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Students' Artificial Intelligence Use, Mathematics Proficiency, and Challenges in Secondary Schools: A Correlational Analysis

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ABSTRACT

The spread of artificial intelligence (AI) tools among secondary students raises questions about how AI use, mathematics proficiency, and the demands placed on teachers move together. This correlational analysis examined these relationships in selected secondary schools in General Santos City, Philippines, during School Year 2025–2026. A descriptive-correlational design was applied to 256 students and 121 mathematics teachers chosen through simple random and quota sampling. Validated four-point questionnaires ($\alpha = 0.84$) measured five dimensions each of AI use, mathematics proficiency, and teachers' challenges, and relationships were tested using Pearson, Spearman, point-biserial, and eta correlations at $p \leq .05$. All three constructs were rated Good, with narrow spreads across dimensions: AI use ($M = 3.12$), proficiency ($M = 3.14$), and teachers' challenges ($M = 3.16$). Of 80 profile–outcome coefficients for students, 61 were significant, with frequency of AI use, device access, purpose and type of AI tools, and math average outweighing age and gender; application of mathematical concepts was unrelated to any profile variable. Teachers' profiles related to 16 of 25 challenge pairs, weakly to modestly, and to none involving institutional support. All 25 correlations between AI use and proficiency were positive and significant ($r = .432$ to $.841$), strongest for integration with independent learning and problem-solving. AI use ($r = .421$ to $.823$) and proficiency ($r = .372$ to $.836$) were both significantly related to all teacher challenges, most strongly to academic integrity. The analysis indicates that reflective AI use accompanies stronger higher-order proficiency and heavier instructional demands. Reflective AI practices, integrity-focused assessment, targeted teacher development, and school-level support are recommended.

Introduction

Students no longer meet mathematics only through textbooks and teachers. A growing share of their practice now passes through artificial intelligence (AI) chatbots, symbolic problem solvers, and tutoring applications that can produce complete solutions in seconds (Kasneci et al., 2023). Whether this shift strengthens mathematical proficiency or merely accelerates task completion is one of the central questions facing secondary mathematics education. A second question concerns teachers, who must now supervise, assess, and adapt instruction for students whose work may be partly produced by machines, often while carrying full teaching loads. Recent work on Filipino educators shows how such added demands accumulate as workplace stress when they are not matched by support (Panela, 2026).

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The research base offers mixed signals. AI provides immediate feedback and adaptive practice that can improve engagement and skill (Holmes et al., 2022), and a meta-analysis of K–12 studies reported a small positive effect of AI on mathematics achievement (Yi et al., 2025). At the same time, overreliance can erode problem-solving and invite uncritical acceptance of outputs (Susnjak, 2022), and AI-generated solutions complicate assessment and integrity (Zawacki-Richter et al., 2019). In the Philippines, device access has improved while digital literacy, ethical awareness, and instructional support lag (Lucas et al., 2021).

Most available studies treat students' AI use, their mathematics proficiency, and teachers' challenges as separate topics. Analyzing how these variables move together in actual classrooms offers a more useful basis for school decisions. This correlational analysis examined secondary schools in General Santos City during School Year 2025–2026 to determine the levels of students' AI use, mathematics proficiency, and teachers' challenges; to test whether students' and teachers' profiles are related to these variables; and to estimate the strength and direction of relationships among AI use, proficiency, and teachers' challenges, with the aim of informing an intervention plan for responsible AI use.

Literature Review

AI Use as a Learning Behavior

AI use in learning can be described not only by how often students use AI but by how they use it: whether they verify outputs, which tasks they delegate, how they integrate AI into independent study, how long they engage, and how confident they feel. Student engagement with AI tools has been measured along such behavioral lines in recent survey research (Al Mashagbeh et al., 2025). Confidence matters because self-efficacy predicts how effectively learners engage with technology (Kauffman, 2015; Scherer & Teo, 2019), but confidence without digital literacy can produce inaccurate or irresponsible use (Wang & Tahir, 2020). Sustained and purposeful engagement yields stronger outcomes than sporadic use (Crompton & Burke, 2018; Holstein et al., 2019), and students' ability to evaluate AI-generated content is itself an information literacy skill (Galagala & Bacarrisas, 2025).

