Journal of Research in Education and Pedagogy
ISSN 3047-7131 (online) & 3047-6410 (print)
August 2026, Vol. 3, No. 3, pp. 451–473

Research Article

Artificial Intelligence Competence Levels Among Secondary Mathematics Teachers in Northern Samar, Philippines

Levi V. Calubag[1,2]

[1]Eladio T. Balite Memorial School of Fisheries, Department of Education, Division of Northern Samar, Bobon, Northern Samar, Philippines
[2]Graduate School, Northwest Samar State University, Calbayog City, Philippines

Abstract
As Artificial Intelligence (AI) tools become more common in schools, mathematics teachers are increasingly expected to use them in ways that support learning without weakening reasoning or academic integrity. However, baseline evidence on the AI competence of K to 12 mathematics teachers and the profile factors associated with it remains limited, especially in resource-constrained settings. This study examined the relationship between the teaching-related profile and AI competence of public secondary mathematics teachers using UNESCO's AI Competency Framework for Teachers (AI-CFT). A cross-sectional descriptive-correlational survey was conducted among 215 public secondary mathematics teachers in the Department of Education (DepEd) Schools Division of Northern Samar during School Year 2025–2026. The instrument measured educational attainment, years of teaching experience, teaching position, relevant AI/ICT-related training exposure, access to AI tools, and AI competence across five AI-CFT domains. Data were analyzed using descriptive statistics and correlational procedures. Results showed that respondents were largely mid-career, mostly in Teacher I to III positions, had limited AI/ICT-related training exposure, and largely reported access to at least one AI tool (91.2%). Overall AI competence was at the Competent level ($\bar{x}$ = 3.53, SD = 0.75), with relatively stronger ratings in Human-Centered Mindset (3.71), AI Pedagogy (3.58), and AI Ethics (3.55), but lower ratings in AI Foundations and Applications (3.43) and AI for Professional Development (3.39). Educational attainment and teaching position were not significantly related to AI competence, while years of teaching experience showed a small negative relationship ($r = -0.229$, $p < .001$). In contrast, training exposure ($r_s = 0.293$, $p < .001$) and access to AI tools ($r_s = 0.476$, $p < .001$) were positively related to AI competence. The findings support targeted AI upskilling and equitable tool access to strengthen responsible AI integration in mathematics instruction.

Keywords: AI Competency Framework for Teachers, Artificial Intelligence, Educational Technology, Mathematics Teachers

Correspondence
Levi V. Calubag
levicalubagoffice@gmail.com
levi.calubag@deped.gov.ph

Received
February 20, 2026
Accepted
July 14, 2026
Published
August 3, 2026

Citation: Calubag, L. V. (2026). Artificial intelligence competence levels among secondary mathematics teachers in Northern Samar, Philippines. *Journal of Research in Education and Pedagogy, 3*(3), 451–473.

DOI: 10.70232/jrep.v3i3.197

1. INTRODUCTION

As Artificial Intelligence (AI) rapidly enters mathematics classrooms, teachers are increasingly challenged to keep pace with changing educational trends as more and more learners access these emerging technologies with little regulation; thus, the urgent question is no longer whether teachers should use AI technologies, but how they can use them competently and responsibly to support meaningful learning. Mathematics teachers, accordingly, must learn how to coexist with the presence of AI-assisted tools and systems and learn how to effectively incorporate them in their professional practice. This shift is particularly crucial in mathematics because AI tools can influence not only productivity but also mathematical reasoning, problem-solving processes, and academic integrity.

Evidence shows both opportunities and risks amid the rising use of AI. In the United States, as student use expands, evidence points to both potential benefits and risks when AI tools are used without clear guidance, especially from teachers (Bastani et al., 2024; Sidoti et al., 2025). Nonetheless, UNESCO's guidance highlights the centrality of teacher competence, and the AI Competency Framework for Teachers (AI-CFT) provides a structured approach for describing progression from safe tool selection to accountable integration and innovation (Miao & Holmes, 2023). In the Philippines, AI use is already common among learners, while persistent challenges in mathematics learning achievement and digital distraction heighten the urgency for competent, classroom-grounded AI integration (De Guzman, 2025; OECD, 2023). As learners increasingly resort to AI tools for mathematical tasks, teacher competence in responsible AI integration becomes more urgent. This warrants that Filipino teachers, as well, should be capacitated in the responsible and effective integration of emerging AI technologies. To that end, the Department of Education (DepEd) has begun institutional efforts to integrate AI in education, including establishing the Education Center for AI Research (E-CAIR) (Department of Education, 2025a; DepEd NCR, 2024). For a resource-constrained school division, teacher competence must be strengthened to optimize the use of AI in mathematics education.

For the DepEd Schools Division of Northern Samar, Philippines, local data on mathematics teachers' AI competence remains limited, creating a practical gap for targeted professional development and support. Specifically, two gaps are evident: (1) the absence of division-level baseline evidence on mathematics teachers' AI competence using the UNESCO AI-CFT as a recognized framework; (2) limited evidence on which profile factors of secondary mathematics teachers relate to AI competence. Accordingly, this study establishes a division-level baseline of public secondary mathematics teachers' AI competence using the UNESCO AI-CFT, presents domain-specific competence profiles across the five AI-CFT domains, and examines how selected teaching-related profile variables are associated with teachers' AI competence in a K to 12 secondary mathematics context.

1.1. Literature Review

1.1.1. Conceptual Literature

Artificial intelligence (AI) refers to computational systems that process vast amounts of information, generate new content, recognize patterns across multiple data formats, and support human decision-making through predictive analytics (Miao & Cukurova, 2024). AI in education integrates various technologies in the teaching and learning contexts that mimic human capacity and intelligence. With AI technology, certain tasks previously associated with humans, such as reasoning, management, and decision-making, are now integrated and can be performed by computer machines. In mathematics education, current applications of AI leverage computer algorithms and machine learning to analyze and interpret student data to provide personalized learning, intelligent tutoring systems, automated grading feedback, and administrative applications (University of Iowa, 2024). Hence, in recent years, the previously inconceivable power of AI has made an unprecedented shift in how mathematics teachers teach and facilitate learning. In K to 12 education, this shift alters who carries the cognitive work that traditionally makes mathematical learning visible to the teacher.

While AI has provided potential to address some of the biggest challenges in education today, it also has its perils and pitfalls. Challenges concerning the lack of creativity and problem-solving skills, inability to explain reasoning, bias in data and algorithms, absence of emotional intelligence, and data privacy and security are just a few among many (Chasokela, 2025; Opesemowo, 2024). Meanwhile, UNESCO has also recognized that there are clear risks in the use of AI in education. These include challenges such as weakened human agency, privacy violations, widened inequalities and discrimination, and an over-automation of instruction that can devalue teacher judgment and narrow learning to what machines can compute (Miao & Cukurova, 2024). These imperfections of AI tools and AI-assisted systems call for new collaborative roles of teachers—as co-designers, data providers, and evaluators in every academic endeavor of learners. Similarly, it has prompted teacher-researcher partnerships to translate AI innovations into meaningful practice (Chiu, 2024; Meylani, 2024; Nazaretsky et al., 2022). As a result, teachers are increasingly called to serve as gatekeepers of productive and ethical use of AI in mathematics classrooms that serve as guardrails for students. For mathematics classrooms, these risks become concrete when an AI tool supplies a correct-looking answer while concealing flawed reasoning, or when students begin to treat "generated" work as equivalent to "understood" work. The teacher's task is therefore epistemic as much as managerial: to preserve the conditions under which mathematical thinking can be examined, challenged, and improved. Although articulated primarily in higher education, the critical perspective advanced by Bozkurt et al. (2024) remains relevant to the present study because it emphasizes that generative AI in teaching and learning is not a neutral technology. While it may offer possibilities for personalization, efficiency, and expanded access, it also raises concerns related to bias, misinformation, weakened human agency, and the erosion of authentic intellectual and interpersonal engagement. This broader educational perspective reinforces the view that teacher competence in AI should not be understood merely as technical readiness, but also as the capacity to exercise ethical, reflective, and human-centered judgment in the use of AI for teaching and learning. Recent work in mathematics education brings this concern closer to classroom practice. Garcia et al. (2026) argued that mathematics educators need critical competencies in AI literacy so that they can better understand how AI systems affect the feedback students receive, influence the way learning experiences are organized, and inform how students come to see themselves as learners of mathematics. This view is important in the present study because it suggests that competence in AI is not only about operating tools, but also about making informed decisions about how such tools may affect mathematical understanding, participation, and equity in the classroom.

In parallel, the ongoing 2025 review draft of the Organization for Economic Co-operation and Development European Commission's (OECD-EC) AI Literacy Framework organized what students should know and be able to do under a Knowledge-Skills-Attitudes framework across the four domains of interaction with AI—the Engaging, Creating, Managing, and Designing domains (OECD, 2025a). This framework complements the teachers' view and focuses on the students' capabilities in interaction with AI. This approach not only focuses on the technical know-how of utilizing AI technologies but also on cultivating critical awareness and positive attitudes towards responsible use among learners. The draft further ties directly to PISA 2029 development and notes the European Union AI Act that requires providers and deployers to ensure adequate AI literacy among users, including teachers and students (Miao & Holmes, 2023). Looking ahead, this initiative can also provide insightful global benchmarks for developing countries, such as the Philippines, to adopt in their local context. Although this framework focuses on learners, it is imperative that teachers must first achieve AI literacy themselves, develop positive attitudes towards AI technology use, and be AI-ready before effectively guiding learners to avoid harm and enable potential benefits. This creates a practical asymmetry: teachers are expected to regulate and teach with tools that students may already be using, often more frequently, outside formal instruction.

