts.

Conclusions and implications

The findings of this study provide evidence suggesting that AI-based tutoring delivered through Meta Messenger may support improvements in students' graphical reasoning in rotational kinematics, as well as in their basic and integrated SPSs. Compared with traditional instruction, the AI-assisted approach was associated with greater learning gains across the assessed domains, with effect sizes that indicate potentially meaningful enhancements in both conceptual understanding and procedural competencies. These outcomes are consistent with the growing body of research indicating the value of mobile-based conversational AI tools for facilitating complex conceptual learning and inquiry-oriented practices in physics education.

Moreover, the use of a widely accessible, low-bandwidth platform such as Meta Messenger highlights the feasibility of implementing technology-enhanced instructional interventions even in low-resource school environments. While the results are promising, they should be interpreted within the constraints of the study design and population, and further research is warranted to examine long-term impacts, generalizability to other contexts, and differential effects across learner profiles.

Nonetheless, the study offers practical insights for key stakeholders. For STEM educators, adaptive AI tutoring systems may provide an additional avenue for delivering personalized scaffolding and formative feedback on conceptually demanding topics such as rotational motion. For curriculum designers, embedding SPSs within AI-mediated interactions aligns with contemporary science education frameworks emphasizing inquiry and reasoning. For policymakers, leveraging familiar communication platforms for instructional support may represent a cost-effective and equitable strategy for expanding STEM learning opportunities in public schools where access to advanced educational technologies remains limited.

Limitations

Several limitations should be considered in interpreting the findings of this study. First, although a quasi-experimental design with pretest and posttest measures was employed, full randomization of participants was not feasible. Group equivalence was established through baseline comparisons of pretest scores, which showed no statistically significant differences; however, unmeasured variables such as prior exposure to digital tools, motivational levels, or teacher expectations may still have influenced outcomes. Second, the unusually large effect sizes observed (Cohen's $d \approx 2.0$) are uncommon in education research and should be interpreted cautiously. It is possible that contextual factors – including the novelty of AI tutoring, increased time-on-task for the experimental group, or differential teacher enthusiasm – contributed to inflated gains. Third, the intervention was conducted in a single school with Grade 12 students in the Philippines, which limits the generalizability of results to other grade levels, subject areas, or cultural contexts. Fourth, while META Messenger provided an accessible platform, variations in device availability, Internet connectivity, and students' prior familiarity with messaging apps may have shaped their engagement with the AI tutor.

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Future research should employ randomized controlled trials across multiple sites, incorporate longitudinal designs to assess retention, and include measures of teacher influence and time-on-task to more accurately estimate the true impact of AI tutoring on science learning.

Research ethics

Informed consent statement

Informed consent was obtained from all research participants.

Data availability statement

The raw datasets generated and analyzed in this study cannot be shared publicly due to ethical and institutional restrictions involving research with minors and school-governed academic performance records. However, de-identified summary data, statistical output files, and analysis code used for computing effect sizes and reliability coefficients are available from the corresponding author upon reasonable request, subject to approval by the school division research committee and compliance with data-privacy regulations.

Conflicts of interest

The authors declare no conflicts of interest.

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