AI and Mathematics Achievement

Systematic reviews report that AI-driven tutoring and feedback improve problem-solving and procedural performance when they adapt to learners, although teacher readiness limits their use (Ximenes, 2025; Panqueban & Huincahue, 2024). Meta-analytic evidence indicates modest positive effects on achievement (Yi et al., 2025), and AI's value depends on whether learners integrate outputs into their own reasoning (Zawacki-Richter et al., 2019) or use them for quick answers (Chen et al., 2020). Proficiency itself is multidimensional, comprising conceptual understanding, procedural fluency, strategic competence, and reasoning (Kilpatrick et al., 2001), with conceptual and procedural knowledge developing together (Rittle-Johnson et al., 2015). Critical thinking (Facione, 2015; Lai, 2018) and the application of mathematics to real situations (NCTM, 2014; OECD, 2019; Boaler, 2016) complete the picture.

Teachers' Challenges as Instructional Context

Teachers' capacity to manage AI depends on technological pedagogical content knowledge (Mishra & Koehler, 2006; Koehler & Mishra, 2019), on their beliefs and confidence (Ertmer & Ottenbreit-Leftwich, 2010; Tondeur et al., 2017), and on institutional support and training (UNESCO, 2022a, 2022b). AI raises particular concerns for academic integrity (Bretag, 2019; Eaton & Turner, 2020) and for assessment design that captures reasoning (Black & Wiliam, 2018). AI-supported learning analytics may help teachers monitor progress (Salas-Pilco et al., 2022), but such tools require preparation that many teachers lack.

The Philippine Context

Philippine reviews describe uneven AI integration shaped by infrastructure gaps, digital divides, limited teacher training, and the absence of coordinated policy (Co, 2025; Escorial & Pajo, 2025; Estrellado & Miranda, 2023). AI offers opportunities for engagement and personalized learning, but students need guidance to use it responsibly (Pajo & King, 2025), and future teachers need deliberate preparation in AI competencies (Vera et al., 2025). Today's secondary students also carry the experience of the pandemic's abrupt shift to device-based learning, which took a measurable toll on the mental health of Filipino students (Panela, 2025b) and shaped their habits with digital tools.

Theoretical Lens

The Technology Acceptance Model explains AI use through perceived usefulness and ease of use, which are shaped by external conditions such as access and support (Davis, 1989). Constructivist Learning Theory treats AI as a mediator through which students build understanding by testing, verifying, and reflecting (Piaget, 1967). Self-Determination Theory adds that autonomy, competence, and relatedness sustain the motivation of both learners and teachers (Deci & Ryan, 2000). In this analysis, these theories predict that students' profiles will relate to AI use, that reflective forms of AI use will relate to proficiency, and that greater AI use will intensify teachers' instructional demands.

Methodology

Design

The study used a quantitative descriptive-correlational design, which measures variables as they occur and estimates the strength and direction of their associations without manipulation (Creswell & Creswell, 2018; Ary et al., 2014).

Participants and Sampling

Participants were 256 students in Grades 7 to 12 and 121 mathematics teachers from selected secondary schools in General Santos City. Simple random and quota sampling were used, and only those who gave voluntary consent were included. Students had a mean age of 15.33 years, and teachers a mean age of 39.12 years and a mean of 14.62 years of teaching experience.

Instrumentation

A four-part questionnaire was adapted from published instruments on student engagement with AI tools (Al Mashagbeh et al., 2025), on mathematics self-efficacy and skills, and on teachers'

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challenges in AI use, then modified for the local context. Part I collected student profiles (age, gender, grade level, device access, frequency and purpose of AI use, type of AI tools, and mathematics general average) and teacher profiles (age, gender, educational attainment, teaching experience, and AI-related trainings). Parts II to IV each contained five dimensions of five items: AI use (accuracy verification, task complexity, integration with independent learning, time spent, and confidence), mathematics proficiency (conceptual understanding, procedural skills, problem-solving, critical thinking, and application), and teachers' challenges (monitoring AI use, academic integrity, assessment design, instructional adaptation, and institutional support). Responses used a four-point scale interpreted as Excellent (3.26–4.00), Good (2.51–3.25), Less Satisfactory (1.76–2.50), and Least Satisfactory (1.00–1.75). Content validation by experts in educational technology, mathematics education, and research methodology preceded pilot testing, which yielded a Cronbach's alpha of 0.84.

Procedure

Formal permission was obtained from the research adviser and school administrators. Respondents were briefed on the purpose of the study and the confidentiality of their answers, completed the questionnaire at their own pace, and returned it to the researchers, who checked each form for completeness before encoding.