The discourse on K to 12 education further frames AI literacy in two complementary ways: (a) learning experiences that build technical, conceptual, and applied skills, and (b) theoretical models that structure what should be taught. These two perspectives point to the need for competency frameworks that are modular, personalized, and co-designed with teachers, with stronger attention to conceptual understanding and potential unintended consequences of AI use (Casal-Otero et al., 2023). At the course level, a practical AI Curriculum Alignment Model (AI-CAM) introduced by Schofield and Zhou (2025) emphasizes constructive alignment. First, there is a need to clarify learning outcomes, then design assessments, select appropriate GenAI tools, plan active and hands-on learning activities, and finally monitor and improve learning outcomes to ensure that AI serves pedagogy rather than drives it (Schofield & Zhou, 2025). Yet alignment models address the design of instruction more than the competence of the teacher who must exercise judgment about what AI can be trusted to do and what must remain human work. For that purpose, a teacher-focused competence framework is needed, and this study adopts UNESCO's AI Competency Framework for Teachers (AI-CFT) as its organizing lens.

Teachers' AI integration and adoption in the classroom can be impacted by teacher-related factors, such as actual familiarity with tools, prior training, access to AI or technology infrastructure, and the level of institutional support they receive. Accounts in the Philippines describe a generally positive orientation towards using AI to personalize learning and to streamline administrative work, even while teachers hold reservations about diminished personal interaction and privacy (Sibug et al., 2024). At the same time, widespread unfamiliarity with AI-assisted technology or AI systems, such as the generative AI tool ChatGPT, among teachers calls for substantial demand for technical and pedagogical training to effectively integrate them in teaching (Magat & Sangalang, 2024). These factors make professional development, holistic technical support, and clear data protection practices drivers of meaningful integration of AI technology in education. Thus, where teacher factors reflect strong institutional support, access to tools, and sustained capacity-building, this can translate to informed, ethical use of AI. On the contrary, where there is lag, especially in terms of persistent reservations or hesitancy in the use of these technologies, the role of teachers as gatekeepers and guardrails becomes even more essential. In resource-constrained school divisions, this relationship between competence and enabling conditions becomes more salient because access and training are uneven, and policy expectations may outpace classroom realities.

A long-standing foundation for technology-related competence is UNESCO's Information and Communication Technology Competency Framework for Teachers (ICT CFT), which frames teacher technology competence as progressive development across curriculum, pedagogy, and professional practice, linked to organizational improvement (UNESCO, 2018). Building specifically for AI, further developments on UNESCO's AI Competency Framework for Teachers (AI-CFT) set six new guiding principles and operationalizes teachers' competence through five aspects—the human-centered mindset, AI ethics, AI foundations and applications, AI pedagogy, and AI for professional development, through acquire, deepen, and create levels (Miao & Cukurova, 2024). In this framework, competence is not just reduced to tool familiarity. A key implication is that competence is also being able to justify use, set boundaries, and sustain professional learning as technologies evolve.

Operational tools make these concepts of AI competence of teachers measurable and actionable. The Teacher Artificial Intelligence Competence Self-efficacy Scale (TAICS) model articulates six competence domains—AI knowledge, AI pedagogy, AI assessment, AI ethics, human-centered education, and professional engagement—that can be used to examine interventions and correlational research, as well as inform strategies for teacher development (Chiu et al., 2025). For assessing teachers' generative AI competencies, specifically, T-GAIC details five dimensions—technological proficiency, pedagogical compatibility, preparing students for effective practices, GenAI-related professional development and communication, and risk/ethical awareness—that help align training, curriculum, and evaluation with GenAI's distinctive affordances and risks (Shi, 2025; Zhou et al., 2025). However, despite expanding measures, fewer studies provide domain-level baselines using UNESCO AI-CFT and relate competence to practical teacher conditions such as training exposure and access, especially among K to 12 mathematics teachers.

1.1.2. Research Literature

Recent empirical work suggests that teachers' AI-related competence is shaped by both personal and contextual conditions, and that competence is increasingly treated as a multidimensional construct that can be assessed using validated measures. For instance, Younis (2025) developed an Artificial Intelligence Literacy (AIL) scale and reported that teachers' AI-related competence varies across profile-related factors such as teaching experience and specialization. At the same time, evidence on innovation uptake implies that exposure to AI practices is not determined solely by formal policy but also by diffusion through networks and opportunity structures, which can accelerate adoption in ways that differ across groups (Phillips, 2025). Across related strands of literature, enabling conditions repeatedly emerge as central: clarity of direction and training quality support school innovation (Nueva, 2022), perceived ease of use and technical support shape engagement with AI tools (Wang, 2025), and foundational digital competence is associated with more favorable orientations toward AI even when direct experience remains limited (Galindo-Domínguez et al., 2024). These findings collectively indicate that competence development and AI uptake are tied to practical conditions, such as training, support, and access.

Philippine and local studies point to similar patterns but leave AI competence itself less clearly documented, particularly at the division level and in K–12 mathematics. In Northern Samar, Philippines, the author's earlier unpublished master's thesis showed that teachers' ICT competence was strongly associated with ICT utilization and that training and access to tools were related to utilization outcomes despite constraints such as limited facilities and connectivity. Extending to AI-specific contexts, Silagan and Tumapon (2025) reported that technological competence and training/support are associated with teachers' acceptance of AI, while qualitative accounts of generative AI in classrooms highlight concerns about academic integrity and the quality of learner outputs and point to the need to revise instructional practices (Lodge, 2024; Manczka, 2024). With the emergence of AI technology use in several contexts, this present study specifically fills content gaps on how teaching-related profile variables are related to AI-specific competence levels of public secondary mathematics teachers in the DepEd Schools Division of Northern

Samar, similar to how, in previous studies prior to the emergence of AI technologies, ICT competence was linked with teacher factors.

1.3. Theoretical Framework

The AI Competency Framework for Teachers (AI CFT), developed by Miao and Cukurova (2024) under the auspices of UNESCO, serves as a theoretical anchor of this study. It articulates the progressive development of teachers' competence in artificial intelligence through five domains: Human-Centered Mindset (orienting AI use toward human agency, well-being, and accountability), AI Ethics (applying ethical principles and safeguards such as privacy, fairness, and inclusion), AI Foundations and Applications (understanding core AI concepts and using AI tools appropriately for educational tasks), AI Pedagogy (integrating AI into instruction, learning activities, and assessment while preserving meaningful human judgment), and AI for Professional Development (using AI to support continuous professional growth, collaboration, and professional improvement). These five domains are distributed across the Acquire, Deepen, and Create progression levels. The main premise of the framework also clarifies that AI competence among teachers is a multidimensional and evolving construct that encompasses knowledge, skills, and ethical dispositions that enable teachers to use, adapt, and innovate with AI in education. In the context of this study, the AI-CFT provides the foundation for measuring the AI competence levels of public secondary mathematics teachers in the DepEd Schools Division of Northern Samar, Philippines, with its five domains to be used as subscales of the AI Competency Framework levels of teachers. Complementarily, the Will–Skill–Tool (WST) model proposes that meaningful technology integration depends on teachers' motivation and attitudes (will), capability (skill), and access to resources (tool) (Knezek & Christensen, 2015). Hence, in this study, the teaching-related profile variables such as teachers' education, experience, training, and access to AI technologies may serve as manifest conditions of WST. In addition, the Diffusion of Innovations theory explains how new practices and technologies spread through social systems via adopter categories and communication networks (García-Avilés, 2020; Rogers, 1962). Based on this theory, these categories help describe the pattern and speed at which new ideas, practices, or products spread through a population. Relatedly, this also provides a socio-organizational lens for understanding how AI competence may spread among teachers in the DepEd Schools Division of Northern Samar.

It is for these reasons that this study determines the teaching-related profile and the AI competence of public secondary mathematics teachers in the DepEd Schools Division of Northern Samar, Philippines, using the UNESCO AI Competency Framework for Teachers (AI-CFT). Specifically, it sought to answer the following questions: (1) What is the teaching-related profile of the respondents in terms of (a) highest educational attainment, (b) years of teaching experience, (c) teaching position, (d) number of relevant AI/ICT-related trainings attended, and (e) access to AI technologies/tools? (2) What is the level of AI competence of the respondents based on the AI-CFT domains, in terms of: (a) Human-centered Mindset, (b) AI Ethics, (c) AI Foundations and Applications, (d) AI Pedagogy, and (e) AI for Professional Development? (3) Is there a significant relationship between the respondents' teaching-related profile variables and their AI competence?

2. METHODOLOGY

This section presents the methods and procedures that the researcher used in the course of the study. It specifically describes the research design, population and sample of the study, measures and instruments, specific procedures, and the data processing throughout this study.

2.1. Research Design

This study employed a descriptive-correlational design using a cross-sectional survey, which is well-suited to determine the teaching-related profiles and the AI competency levels of public secondary mathematics teachers in the DepEd Division of Northern Samar, Philippines. This method describes variables and examines the relationships between them without manipulation, aiming to identify patterns and associations. Moreover, this design also provides a systematic way of identifying relationships that can serve as the basis for predictions and further inquiry (Creswell & Creswell, 2022; Mills & Jordan, 2022). In particular, the cross-sectional survey was used to collect data from the population at a single point in time in order to provide a snapshot of the teachers' profile and level of AI competency framework during the school year 2025-2026.

2.2. Population and Sample

The respondents of this study were public secondary mathematics teachers in the DepEd Schools Division of Northern Samar, Philippines, who had at least one year of teaching experience during School Year 2025 to 2026. Division records indicated a population of 457 eligible teachers. A minimum target sample of ≥ 209 was determined using Raosoft's calculator based on Cochran's formula (Raosoft, Inc., 2004) at 95% confidence and 0.05 margin of error. The study employed proportional simple random sampling across the division's major cluster areas, yielding 215 respondents: 39 (18.14%) from Balicuatro, 106 (49.30%) from Central, and 70 (32.56%) from Pacific.