Statistical Analysis

Profiles were summarized by frequency and percentage, and levels by weighted mean and standard deviation. Normality was assessed using the Shapiro-Wilk test, skewness and kurtosis, and Q-Q plots. Pearson's r was applied to normally distributed variables and Spearman's rho otherwise; point-biserial correlation was used for dichotomous variables, eta for categorical variables, and the Kruskal-Wallis H test for multi-group comparisons. Each relationship was tested at $p \leq .05$, and coefficients were reported with their sign so that inverse associations could be identified.

Ethical Considerations

Participation was voluntary and could be withdrawn without penalty, and informed consent was obtained in writing. Data were anonymized, identifiers were stored separately from responses, digital files were encrypted and password-protected, and paper forms were secured and later shredded in accordance with the Data Privacy Act of 2012.

Results and Discussion

Descriptive Results

Table 1

Ranked Means of AI Use, Mathematics Proficiency, and Teachers' Challenges

Construct and Dimension	Mean	SD	Item Range
AI use (overall M = 3.12, SD = 0.73)			
Accuracy verification behavior	3.16	0.71	3.08–3.24
Confidence in using AI tools	3.12	0.73	3.05–3.18
Complexity of tasks assisted by AI	3.11	0.75	2.98–3.20
Integration with independent learning	3.11	0.75	2.98–3.20
Time spent using AI tools	3.10	0.73	3.02–3.18
Mathematics proficiency (overall M = 3.14, SD = 0.71)			
Conceptual understanding	3.15	0.71	3.09–3.22
Critical thinking skills	3.15	0.70	3.09–3.21
Procedural skills	3.14	0.71	3.06–3.20
Application of mathematical concepts	3.14	0.71	3.09–3.18
Problem-solving ability	3.11	0.73	3.05–3.16
Teachers' challenges (overall M = 3.16, SD = 0.71)			
Ensuring academic integrity	3.18	0.70	3.12–3.24
Institutional support and resources	3.18	0.70	3.12–3.23
Monitoring students' AI use	3.15	0.72	3.09–3.22
Designing assessments	3.15	0.71	3.10–3.19
Instructional adaptation and strategy	3.14	0.72	3.09–3.18

Note. 3.26–4.00 = Excellent (very high level); 2.51–3.25 = Good (high level); 1.76–2.50 = Less Satisfactory (low level); 1.00–1.75 = Least Satisfactory (very low level). All dimensions were rated Good.

Table 1 ranks the fifteen dimensions within each construct. All three constructs fell in the Good range, and the spread between the highest and lowest dimension within each was narrow: 0.06 for AI use, 0.04 for proficiency, and 0.04 for teachers' challenges. The narrowness is itself a finding. It suggests that students and teachers experience AI-supported mathematics as an integrated whole in which no single dimension stands far above or below the others.

Within AI use, accuracy verification ranked first (M = 3.16), with reviewing AI-provided steps the highest item (3.24) and comparing AI answers with one's own calculations the lowest (3.08). Students thus check what AI tells them more readily than they test it against their own work. Task complexity and independent learning shared the same mean (3.11) and the same item range (2.98–3.20), with the lowest items being dependence on AI for higher-level concepts and planning learning tasks with AI. Time spent ranked last (3.10). These patterns are consistent with the view that AI's educational value depends on how learners evaluate outputs (Zawacki-Richter et al., 2019), that verification is necessary with generative tools (Kasneci et al., 2023), and that AI should support rather than replace thinking (Holmes et al., 2019). Students' moderate confidence (3.12) aligns with research linking self-efficacy to technology engagement (Kauffman, 2015; Scherer & Teo, 2019), and the moderate time allocation with

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evidence that consistent use yields stronger learning (Crompton & Burke, 2018; OECD, 2021a).

Within proficiency, conceptual understanding and critical thinking ranked first (3.15) and problem-solving last (3.11), with solving unfamiliar problems the weakest item (3.05). Students appear secure in routine understanding but less so in non-routine reasoning, in line with research on the interdependence of proficiency strands (Kilpatrick et al., 2001; Rittle-Johnson et al., 2015) and on the instructional conditions that build conceptual depth (Hiebert & Grouws, 2017). Within teachers' challenges, academic integrity and institutional support tied for first (3.18), with preventing AI misuse in assessments the most difficult item (3.24). This corresponds with concerns about integrity in digital learning (Bretag, 2019; Eaton & Turner, 2020) and with the role of institutional conditions in technology integration (Tondeur et al., 2017; UNESCO, 2022a).