2.3. Research Instruments

Data were collected through a structured cross-sectional survey questionnaire, which incorporated two parts. Part I of the questionnaire was composed of questions that described the teaching-related profile of mathematics teachers such as their highest educational attainment, years of teaching, teaching position, the number of AI/ICT-related trainings attended in the past three years, and whether or not AI technologies were available or accessible to them, specifying as well which AI tools were available and accessible as informed by the categories and identification of AI-based mathematical education tools (Awang et al., 2025; Schofield & Zhou, 2025). Part II consisted of researcher-developed items mapped to UNESCO's AI-CFT. Items were adapted from, and explicitly traced to, the framework's Learning Objectives (LOs) and Contextual Activities (CAs). The wording was tailored for clarity, single-idea focus, and suitability to Likert-type measurement. Coverage was ensured by constructing five subscales—human-centered mindset, AI Ethics, AI foundations and applications, AI pedagogy, and AI for professional development—with 12 items each, for a total of 60 items. All items were positively worded; thus, no reverse scoring was applied during data analysis. Within each subscale, items span the framework's progression levels (Acquire, Deepen, Create) to reflect a range of behaviors and difficulty; however, progression levels were used only for descriptive profiling and were not analyzed as separate variables. Respondents were asked to indicate how true each statement is of their AI competence and current practice using a five-point Likert scale: 5 – Completely True (CT), 4 – Somewhat True (ST), 3 – Neutral (N), 2 – Somewhat False (SF), 1 – Completely False (CF). For the AI competence scale, the possible raw total scores ranged from 60 to 300, while each domain subscale ranged from 12 to 60. For interpretation and analysis, the dimensions under the AI Competency Framework levels were computed as the mean of answered items and interpreted as Very Competent (VC), Competent (C), Moderately Competent (MC), Less Competent (LC), and Incompetent (I), respectively. The questionnaire was designed to be completed in approximately 15 to 20 minutes.

2.4. Validity and Reliability

In conducting the validation of the instrument, six (6) DepEd content experts were purposively invited for their expertise in mathematics and technology education, quantitative and qualitative research, language, educational administration and management, human resource development, and professional development, as well as their expertise in the context of the DepEd Schools Division of Northern Samar. To improve the face and content validity of the instrument, they reviewed scales for AI competence levels. Using a 4-point relevance scale, the Content Validity Index (CVI) and modified kappa were computed at the item level (I-CVI) with I-CVI ≥ 0.78 and scale level (S-CVI) with S-CVI/Ave ≥ 0.90 used as decision thresholds (Lynn, 1986; Polit & Beck, 2006). The I-CVI and modified kappa values ranged from 0.67 to 1.00, while the S-CVI/Ave = 0.897 for AI-CFT, indicating strong scale-level content validity. Two items were flagged for revision to improve clarity and construct fit (each I-CVI = 0.67, k*=0.56). Meanwhile, all the remaining items met the decision threshold and were retained. Experts also affirmed face validity and recommended simplifying select technical terms, which were incorporated into the revised items prior to pilot testing. Thereafter, a pilot test with 30 mathematics teachers from another division (DepEd Calbayog City, Philippines) assessed clarity and internal consistency. The Cronbach's alpha coefficients were calculated for each AI competence dimension. The scale consisted of 60 items with 12 items for each of the five domains. The five AI competence domains showed excellent internal consistency: Human-centered mindset ($\alpha = 0.869$) – excellent reliability, AI Ethics ($\alpha = 0.953$) – excellent reliability, AI Foundations & Applications ($\alpha = 0.966$) – excellent reliability, AI Pedagogy ($\alpha = 0.957$) – excellent reliability, and AI for Professional Development ($\alpha = 0.962$) – excellent reliability. The overall instrument for AI competence levels yielded a Cronbach's alpha of 0.983, indicating excellent reliability (DeVellis, 2016; George & Mallery, 2006; Nunnally & Bernstein, 1994). The analysis further revealed that most items were worthy of retention because deleting them resulted in a decrease in alpha. A few items would yield only trivial alpha increases if removed—Item 25 under AI Foundations and Applications ($\alpha = 0.969$ if deleted), Item 37 under AI Pedagogy ($\alpha = 0.958$ if deleted), and Item 59 under AI for Professional Development ($\alpha = 0.965$ if deleted)—therefore, the researcher opted not to delete these items.

2.5. Procedures

Institutional permissions were secured from the Graduate School of Northwest Samar State University, the DepEd Region 8, and the DepEd Northern Samar Division offices prior to data collection. The questionnaire was administered in hybrid mode using Google Forms and printed copies to accommodate varying access and preferences. Printed instruments included a QR code linking to the online form, and respondents were allowed to choose their preferred mode. Informed consent was obtained from all participants, and confidentiality/anonymity procedures were observed. Completed forms were retrieved and subjected to data cleaning and screening for completeness prior to analysis.

2.6. Data Analysis

Descriptive statistics (frequency, percentage, mean, and standard deviation) were used to summarize teaching-related profile variables and AI competence domain scores. Distributional properties were examined using the Shapiro–Wilk test, skewness and kurtosis indices, and Q–Q plots to inform the selection of correlation procedures (Demir, 2022; Kamath et al., 2025; Shatz, 2024). Specifically, for access to technology, the raw data initially consisted of a multi-response item listing the specific AI technologies and tools used and accessible by respondents, and coded 0 when respondents reported not using any AI tools at all; then counting the number of distinct AI tools each respondent had access to or used, and treating that number as the access variable. Meanwhile, the grouped categories were also used to present the distribution of the years of teaching experience and the number of relevant AI/ICT-related trainings attended in the last three years. Mean and standard deviation were also used for the respondents' years of teaching experience, the number of relevant AI/ICT-related trainings attended under the teaching-related profile variable, and the respondents' level of AI competence variable. To determine significant relationships between the teaching-related profiles of the respondents and their association with the main variable, different statistics were applied depending on the profile variable. Associations between AI competence scores and the highest educational attainment and teaching position, being categorical variables, were summarized using the eta (η) correlation (Metsämuuronen, 2023). The relationship between years of teaching experience and AI competence scores was tested using Pearson's product–moment correlation coefficient (r) (Bishara & Hittner, 2012; Janse et al., 2021; Kwak & Kim, 2017), and the relationships of training counts and access counts to AI competence scores were tested using Spearman's rho (r_s) (Bishara & Hittner, 2012; Shreffler & Huecker, 2025). All inferential tests conducted in this study were two-tailed and were evaluated at the 0.05 level of significance ($p < .05$). Data were analyzed using JASP statistical software, version 0.95.4 (JASP Team, 2025).

3. RESULTS

This section presents the results and discussion of the analyzed data taken from the public secondary mathematics teachers in the DepEd Schools Division of Northern Samar, Philippines, during the School Year 2025-2026 to shed light on their teaching-related profile and their AI Competence.

3.1. Teaching-related Profile of the Respondents

The findings in Table 1 show that the public secondary mathematics teachers in the DepEd Schools Division of Northern Samar are mostly mid-career and clustered in the lower career ranks. Nearly half (48.8%) have earned master's units, followed by completed master's degrees (24.2%), bachelor's degree holders (20.9%), and a small fraction with doctoral units (3.7%) and completed doctoral degrees (2.3%). Teaching experience averaged about 10 years ($\bar{x}$ = 9.94, SD = 6.12), with most having 6 to 10 years in service (40.0%), followed by 11 to 15 years (22.8%) and 1 to 5 years (20.5%). In terms of teaching position, most are Teacher III (50.2%), followed by Teacher I (23.3%) and Teacher II (13.5%), while only a small proportion occupy Master Teacher ranks (13.1% cumulative). Relevant AI/ICT-related training exposure among teachers remains limited, with 58.6 percent reported none, 35.8 percent attending one to two trainings, and 5.6 percent of teachers participating in three or more ($\bar{x}$ = 0.71, SD = 1.12), which suggests that the teacher respondents are quite spread out in terms of participation in trainings, since there is a small cluster who have relatively more trainings, but the majority of the mathematics teachers had little or no structured opportunity to build their skills on the use of Artificial Intelligence and even in Information, Communication, and Technology and potentially rely only on self-study or informal sharing with colleagues.

Table 1. Teaching-related Profile of the Respondents in terms of Highest Educational Attainment, Years of Teaching Experience, and Number of Relevant AI/ICT-related Trainings Attended

Teaching-related Profile		f	Percent (%)
Highest Educational Attainment	Bachelor's Degree	45	20.9
	With Master's Units	105	48.8
	Master's Degree	52	24.2
	With Doctoral Units	8	3.7
	Doctoral Degree	5	2.3
Years of Teaching Experience	1 to 5 years	44	20.5
($\bar{x}$ = 9.94, SD = 6.12)	6 to 10 years	86	40.0
	11 to 15 years	49	22.8
	16 to 20 years	21	9.8
	21 years and above	15	7.0
Teaching Position	Teacher I	50	23.3
	Teacher II	29	13.5
	Teacher III	108	50.2
	Master Teacher I	20	9.3
	Master Teacher II	4	1.9
	Master Teacher III	4	1.9
Number of Relevant AI/ICT Trainings	No Trainings	126	58.6
Attended	1 to 2 Trainings	77	35.8
($\bar{x}$ = 0.71, SD = 1.12)	3 or More Trainings	12	5.6

Note. N = 215. f = frequency; Percent (%) = percentage of respondents. $\bar{x}$ = mean; SD = standard deviation. Years of teaching experience and the number of relevant AI/ICT-related trainings attended are also reported as grouped categories for the distributional summary.

Table 2 shows that almost all of the mathematics teacher respondents have some access to AI tools. Out of 215 respondents, 196 (91.2%) teachers reported using at least one AI application or tool, while 19 teachers (8.8%) said they were not using AI yet in their work as mathematics teachers. It is interesting to note, however, that when it comes to specifics, a few tools clearly stand out as most utilized by the mathematics teachers. At the top of the list is OpenAI's ChatGPT, with 176 teachers (81.9%) reporting that they are using this generative AI tool. Canva places second with 127 teacher respondents (59.1%) using it for teaching preparation and visual aids. The teachers have also reported other notable generative and math-specific AI tools, such as Meta AI, which is utilized by 103 teachers (47.9%); the AI math solver of GeoGebra, reported to be used by 102 teachers (47.4%); and Photomath, with 78 teacher-users (36.3%). They form the core for most respondents, while the other listed apps are used by much smaller proportions of respondents.

Table 2. Distribution of Teaching-Related Profile of the Respondents in terms of Access to AI Technologies and Types of AI Tools Utilized

Access to AI Technologies		Frequency	Percent (%)
Not using AI		19	8.8
With Access to AI		196	91.2
Total		215	100.0
Generative AI and Chatbots	ChatGPT	176	81.9
	Meta AI	103	47.9
	Gemini (formerly Bard)	75	34.9
	Copilot	72	33.5
	MathBox	30	14.0
	Perplexity	12	5.6
	Cici	9	4.2
	Others	9	4.2
AI Math Solvers/Explainers	GeoGebra	102	47.4
	PhotoMath	78	36.3
	Mathway	50	23.3
	Microsoft Math Solvers	16	7.4
	Wolfram Alpha	16	7.4
	Math Solver by Cymath	16	7.4
	Others	30	14.0
Adaptive Learning System/Intelligent Tutoring	e-Mathematics Learning Strategies	50	23.3
	SchoolAI	13	6.0
	MathE	11	5.1
	Squirrel AI	5	2.3
	ALEKS	4	1.9
AI-Powered Assessment Feedback	Wayground (formerly Quizizz)	50	23.3
	Century Tech	9	4.2
	Gradescope	8	3.7
	Others	4	1.9
Augmented Reality for Math Visualization	Geogebra AR	67	31.2
	Mobile Math Trail Apps	23	10.7
	Others	4	1.9
Virtual Reality for Math/3D Visualization	CalcVR	16	7.4
	Eclipse VR	8	3.7
	Others	8	3.7
AI-supported Serious Games	Gea2 (STEM serious game)	19	8.8
AI-Assisted Classroom Workflow/ Teaching Support	Canva	127	59.1
	Khan Academy	15	7.0
	Classpoint AI	12	5.6
	Magic School AI	9	4.2
	Others	5	2.3

3.2. Level of AI Competence of the Respondents

Table 3 shows the level of Artificial Intelligence Competence of the secondary mathematics teachers of the DepEd Schools Division of Northern Samar on the AI Competency Framework for Teachers (AI-CFT).

Human-centered Mindset. As can be gleaned from Table 3, the mathematics teachers rated themselves overall competent in the human-centered mindset domain of the AI Competency Framework, with an average mean of 3.71 and a standard deviation of 0.74. This indicates that most of the teachers' ratings concentrate around that "competent" level rather than being spread out to the extremes. This clearly shows that there is a fairly consistent sense that the teacher respondents can keep human agency in view when working with any AI application or tools. Among the specific indicators, the strongest area is item 1, in which teachers reported being competent in weighing the benefits and risks of an AI tool before using it in class ($\bar{x}$ = 4.33, SD = 0.87). Many teachers are also competent in sharing the simple dos and don'ts to protect human agency when using AI, as in item 4 ($\bar{x}$ = 4.14, SD = 0.89), and explaining why certain tools should not be used with students, as in item 2 ($\bar{x}$ = 4.09, SD = 0.85). Hence, teachers are relatively confident about making day-to-day decisions on whether and how AI should be used with their learners. However, the lowest item tends to be in helping draft or consult on policies defining rights and responsibilities in the AI era in item 11 ($\bar{x}$ = 3.18, SD = 1.10). Teachers also feel only moderately competent in citing local or international rules or policies to defend teacher accountability in item 6 ($\bar{x}$ = 3.38, SD = 0.96), and in item 10, which is about organizing dialogues that foster human-centered social cohesion in the AI era ($\bar{x}$ = 3.40, SD = 1.07). These are more system-level and advocacy-oriented tasks, under the deepen and create levels of UNESCO's AI-Competency Framework for Teachers, having slightly lower means.

Table 3. Mean and Standard Deviation on the Level of AI Competency Framework for Teachers of the Respondents in terms of Human-centered Mindset

Indicators	$\bar{x}$	Int.	SD
1. Before using an AI tool, I weigh its benefits and risks for my class.	4.33	C	0.87
2. I can explain why certain AI tools should not be used with my students.	4.09	C	0.85
3. I identify ways an AI tool might reduce teacher or student agency.	3.96	C	0.89
4. I share simple 'dos and don'ts' that protect human agency when using AI.	4.14	C	0.89
5. I can trace who remains accountable when AI assists school decisions.	3.41	MC	1.00
6. I cite local or international rules/policies to defend teachers' accountability.	3.38	MC	0.96
7. I design activities that preserve human interaction when students use AI.	3.65	C	1.03
8. I prevent AI uses that could replace teacher judgment or students' thinking.	3.77	C	1.09
9. I advocate for human and planetary well-being when AI use is discussed at school.	3.73	C	0.99
10. I organize dialogues that promote human-centered social cohesion in the AI era.	3.40	MC	1.07
11. I help draft or consult on policies that define rights and responsibilities in the AI era.	3.18	MC	1.10
12. I report harmful AI uses and help our community respond constructively.	3.51	C	1.07
Average on Human-centered Mindset	3.71	C	0.74

Note. $\bar{x}$ = mean; SD = standard deviation; Int. = interpretation. Scale: 4.51–5.00 = Very Competent (VC); 3.51–4.50 = Competent (C); 2.51–3.50 = Moderately Competent (MC); 1.51–2.50 = Less Competent (LC); 1.00–1.50 = Incompetent (I).

Table 4. Mean and Standard Deviation on the Level of AI Competency Framework for Teachers of the Respondents in terms of AI Ethics

Indicators	$\bar{x}$	Int.	SD
1. I use ethical perspectives (privacy, agency, inclusion) when planning AI use at school.	3.98	C	0.89
2. I can map core AI-ethics principles and connect them to the regulations we follow in our institution or school.	3.45	MC	1.01
3. I check whether local AI regulations apply to my classroom practice.	3.74	C	0.95
4. I watch for biased AI outputs that could exclude or harm students, and I report risks.	3.66	C	1.00
5. I maintain a personal AI-safety tracker of common risks and mitigations.	3.46	MC	1.08
6. I review and whitelist AI tools based on safety, accessibility, and bias criteria.	3.66	C	1.01
7. I teach and update clear 'dos and don'ts' for responsible AI use.	3.89	C	0.98
8. I prevent misuse of AI by adding human validation steps to ambiguous cases.	3.78	C	1.05
9. I assess and improve the user guidance of AI tools used in our school.	3.57	C	1.05
10. I lead awareness efforts and dialogues on AI ethics in my community.	3.41	MC	1.13
11. I help co-design ethical prototypes of AI tools for education.	3.02	MC	1.16
12. I translate global debates on AI's social impact into concrete local actions.	2.93	MC	1.14
Average on AI Ethics	3.55	C	0.85

Note. $\bar{x}$ = mean; SD = standard deviation; Int. = interpretation. Scale: 4.51–5.00 = Very Competent (VC); 3.51–4.50 = Competent (C); 2.51–3.50 = Moderately Competent (MC); 1.51–2.50 = Less Competent (LC); 1.00–1.50 = Incompetent (I).

AI Ethics. On the ethics sub-domain, the mathematics teacher respondents once again were placed in the "competent" range. As shown in Table 4, the overall mean for AI ethics is 3.55 with a standard deviation of 0.85, suggesting that, on average, the teachers feel reasonably capable of handling the ethical dimensions of AI. The standard deviation is a bit wider here than in the previous sub-domain, indicating that some teachers are fairly consistent with their belief regarding their competence on AI ethics, while others are still finding their footing. Specifically, the highest three indicators—item 1, item 7, and item 8—fall under everyday classroom practice. Most teachers reported being competent in using ethical perspectives like privacy, agency, and inclusion when planning to use AI at school ($\bar{x}$ = 3.98, SD = 0.89).

Many also reported their competence in teaching and regularly updating clear “dos and don’ts” for responsible AI use ($\bar{x}$ = 3.89, SD = 0.98), and competence in preventing misuse of AI by inserting human validation steps when cases are ambiguous, as seen in item 8 ($\bar{x}$ = 3.78, SD = 1.05). These indicators sit at the acquire and deepen levels of UNESCO’s AI competency framework, which is somewhat expected of the teachers with the aforementioned profiles. Put simply, teachers seem most confident when ethics is tightly tied to lesson planning, classroom rules, and concrete safeguards around how students actually use the AI tools. Where the competences of teacher respondents are lower is at the more advanced and outward-facing tasks under the create level of the AI competency framework. The lowest means appear in item 12 with moderate competence, which is about teachers’ translating global debates on the social impact of AI into concrete local actions ($\bar{x}$ = 2.93, SD = 1.14), and in item 11, co-designing ethical prototypes of AI tools for education ($\bar{x}$ = 3.02, SD = 1.16). Even item 10 on leading broader awareness efforts and dialogues on AI ethics in the community ($\bar{x}$ = 3.41, SD = 1.13) draws only a moderately competent rating. In other words, while mathematics teachers appear able to operationalize ethical guidance within their immediate teaching practice, only a few feel prepared to engage in higher-order ethical leadership roles beyond the classroom.

Table 5. Mean and Standard Deviation on the Level of AI Competency Framework for Teachers of the Respondents in terms of AI Foundations and Applications

Indicators	$\bar{x}$	Int.	SD
1. I can explain what AI is, common techniques, and functions of common AI tools.	3.74	C	0.95
2. I locate and operate AI tools that fit my local teaching context.	3.79	C	1.00
3. I can draw a simple concept map showing how a chosen AI system is trained and used in school tasks.	3.41	MC	0.97
4. I help curate a set of validated, trustable AI tools for teachers.	3.21	MC	1.08
5. I skillfully operate widely used AI tools for typical school tasks.	3.88	C	1.01
6. I visualize how selected AI systems work (training, models, datasets).	3.64	C	0.94
7. I apply knowledge of data/algorithm/coding to solve problems.	3.69	C	1.04
8. I investigate design-rooted bias or accessibility issues in AI tools.	3.27	MC	1.04
9. I customize or assemble AI tools to improve accessibility for diverse learners.	3.25	MC	1.10
10. I co-create AI tools that promote climate-friendly actions.	2.98	MC	1.16
11. I define testing criteria and iterate on AI tools I help create or adapt.	3.14	MC	1.14
12. I contribute to a shared repository of trustworthy, locally relevant AI tools.	3.14	MC	1.15
Average on AI Foundations and Applications	3.43	MC	0.87

Note. $\bar{x}$ = mean; SD = standard deviation; Int. = interpretation. Scale: 4.51–5.00 = Very Competent (VC); 3.51–4.50 = Competent (C); 2.51–3.50 = Moderately Competent (MC); 1.51–2.50 = Less Competent (LC); 1.00–1.50 = Incompetent (I).