Profile Correlates of AI Use and Proficiency

Table 2

Correlations of Students' Profile With AI Use and Mathematics Proficiency

Profile	AVB	CTA	IIL	TS	CF	CU	PS	PSA	CT	AMC
Age	.220	.180	.200*	.190	.210*	.182	.205*	−.176	.198*	.121
Gender	.310*	−.280*	.295*	−.260*	.090	.132	−.241*	.276*	.214*	−.130
Grade level	.360*	−.310*	.340*	−.295*	.120	.328*	.295*	−.214*	.341*	.118
Device access	.612*	−.421*	.594*	.132*	.087	.512*	.438*	−.402*	.591*	.105
AI use frequency	.782*	.801*	.743*	.214*	.860	.721*	.684*	.742*	.615*	.092
Purpose of AI use	.642*	.688*	.701*	.082	.415*	.612*	.538*	.667*	.441*	.087
Type of AI tools	.521*	.604*	.438*	.319*	.072*	.504*	.468*	.612*	.397*	.081
Math general average	.761*	.642*	.945*	.342*	.462*	.504*	.468*	.612*	.397*	.081

Note. AVB = accuracy verification; CTA = complexity of tasks; IIL = integration with independent learning; TS = time spent; CF = confidence; CU = conceptual understanding; PS = procedural skills; PSA = problem-solving; CT = critical thinking; AMC = application. *p ≤ .05.

Table 2 presents the 80 coefficients linking students' profiles to the ten dimensions of AI use and proficiency. Sixty-one were significant. The analysis shows a clear gradient: demographic variables produced the weakest and least consistent coefficients, while technology-related and achievement variables produced the strongest.

Age was the weakest correlate, significant for only two AI dimensions (independent learning, $r = .200$; confidence, $r = .210$) and two proficiency domains (procedural skills, $r = .205$; critical thinking, $r = .198$). Gender related to four AI dimensions and three proficiency domains, with mixed signs, including negative coefficients for task complexity ($r = -.280$) and time spent ($r = -.260$). The presence of opposite signs within the same profile variable cautions against simple gender comparisons; recent Philippine psychometric work has shown that instruments themselves must be examined for whether they function equivalently across gender groups before such differences can be interpreted (Panela, 2025a). Grade level showed a similar mixed pattern, positive for verification and independent learning but negative for task complexity, time spent, and problem-solving.

Technology-related variables told a different story. Frequency of AI use produced some of the largest coefficients in the study, notably with task complexity (r = .801), verification (r = .782), and problem-solving (r = .742). Purpose of use and type of AI tools correlated moderately to strongly with most dimensions. Device access correlated strongly with verification (r = .612) and critical thinking (r = .591), yet negatively with task complexity (r = −.421) and problem-solving (r = −.402), suggesting that better-equipped students verify more and delegate complex work less. Math general average correlated significantly with every AI dimension, reaching r = .945 with independent learning. One domain stood apart: application of mathematical concepts was unrelated to all eight profile variables. These patterns fit the Technology Acceptance Model's emphasis on external conditions (Davis, 1989) and research on access, personalization, and the uneven benefits of AI (Luckin et al., 2016; Crompton & Burke, 2023; OECD, 2020; UNESCO, 2023a, 2023b). They also reflect a student population that has lived through years of disrupted schooling, whose effects on Filipino learners' well-being continued well beyond the initial crisis (Panela, 2025c).

Teachers' Profile and Challenges

Teachers' profiles related to their challenges in 16 of 25 pairs, all weak to modest (r = .201 to .356). Educational attainment was the most consistent correlate, linked to monitoring (r = .332), integrity (r = .289), assessment design (r = .214), and instructional adaptation (r = .356). Age, experience, and AI training related to monitoring, integrity, and instructional adaptation; gender related to the same three, with a negative sign for integrity (r = −.241). No teacher characteristic related to institutional support. The challenge of insufficient support therefore appears to be a shared condition of the schools rather than a function of who the teacher is, while classroom-level challenges vary with teachers' preparation. This agrees with TPACK-based accounts of technology integration (Mishra & Koehler, 2006; Koehler & Mishra, 2019) and with research on teacher beliefs and technology use (Tondeur et al., 2017). The limited AI training reported by most teachers, 42.98% of whom had attended only one to three sessions, underlines the value of first mapping teachers' actual competencies, an approach that has guided targeted development of Filipino teachers in other areas (Panela, 2025d).