AI Foundations and Applications. In Table 5, the competence of the respondents of this study in terms of AI foundations and the applications domain is relatively lower compared with the previous areas. The overall mean is 3.43 with a standard deviation of 0.87, rating themselves to be in the “Moderately Competent” range. The obtained standard deviation conveys that ratings on the scale are fairly spread out, potentially having teachers who are quite at ease with the foundations and applications of AI, while others are still somewhere near the getting familiar stage of AI utilization. Among the indicators, the strongest areas are those that involve locating and operating existing AI tools rather than creating or redesigning them. The highest-rated indicator is Item 5, where teachers reported being competent in skillfully operating widely used AI tools for typical school tasks ($\bar{x}$ = 3.88, SD = 1.01). Teachers were also competent in locating and operating AI tools that fit their local teaching context (Item 2; $\bar{x}$ = 3.79, SD = 1.00) and explaining what AI is, including common techniques and functions of familiar AI tools (Item 1; $\bar{x}$ = 3.74, SD = 0.95). These results suggest that many teachers can use off-the-shelf AI applications and articulate their basic functions in school-related tasks. However, the lowest ratings were observed in indicators that reflect more design- and creation-oriented competencies. The lowest mean is Item 10 on co-creating AI tools that promote climate-friendly actions ($\bar{x}$ = 2.98, SD = 1.16). Teachers also rated themselves only moderately competent in defining testing criteria and iterating on AI tools they help create or adapt (Item 11; $\bar{x}$ = 3.14, SD = 1.14) and contributing to a shared repository of trustworthy, locally relevant AI tools (Item 12; $\bar{x}$ = 3.14, SD = 1.15). These tasks require deeper technical knowledge, tool design skills, and collaboration beyond one’s own classroom, which may explain the relatively lower self-ratings.

AI Pedagogy. Table 6 indicates that mathematics teachers are competent in terms of the AI pedagogy domain of the competency framework. The overall mean of 3.58 and a standard deviation of 0.86 suggest that most teacher respondents feel reasonably competent about using AI to support teaching and learning in the classroom, although there is still a considerable variability in how strongly they feel about their competence. Some are clearly very comfortable designing teaching-learning experiences that are assisted and supported by AI, while others are not so comfortable. The highest ratings clustered around classroom-facing instructional decisions. Teachers were most competent in starting from teaching needs to judge whether an AI tool is appropriate (Item 1; $\bar{x}$ = 3.92, SD = 0.91). They also reported competence in keeping humans in the decision process when using AI for assessment (Item 8; $\bar{x}$ = 3.80, SD = 1.05) and in finding and validating basic educational AI tools for instruction (Item 4; $\bar{x}$ = 3.76, SD = 0.97). These results indicate that teachers can exercise professional judgment in selecting tools, maintaining human oversight in assessment, and vetting tools before classroom use. However, the lowest ratings were observed in more complex, design-oriented competencies that require deliberate redesign of AI-supported learning environments. Teachers were only moderately competent in co-creating accessible and inclusive resources with AI and validating them through human review (Item 11; $\bar{x}$ = 3.24, SD = 1.05), designing AI-immersed learning that preserves student control and human interaction (Item 10; $\bar{x}$ = 3.35, SD = 1.04), and engineering teacher–AI–student interaction patterns for learning (Item 9; $\bar{x}$ = 3.36, SD = 1.04). Evidently, these activities require not just tool familiarity but sophisticated instructional design and a strong vision of how AI reconfigures classroom roles. The moderate scores of the mathematics teachers demonstrate that while teachers can plug AI into existing lessons, fewer teachers appear to be fully prepared to redesign the learning experience around AI in a deliberate, student-empowering way.

Table 6. Mean and Standard Deviation on the Level of AI Competency Framework for Teachers of the Respondents in terms of AI Pedagogy

Indicators	$\bar{x}$	Int.	SD
1. I start from teaching needs to judge whether an AI tool is appropriate.	3.92	C	0.91
2. I run design–implement–reflect cycles for AI-assisted lessons.	3.40	MC	0.98
3. I evaluate whether AI use achieved the intended learning outcomes.	3.75	C	1.03
4. I can find and validate basic educational AI tools for my instruction.	3.76	C	0.97
5. I relate AI tools to their pedagogical affordances for student-centered learning.	3.66	C	1.01
6. I examine the pedagogical assumptions built into an AI tool or system.	3.54	C	1.08
7. I facilitate AI-supported activities that build higher-order thinking and collaboration.	3.61	C	1.05
8. I keep humans in the decision process when using AI for assessment.	3.80	C	1.05
9. I engineer teacher–AI–student interaction patterns for learning.	3.36	MC	1.04
10. I design AI-immersed learning that preserves student control and human interaction.	3.35	MC	1.04
11. I co-create accessible, inclusive resources with AI and validate them through human review.	3.24	MC	1.05
12. I plan activities that empower learners with special needs using assistive AI.	3.52	C	1.05
Average on AI Pedagogy	3.58	C	0.86

Note. $\bar{x}$ = mean; SD = standard deviation; Int. = interpretation. Scale: 4.51–5.00 = Very Competent (VC); 3.51–4.50 = Competent (C); 2.51–3.50 = Moderately Competent (MC); 1.51–2.50 = Less Competent (LC); 1.00–1.50 = Incompetent (I).

AI for Professional Development. From Table 7, it can be seen that the average score of the respondents in the sub-domain of AI for professional development is 3.39 with a standard deviation of 0.86, which indicates "Moderately Competent" performance. It can be interpreted that the teachers are aware of the potential of AI for their professional development, yet their level of competence in the use of AI for this objective is still somewhat lower compared to the other areas of AI-CFT. Standard deviation reveals that the level of variation lies in the medium range, signifying that some teachers are quite proactive in applying AI for professional development, whereas others are in the process of exploring it. From the top three highest-rated indicators, it can be seen from the table that teachers are more comfortable when it comes to individual and planning tasks. As shown in item 1, the respondents are competent about explaining the rights and responsibilities of teachers in the age of AI ($\bar{x}$ = 3.78, SD = 0.91), selecting cost-effective AI for the classroom that aligns with their professional development needs in item 4 ($\bar{x}$ = 3.75, SD = 0.98), and evaluating their readiness for the use of AI and planning an action plan to develop it in item 2 ($\bar{x}$ = 3.70, SD = 0.95). With all indicators falling within the Acquire level of the framework, it can be seen that many already articulate how AI affects their role as professionals and can identify tools and learning pathways that align with their individual development needs. In contrast, their lowest means pertain to more collaborative and design-oriented tasks. Table 7 further shows that teachers' self-rated mean values are only moderately competent for item 11 that is about establishing inclusive AI systems or ethical rules for school ($\bar{x}$ = 3.00, SD = 1.09), item 12 about determining testing parameters and improving professional development tools that teachers co-design ($\bar{x}$ = 3.12, SD = 1.13), and in item 9 on designing an AI-supported coach to aid teachers in self-assessment and feedback ($\bar{x}$ = 3.20, SD = 1.09).

Table 7. Mean and Standard Deviation on the Level of AI Competency Framework for Teachers of the Respondents in terms of AI for Professional Development

Indicators	$\bar{x}$	Int.	SD
1. I can describe teachers' rights and obligations in the AI era.	3.78	C	0.91
2. I assess my AI readiness and set a realistic upskilling plan.	3.70	C	0.95
3. I use AI to discover mentors or peers for my professional learning.	3.67	C	0.95
4. I choose affordable, teacher-facing AI tools that fit my Professional Development goals.	3.75	C	0.98
5. I regularly upskill on AI and coach peers in my school.	3.40	MC	0.98
6. I use data/AI analytics to track my growth and plan next steps.	3.23	MC	1.03
7. I build or use AI simulations to practice teaching or policy scenarios.	3.28	MC	1.07
8. I keep AI platforms for PD under human control to avoid ethical risks.	3.35	MC	1.06
9. I configure an AI-assisted coach to support teachers' self-assessment and feedback.	3.20	MC	1.09
10. I use AI to help design accessible training programs validated by experts.	3.24	MC	1.12
11. I co-create communities that build inclusive AI tools or ethical rules for schools.	3.00	MC	1.09
12. I set testing criteria and iterate on PD tools we co-create.	3.12	MC	1.13
Average on AI for Professional Development	3.39	MC	0.86

Note. $\bar{x}$ = mean; SD = standard deviation; Int. = interpretation. Scale: 4.51–5.00 = Very Competent (VC); 3.51–4.50 = Competent (C); 2.51–3.50 = Moderately Competent (MC); 1.51–2.50 = Less Competent (LC); 1.00–1.50 = Incompetent (I).

Table 8. Mean and Standard Deviation on the Level of AI Competency Framework for Teachers (AI-CFT) of Public Secondary Mathematics Teachers in the Division of Northern Samar

Indicators	$\bar{x}$	Int.	SD
Human-centered Mindset	3.71	C	0.74
AI Ethics	3.55	C	0.85
AI Foundations and Applications	3.43	MC	0.87
AI Pedagogy	3.58	C	0.86
AI for Professional Development	3.39	MC	0.86
Average	3.53	C	0.75

Note. $\bar{x}$ = mean; SD = standard deviation; Int. = interpretation. Scale: 4.51–5.00 = Very Competent (VC); 3.51–4.50 = Competent (C); 2.51–3.50 = Moderately Competent (MC); 1.51–2.50 = Less Competent (LC); 1.00–1.50 = Incompetent (I).

Table 8 above shows the consolidated means of the AI competence levels among the secondary mathematics teachers of the DepEd Schools Division of Northern Samar, Philippines. In general, the mean score of the respondents for AI-CFT is 3.53 with an SD of 0.75, identified to be at the "Competent" level. The reported standard deviation indicates that the score is moderately dispersed in that the majority of teachers generally ranked around the competent level, while some ranked well above or below others on some scales. Across the sub-domains, the highest mean score is in Human-centered Mindset, rated as competent ($\bar{x}$ = 3.71, SD = 0.74), followed by AI Pedagogy, rated as competent ($\bar{x}$ = 3.58, SD = 0.86), and finally in AI Ethics, which is also rated as competent ($\bar{x}$ = 3.55, SD = 0.85). This result reveals that teachers are somewhat more confident in preserving human-centeredness in the use of AI, integrating AI in teaching, and applying basic principles in making decisions about AI in various school and classroom contexts. Nevertheless, the AI Foundations and Applications sub-domain ($\bar{x}$ = 3.43, SD = 0.87) and AI for Professional Development sub-domain ($\bar{x}$ = 3.39, SD = 0.86) recorded slightly lower mean values and were classified as moderately competent. These domains involve a deeper understanding of how AI systems work, as well as more sustained use of AI to mediate one's own professional learning. The mathematics teachers are capable of making well-informed and ethics-based decisions in their classrooms, yet many of the mathematics teachers are in the process of building better foundational and professional applications of AI as a tool for professional development.

3.3. Relationship between the Respondents' Teaching-related Profile and their Level of AI Competence

Inferential statistics were performed to test whether significant relationships exist between the respondents' teaching-related profile and their level of AI Competence. Table 9 shows the results of the correlation analyses performed in testing the relationship between the teaching-related profiles of the secondary mathematics teachers in the DepEd Schools Division of Northern Samar, Philippines.

Table 9. Relationship Between the Respondents' Teaching-related Profile and their Level of AI Competency Framework for Teachers (AI-CFT)

Variable	Highest Educational Attainment		Years of Teaching Experience		Teaching Position		No. of Relevant AI/ICT Trainings Attended		Access to AI Technology	
	η	p	r	p	η	p	r_s	p	r_s	p
HCM	0.084^{ns}	.815	-0.297**	< .001	0.167^{ns}	.303	0.214**	.002	0.374**	< .001
AIE	0.141^{ns}	.378	-0.226**	< .001	0.134^{ns}	.560	0.247**	< .001	0.419**	< .001
AIFA	0.155^{ns}	.268	-0.256**	< .001	0.202^{ns}	.116	0.296**	< .001	0.432**	< .001
AIP	0.134^{ns}	.423	-0.164*	.016	0.114^{ns}	.739	0.284**	< .001	0.467**	< .001
AIPD	0.118^{ns}	.561	-0.103^{ns}	.133	0.083^{ns}	.924	0.233**	< .001	0.451**	< .001
AI-CFT	0.134^{ns}	.424	-0.229**	< .001	0.141^{ns}	.503	0.293**	< .001	0.476**	< .001

Note. HCM = Human-centered Mindset; AIE = AI Ethics; AIFA = AI Foundations and Applications; AIP = AI Pedagogy; AIPD = AI for Professional Development; AI-CFT = Artificial Intelligence Competency Framework for Teachers (overall score); η = eta correlation ratio (used for categorical group variables); r = Pearson product–moment correlation; r_s = Spearman's rho. Negative values indicate inverse relationships. p < .05 (*), p < .01 (**). Correlation magnitude guide: |.00–.20| negligible; |.21–.40| low; |.41–.70| moderate; |.71–.90| high; |.91–.99| very high; |1.00| perfect.

The eta correlation analyses between the highest educational attainment and the level of the AI Competency Framework for Teachers (AI-CFT), and its five sub-domains, reveal no statistically significant relationships. The highest educational attainment of the secondary mathematics teachers in the division demonstrated insignificant positive correlation with human-centered mindset (η = 0.084; p = .815); insignificant positive correlation with AI Ethics (η = 0.141; p = .378); insignificant positive correlation with AI Foundations and Applications (η = 0.155; p = .268); insignificant positive correlation with AI Pedagogy (η = 0.134; p = .423); insignificant positive correlation with AI for Professional Development (η = 0.118, p = .561); and insignificant positive correlation with the overall level of AI Competency Framework for Teachers (η = 0.134; p = .424). However, when the years of teaching experience are considered, the data reveal a negative trend in relation to the AI competence of the secondary mathematics teachers. In this case, Pearson's correlations are negative and mostly statistically significant. Years of experience showed a significant negative correlation with the Human-centered Mindset (r = −0.297, p < .001), as well as a significant negative correlation with AI Ethics (r = −0.226, p < .001) and a significant negative correlation with AI foundations and Applications (r = −0.256, p < .001). However, the correlation with AI Pedagogy is weak but still statistically significant (r = −0.164, p = .016). Only AI for professional development fails to attain significance (r = −0.103, p = .133). Overall, AI-CFT levels of the respondents likewise show a statistically significant negative correlation with years of experience (r = −0.229, p < .001). Meanwhile, when the teaching position of the secondary math teachers is used as the profile variable, the eta correlation coefficient again reveals no statistically significant relationship with their level of AI competence, as well as across its five domains. Teaching position has a negligible relationship with human-centered mindset of AI competence (η = 0.167; p = .303); with AI ethics (η = 0.134, p = .560), AI foundations and applications (η = 0.202, p = .116), AI pedagogy (η = 0.114, p = .739), and AI for professional development (η = 0.083, p = .924), as well as with the overall AI-CFT score (η = 0.141, p = .503). Yet a clearer relationship appears when looking at the training exposure related to Artificial Intelligence technologies and tools by the teachers. Among the secondary mathematics teachers in the DepEd Schools Division of Northern Samar, the number of relevant AI/ICT-related trainings attended shows positive and highly significant Spearman's rho correlation with overall levels of the AI Competency Framework for Teachers, and across all five of its domains. Specifically, more trainings are statistically significantly associated with higher levels of human-centered mindset ($r_s = 0.214$, $p = .002$); with AI ethics ($r_s = 0.247$, $p < .001$); with AI foundations and applications ($r_s = 0.296$, $p < .001$); with AI pedagogy ($r_s = 0.284$, $p < .001$); and with AI for professional development ($r_s = 0.233$, $p < .001$). The overall AI-CFT score of the respondents also rises with their number of trainings ($r_s = 0.293$, $p < .001$). Finally, access to AI technology, operationalized as the number of different AI tools available to or used by the teacher, emerges as showing the strongest correlations with AI competencies. All the Spearman's rho correlations between access to AI technology, and the AI-CFT dimensions, are positive, moderate, and highly significant, specifically, Human-centered Mindset ($r_s = 0.374$, $p < .001$), AI Ethics ($r_s = 0.419$, $p < .001$), AI Foundations and Applications ($r_s = 0.432$, $p < .001$), AI Pedagogy ($r_s = 0.467$, $p < .001$), and AI for Professional Development ($r_s = 0.451$, $p < .001$). The correlation with the overall level of AI-CFT score is the highest in the table ($r_s = 0.476$, $p < .001$).

4. DISCUSSION

4.1. Teaching-Related Profile

The distribution of the highest educational attainment indicates that while a portion of secondary mathematics teachers still rely primarily on undergraduate preparation, most have already engaged in graduate education, with only a small segment progressing to doctoral-level work. This pattern is consistent with broader trends in teacher qualifications where entry is at the bachelor's level and graduate study is increasingly common, whereas doctoral attainment remains limited (OECD, 2019). In the Philippine context, this aligns with the Philippine Professional Standards for Teachers (PPST) framing of teachers as having a career-long learning trajectory that encourages advanced studies and continuing professional development across career stages (Department of Education, 2017; Samundeeswari, 2024). However, AI competence frameworks emphasize that AI-related competence is less about degree level per se and more about the quality and recency of AI-focused learning opportunities and digital upskilling (Hava & Babayiğit, 2025; Miao & Cukurova, 2024). Thus, the observed blend of degree levels provides an important baseline for interpreting later findings on how profile variables relate to AI-CFT competence.

The profile of the years of teaching experience by the respondents reflects a workforce that is largely mid-career, neither dominated by beginning teachers nor by very senior teachers. This matters because competence is typically refined through iterative practice and professional learning, rather than fixed at entry into the profession. This division of context suggests a potentially productive interplay: experienced teachers contribute deep pedagogical and curricular knowledge, while younger and mid-career teachers may bring greater familiarity with rapidly evolving digital tools. Consistent with the Will–Skill–Tool view, this blend can create favorable conditions for technology integration when pedagogical experience is coupled with openness and access to tools (Knezek & Christensen, 2015; Sasota et al., 2021).

Most respondents fall within Teacher I to III positions, with a smaller but strategically important layer of Master Teachers. This distribution suggests that many teachers are still in early-to-middle career progression, with possible bottlenecks toward master teacher roles. It also has implications for mentoring and instructional leadership, since Master Teachers are positioned to lead Learning Action Cells (LACs) and facilitate school-based professional learning (Department of Education, 2016, 2025b). In this context, a small number of Master Teachers relative to Teacher I to III can still be advantageous if LAC structures enable sustained peer coaching and collegial learning around AI-supported pedagogy. From this perspective, the ratio of a few Master Teachers to Teacher I to III mathematics teachers provides an opportunity to have a reasonable "cell size" for sustained mentoring, peer coaching, and collegial discussion around technology- and AI-enhanced pedagogy within each LAC.

The low average exposure to AI/ICT-related training also suggests limited structured opportunities for formal upskilling, possibly reflecting self-directed learning and peer-supported practice. At the same time, broader evidence consistently points to perceived gaps between teachers' readiness and the demands posed by emerging AI tools (Ng et al., 2023; Yue et al., 2024). Given policy signals in the Philippines toward institutionalizing AI integration (Department of Education, 2025a; Department of Education NCR, 2024;

Miao & Cukurova, 2024), this trend of having a small subgroup with multiple trainings and a majority with none creates a meaningful context for examining how training exposure relates to AI competence.