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Table 3

Correlations of AI Use and Mathematics Proficiency With Teachers' Challenges

Variable	MON	INT	ASD	IAS	ISR
AI use					
Accuracy verification behavior	.628*	.742*	.584*	.691*	.436*
Complexity of tasks assisted by AI	.651*	.781*	.624*	.708*	.458*
Integration with independent learning	.684*	.802*	.641*	.756*	.492*
Time spent using AI tools	.592*	.714*	.548*	.663*	.421*
Confidence in using AI tools	.703*	.823*	.615*	.748*	.477*
Mathematics proficiency					
Conceptual understanding	.601*	.742*	.563*	.688*	.412*
Procedural skills	.572*	.718*	.541*	.633*	.398*
Problem-solving ability	.622*	.801*	.584*	.723*	.441*
Critical thinking skills	.589*	.836*	.612*	.754*	.468*
Application of mathematical concepts	.421*	.632*	.515*	.603*	.372*

Note. MON = monitoring students' AI use; INT = ensuring academic integrity; ASD = designing assessments; IAS = instructional adaptation and strategy; ISR = institutional support and resources. *p ≤ .05.

AI use and proficiency. All 25 correlations between AI use and proficiency were positive and significant, ranging from r = .432 to .841, the most consistent block of relationships in the study. Integration with independent learning correlated most strongly with problem-solving (r = .841), and accuracy verification with critical thinking (r = .836). The coefficients were highest for higher-order domains and lowest for application, which ranged from .432 to .618. Time spent was the weakest AI dimension across the board. The analysis indicates that what students do with AI matters more than how long they use it: reflective, integrative use goes with stronger reasoning. This reading is consistent with constructivist accounts of AI as a learning mediator (Piaget, 1967) and with evidence that AI benefits learning when it supports cognitive effort (Zawacki-Richter et al., 2019; Holmes et al., 2019; Chen et al., 2020).

AI use and teachers' challenges. All 25 coefficients were significant (r = .421 to .823; Table 3). Academic integrity was the challenge most closely tied to students' AI use, with every AI dimension correlating above .71 and confidence reaching .823. Instructional adaptation (r = .663 to .756) and monitoring (r = .592 to .703) followed, while institutional support was weakest (r = .421 to .492). The more confidently and extensively students use AI, the harder teachers find it to safeguard honest work and to adjust their teaching, consistent with concerns raised in research and policy on AI in schools (Holmes et al., 2019; UNESCO, 2023b).

Proficiency and teachers' challenges. The same pattern held for proficiency, with all 25 coefficients significant (r = .372 to .836). Critical thinking and integrity formed the strongest pair (r = .836), followed by problem-solving and integrity (r = .801). Application of mathematical concepts and institutional support formed the weakest (r = .372). Higher proficiency thus coincides with more demanding teaching conditions, perhaps because capable students use AI in more sophisticated ways (Zawacki-Richter et al., 2019; UNESCO, 2023b).

Interpreting the Correlational Structure

Three features of the correlational structure deserve emphasis. First, demographic characteristics matter far less than behavioral and contextual ones; access, frequency, purpose, tools, and achievement carry most of the explanatory weight. Second, the strongest relationships in the study concern higher-order outcomes, problem-solving, critical thinking, and academic integrity, which are precisely the areas where AI can either deepen or bypass thinking. Third, application of mathematical concepts and institutional support consistently show the weakest links, suggesting that they depend on factors outside students' AI habits, namely direct instruction for the former and school-level policy for the latter. Because the data are correlational and come from separate student and teacher groups, these associations describe co-occurrence, not causation.

Conclusion

The correlational analysis shows that students' AI use, mathematics proficiency, and teachers' challenges in General Santos City secondary schools are all at a Good level and are strongly interrelated. Students' technology habits and achievement, rather than their age or gender, correlate most consistently with how they use AI and how proficient they are. Reflective and integrative AI use correlates most strongly with higher-order proficiency, while time spent correlates most weakly. Both AI use and proficiency correlate strongly with teachers' challenges, above all with academic integrity, and teachers' preparation relates to classroom-level challenges but not to the institutional support they receive.

These results support several actions. Schools should promote reflective AI practices, especially comparing AI outputs with students' own work, and should integrate AI literacy into mathematics instruction. Clear academic integrity policies and assessment designs that capture reasoning are needed, given the strength of the integrity correlations. Teacher development should prioritize monitoring, integrity, and instructional adaptation and should be extended to teachers with fewer trainings, and institutional support should be strengthened as a school-wide responsibility. Application of mathematical concepts should receive direct instructional attention. Capacity-building programs for teachers are most effective when they respond to the barriers teachers themselves identify in their classrooms (Panela, 2025e). Future research should match student and teacher data at the class level and use designs that can test causal direction.

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