The results on the respondents' AI access indicate that AI is already part of the digital toolkit of most mathematics teachers in the division, with the prominence of tools such as ChatGPT and Canva suggesting a strong orientation toward platforms that streamline lesson preparation, explanation drafting, and instructional material design. The common use of GeoGebra and Photomath likewise indicates a practical demand for tools that support mathematical problem solving, visualization, and step-by-step explanations that can supplement instruction. However, the same pattern also implies instructional risks that require guidance, such as overreliance on AI-generated answers, possible misconceptions from inaccurate outputs, and academic integrity concerns when AI is used as a shortcut rather than as support for mathematical reasoning. Systematic reviews similarly note high reliance on chatbots and math-solver applications, while more complex AI ecosystems (e.g., learning analytics platforms, intelligent tutoring systems) remain less used (Awang et al., 2025). The concentration in a few low-cost and mobile-accessible tools appears consistent with the realities of a resource-constrained division and may also reflect institutional enablement, such as DepEd's Canva for Education partnership and capacity-building initiatives around GeoGebra (Department of Education, 2024; DepEd NEAP, 2022; UP NISMED, 2022). Overall, these access patterns strengthen the argument for capacity-building and classroom guardrails that keep mathematical thinking visible and assessable.

4.2. Level of AI Competence

Across the five AI Competency Framework for Teachers domains, the competence profile of secondary mathematics teachers in the DepEd Schools Division of Northern Samar, Philippines, suggests that teachers are more confident in classroom-proximal, value-laden responsibilities and less confident in system-facing and innovation-oriented competencies. In practical terms, respondents appear to be translating long-standing professional norms—learner protection, responsible use of digital resources, and teacher judgment—into AI-mediated teaching, which explains why human-centered and ethical orientations emerge relatively stronger than domains that require deeper technical fluency or organizational leadership. This pattern is consistent with studies showing that teachers often report greater confidence in immediate pedagogical decision-making about AI, particularly in areas such as child safeguarding, duty of care, and responsible use of digital resources when making decisions (Filo et al., 2024; Zhou et al., 2025). Although Bozkurt et al. (2024) wrote from a higher education perspective, their manifesto offers a useful critical lens for the present findings by emphasizing that generative AI in education entails both opportunities and risks and must therefore be approached with human oversight, ethical responsibility, and critical reflection.

More specifically, the results indicate that teachers' competence in a human-centered mindset is strongest where decisions are anchored in classroom routines, yet becomes more tentative when competence shifts toward school-level governance, policy citation, and community dialogue. This reflects the current state of AI institutionalization in which teachers are already making frequent classroom decisions about AI tools while formal policy infrastructures remain emergent and unevenly accessible at the school level (Department of Education, 2025a). Similarly, the AI Ethics results suggest that respondents have begun operationalizing ethical guardrails in day-to-day practice but are not yet consistently positioned to lead higher-order ethical work such as co-creating institutional rules, sustaining community dialogue, or shaping system-level accountability. This reading is compatible with broader AI literacy frameworks that treat ethical judgment and social responsibility as core competencies, while also recognizing that competence deepens when teachers can examine consequences in lived classroom contexts rather than treating ethics as rule memorization, a stance that resonates with Dewey's reflective inquiry tradition (Achkovska Leshkovska & Spaseva, 2016; OECD, 2025b; Rodgers, 2002).

In contrast, the moderate competence observed in AI Foundations and Applications and AI for Professional Development suggests that the more technical and developmental side of competence is still developing. This is consequential because practical knowledge of how AI tools work, what they can and cannot do, and when they are instructionally appropriate often serves as the entry point for later pedagogical integration and more innovative use (Hava & Babayiğit, 2025; Yue et al., 2024). From the Will–Skill–Tool perspective, these domains sit close to the "skill" and "tool" conditions that typically need strengthening before teachers can move toward deeper redesign of instruction or AI-enabled professional learning (Knezek & Christensen, 2015). In diffusion terms, this profile is consistent with early-stage competence development where teachers focus on familiarization and selective use of new tools before taking on more complex practices such as tool customization, instructional innovation, or AI-supported professional transformation (García-Avilés, 2020; Ng et al., 2023). The low standing of AI for Professional Development in particular also reflects that structured professional development aspects of AI use remain limited, especially in contexts where formal professional development opportunities are constrained, and teachers rely heavily on self-directed learning and informal peer support (Tan et al., 2025). Given that students increasingly encounter generative and assistive tools outside formal instruction, the present competence levels can be read as a baseline that is functional but incomplete: teachers appear able to regulate classroom use and align tools with immediate instructional needs, yet still require stronger foundations, governance literacy, and professional learning structures to move from cautious use to more systematic, curriculum-aligned integration (Chiu, 2024; Nazaretsky et al., 2022). This result also points to an important professional learning need in mathematics education. Garcia et al. (2026) emphasized the need for critical AI literacy among mathematics teachers. In this light, the comparatively lower confidence in more technical and innovation-oriented AI competencies suggests a need for stronger support that goes beyond tool use and toward more informed classroom application.

Hence, the results suggest that secondary mathematics teachers' AI competence in Northern Samar, Philippines, is developing first through ethically grounded, classroom-facing practice, while technical depth, governance participation, and AI-enabled professional learning remain less developed, broadly consistent with emerging measurement work showing stronger teacher confidence in human-centered and ethical dimensions than in innovation-oriented or design-intensive competencies (Chiu et al., 2025). By applying AI-CFT within a K to 12 mathematics and resource-constrained division context, the present findings add domain-level baseline evidence that can inform differentiated support—strengthening governance and accountability literacy, deepening foundational AI understanding, and expanding access to sustained professional learning structures that allow teachers not only to use AI responsibly, but also to learn and lead with it over time.

4.3. Relationship between the Respondents' Teaching-related Profile and their Level of AI Competence

The present findings address whether teachers' teaching-related conditions are empirically associated with AI competence using a domain-based framework. In this study, the highest educational attainment did not significantly relate to teachers' AI-CFT-based competence, reinforcing evidence that degree level shows minimal or inconsistent effects once actual digital exposure and AI-related learning opportunities are considered (Lucas et al., 2024; Younis, 2025). Likewise, a teaching position was not significantly associated with AI competence, suggesting that formal rank does not automatically translate to AI-related capability, which is observed to be consistent with findings that seniority or role rarely predict AI competence when proficiency and training are accounted for (Younis, 2025; Yue et al., 2024). These results clarify that credentials and rank, by themselves, are weak determinants of teachers' AI competence.

More importantly, the profile variables that reflect opportunity and exposure showed the clearest relationships with AI competence. Relevant AI/ICT trainings were consistently and significantly associated with higher AI-CFT competence across domains, aligning with evidence that participation in AI-oriented professional development is among the strongest predictors of teachers' AI readiness and classroom use (Galindo-Domínguez et al., 2024; Silagan & Tumapon, 2025; Sun et al., 2024). However, the strongest associations in the present study were observed for access to AI technology/tools, indicating that teachers who could access and use a wider range of AI tools tended to report higher competence. Notably, access related most strongly to AI Pedagogy and AI for Professional Development, implying that hands-on engagement with tools is closely tied to teachers' confidence in designing AI-supported instruction and using AI for their own learning and growth. This pattern is consistent with international evidence that access functions as an enabling condition for experimentation and skill-building, even when it is not framed as a direct causal driver of competence (Farooq, 2025; Tomczyk & Majkut, 2025).

Finally, the modest but significant negative relationships with years of teaching experience suggest a small gradient in AI competence, as more experienced teachers tended to rate their AI competence slightly lower than colleagues with fewer years in service. This does not imply weaker pedagogy among veteran teachers; rather, it may be explained by varying exposure to rapidly evolving tools and diffusion pathways shaped by peer networks and opportunity structures (Dringó-Horváth et al., 2025; Phillips, 2025; Younis, 2025; Yue et al., 2024).

5. CONCLUSION

In the DepEd Schools Division of Northern Samar, Philippines, the teaching-related profile of public secondary mathematics teachers reflects a workforce that is largely engaged in graduate studies and is mostly mid-career, with the majority still in Teacher I to Teacher III positions and only a smaller proportion in the Master Teacher ranks. Although participation in AI/ICT-related trainings remains limited for most teachers, AI has already entered the day-to-day work of the majority through access to commonly used tools for instruction and preparation. This suggests that school-based mechanisms such as Learning Action Cells (LACs) can be further maximized as a practical delivery platform for hands-on, mentoring-oriented capacity building that builds from teachers' existing access, while addressing the still limited opportunities for structured AI/ICT trainings. Addressing the gap in the K to 12 evidence using the AI Competency Framework for Teachers (AI-CFT), this study provides an AI competence profile of secondary mathematics teachers in a resource-constrained division. The findings indicate that teachers show stronger competence in the human-centered, ethical, and pedagogical dimensions of AI use, but comparatively lower competence in AI foundations and applications and in AI for professional development, pointing to a remaining gap in deeper technical understanding and sustained use of AI for teachers' own learning. On what teacher conditions actually relate to AI competence, the results show that formal credentials and rank, such as highest educational attainment and teaching position, do not differentiate competence and are not significantly associated with AI-CFT levels, while years of teaching experience show a small but consistent negative relationship. Finally, addressing the practical gap on what factors most strongly align with AI competence in real school settings, training exposure, and access to a wider range of AI tools are positively associated with AI-CFT competence across domains, reinforcing that AI competence is built less through time in service or academic credentials and more through meaningful engagement with tools and continuous, practice-based professional learning.

5.1. Limitations of the Study and Directions for Future Research

This study has several limitations that should be considered in interpreting the findings. First, the study relied on self-reported data gathered through a cross-sectional descriptive-correlational design; hence, the results reflect the respondents' perceived level of AI competence at a single point in time and do not permit causal inferences. Second, the study was limited to public secondary mathematics teachers in the DepEd Schools Division of Northern Samar, Philippines, which may constrain the generalizability of the findings to other subject areas and educational contexts. Third, the study covered only the teaching-related profile variables included in the actual data gathering; thus, demographic characteristics such as age and sex were not included in the approved final instrument and were not examined in the present study. Future research may address these limitations by including broader respondent characteristics, employing longitudinal or mixed-methods designs, incorporating classroom-based or performance-based measures of AI competence, and examining potential mediators and other contextual explanations for the observed positive and negative correlations, particularly given that AI remains an emerging and unevenly distributed technology in the rural context of Northern Samar, Philippines.

5.2. Recommendations

Based on the salient findings and conclusions of the study, it is recommended that teacher education and graduate institutions revisit and enrich their curricula to respond to the emerging demands of 21st-century teaching, particularly the meaningful and ethical use of AI technologies; that secondary mathematics teachers commit to continuous improvement through self-directed learning, such as massive open online courses (MOOCs) and other open learning resources, and by regularly following Department of Education (DepEd)-recognized advisories and partner offerings, with emphasis not only on the frequency of AI use but on the quality of its application in professional practice; that educational leaders in the DepEd Schools Division of Northern Samar, through the Human Resource Development Section (HRDS) and Monitoring and Evaluation (M&E) unit, strengthen the use of updated teacher-profile databases as baseline input in planning In-Service Trainings (INSETs), master classes, and Learning Action Cell (LAC)-based learning spaces that deliberately enable peer mentoring and knowledge-sharing among novice, mid-career, and more experienced teachers; that the Department of Information and Communications Technology (DICT) further strengthen the implementation of the Free Public Internet Access Program ("Free Wi-Fi for All"), particularly in far-flung areas, to improve connectivity that supports teachers' exploration and sustained engagement with AI tools for teaching and learning; that the National Educators Academy of the Philippines (NEAP), together with other professional development providers and the DepEd Division HRDS, develop and roll out targeted resource packages through trainings, LACs, job-embedded learning, and related platforms that build teachers' AI competence and its effective integration in mathematics classes, using this study's results as baseline evidence for prioritizing learning needs.

Acknowledgments. The author expresses sincere gratitude to the Department of Education, Schools Division of Northern Samar, for granting permission to conduct this study and for providing the necessary data that informed the research.

Research Ethics. Ethical safeguards were observed throughout the study, including compliance with the Philippine Data Privacy Act of 2012 (RA 10173), secure handling of responses, reporting of findings only in aggregated form, and limiting the use of all collected data strictly to research purposes.

Data Availability Statement. All data can be obtained from the corresponding author.

Conflicts of Interest. The author declares no conflict of interest.

Funding. This research received no external funding.

Declaration of AI Use. During the preparation of this manuscript, the author used ChatGPT (GPT-5.2) to support language editing and improve the clarity, readability, and organization of the text. The tool was not used to generate or alter the study's data, results, statistical analyses, or interpretations, and all substantive scholarly decisions remained with the author. After using the tool, the author reviewed, verified, and revised the output as necessary and assumes full responsibility for the accuracy, originality, and integrity of the final published work.

REFERENCES

Achkovska Leshkovska, E., & Spaseva, M. (2016). John Dewey's educational theory and educational implications of Howard Gardner's multiple intelligences theory. *International Journal of Cognitive Research in Science, Engineering and Education*, *4*, 57–66. https://doi.org/10.5937/IJCRSEE1602057A

Awang, L. A., Yusop, F. D., & Danaee, M. (2025). Current practices and future direction of artificial intelligence in mathematics education: A systematic review. *International Electronic Journal of Mathematics Education*, *20*(2), em0823. https://doi.org/10.29333/iejme/16006

Bastani, H., Bastani, O., Sungu, A., Ge, H., Kabakcı, Ö., & Mariman, R. (2024). *Generative AI can harm learning* (SSRN Scholarly Paper No. 4895486). Social Science Research Network. https://doi.org/10.2139/ssrn.4895486

Bishara, A., & Hittner, J. (2012). Testing the significance of a correlation with nonnormal data: Comparison of Pearson, Spearman, transformation, and resampling approaches. *Psychological Methods*, *17*, 399–417. https://doi.org/10.1037/a0028087

Bozkurt, A., Xiao, J., Farrow, R., Bai, J. Y. H., Nerantzi, C., Moore, S., Dron, J., Stracke, C. M., Singh, L., Crompton, H., Koutropoulos, A., Terentev, E., Pazurek, A., Nichols, M., Sidorkin, A. M., Costello, E., Watson, S., Mulligan, D., Honeychurch, S., … Asino, T. I. (2024). The manifesto for teaching and learning in a time of generative AI: A critical collective stance to better navigate the future. *Open Praxis*, *16*(4), 487–513. https://doi.org/10.55982/openpraxis.16.4.777

Casal-Otero, L., Catala, A., Fernández-Morante, C., Taboada, M., Cebreiro, B., & Barro, S. (2023). AI literacy in K-12: A systematic literature review. *International Journal of STEM Education*, *10*(1), 29. https://doi.org/10.1186/s40594-023-00418-7

Chasokela, D. (2025). Integrating artificial intelligence in STEM Education: Enhancing 21st century skills in Zimbabwean universities. *Journal of Research in Environmental and Science Education, 2*(2), 68–80. https://doi.org/10.70232/jrese.v2i2.16

Chiu, T. K. F. (2024). *Empowering K-12 education with AI: Preparing for the future of education and work*. Routledge. https://doi.org/10.4324/9781003498377

Chiu, T. K. F., Ahmad, Z., & Çoban, M. (2025). Development and validation of teacher artificial intelligence (AI) competence self-efficacy (TAICS) scale. *Education and Information Technologies*, *30*(5), 6667–6685. https://doi.org/10.1007/s10639-024-13094-z

Creswell, J. W., & Creswell, J. D. (2022). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

De Guzman, M. (2025, June 12). More Filipino students now using AI for learning. *BusinessWorld Online*. https://www.bworldonline.com/technology/2025/06/12/678582/more-filipino-students-now-using-ai-for-learning/

Demir, S. (2022). Comparison of normality tests in terms of sample sizes under different skewness and kurtosis coefficients. *International Journal of Assessment Tools in Education*, *9*(2), 397–409. https://doi.org/10.21449/ijate.1101295

Department of Education NCR. (2024). *RM 1289, s. 2024: Let's be future ready: Strategic integration of artificial intelligence (AI) in education for the digital future*. https://www.depedncr.com.ph/wp-content/uploads/2024/12/RM-No.-1289-s.-2024-Lets-Be-Future-Ready-Strategic-Integration-of-Artificial-Intelligence-in-Education-for-the-Digital-Future-on-Decembe-3-6-2024.pdf

Department of Education. (2016, June 7). *DO 35, s. 2016—The Learning Action Cell as a K to 12 basic education program school-based continuing professional development strategy for the improvement of teaching and learning*. https://www.deped.gov.ph/2016/06/07/do-35-s-2016-the-learning-action-cell-as-a-k-to-12-basic-education-program-school-based-continuing-professional-development-strategy-for-the-improvement-of-teaching-and-learning/

Department of Education. (2017, August 11). *DO 42, s. 2017 – National adoption and implementation of the Philippine Professional Standards for Teachers*. https://www.deped.gov.ph/2017/08/11/do-42-s-2017-national-adoption-and-implementation-of-the-philippine-professional-standards-for-teachers/

Department of Education. (2024, October 30). *Canva gives teachers premium access and training for free*. https://www.deped.gov.ph/2024/10/30/canva-gives-teachers-premium-access-and-training-for-free/

Department of Education. (2025a). *DO 013, s. 2025—Establishment of the center for artificial intelligence research for the department of education*. https://www.deped.gov.ph/2025/04/29/april-29-2025-do-013-s-2025-establishment-of-the-center-for-artificial-intelligence-research-for-the-department-of-education/

Department of Education. (2025b, August 28). *DO 024, s. 2025 – Guidelines on the implementation of the Expanded Career Progression system for teachers and school heads in the Department of Education*. https://www.deped.gov.ph/2025/08/28/august-28-2025-do-024-s-2025-guidelines-on-the-implementation-of-the-expanded-career-progression-system-for-teachers-and-school-heads-in-the-department-of-education/

DepEd NEAP. (2022, August 25). *UP NISMED GeoGebra Batch 2 (Regions 1, 2, 8 & 9) participants!* [Facebook Post]. Facebook. https://www.facebook.com/DepEdNEAP/posts/up-nismed-geogebra-batch-2-regions-1-2-8-9-participantsup-nismed-geogebra-batch-/3424483601116497/

DeVellis, R. F. (2016). *Scale development: Theory and applications* (4th ed.). SAGE Publications.

Dringó-Horváth, I., Zoltán, R., & Nagy, J. T. (2025). University teachers' digital competence and AI literacy: Moderating role of gender, age, experience, and discipline. *Education Sciences*, *15*(7), 868. https://doi.org/10.3390/educsci15070868

Farooq, Y. (2025). Exploring teachers' psychological readiness for effective AI integration in the classroom. *The Critical Review of Social Sciences Studies*, *3*(3), 351–364. https://doi.org/10.59075/fbwe9b83

Filo, Y., Rabin, E., & Mor, Y. (2024). An artificial intelligence competency framework for teachers and students: Co-created with teachers. *European Journal of Open, Distance and E-Learning*, *26*(1), 93–106. https://doi.org/10.2478/eurodl-2024-0012

Galindo-Domínguez, H., Delgado, N., Campo, L., & Losada, D. (2024). Relationship between teachers' digital competence and attitudes towards artificial intelligence in education. *International Journal of Educational Research*, *126*, 102381. https://doi.org/10.1016/j.ijer.2024.102381

Garcia, M. B., Acut, D. P., Arif, Y. M., Maher, D., Alex, J. K., Wardat, Y., Chiu, T. K., & Damaševičius, R. (2026). Modernizing mathematics education with artificial intelligence: A narrative review of AI-powered tools, thematic trends, and instructional applications. *The Convergence of Mathematics and AI: A New Paradigm in Education*, 153–186.

García-Avilés, J. (2020). Diffusion of innovation. *The International Encyclopedia of Media Psychology*, 1–8. https://doi.org/10.1002/9781119011071.iemp0137

George, D., & Mallery, P. (2006). *SPSS for Windows step-by-step: A simple guide and reference* (7th ed.). Allyn & Bacon.

Hava, K., & Babayiğit, Ö. (2025). Exploring the relationship between teachers' competencies in AI-TPACK and digital proficiency. *Education and Information Technologies*, *30*(3), 3491–3508. https://doi.org/10.1007/s10639-024-12939-x

Janse, R. J., Hoekstra, T., Jager, K. J., Zoccali, C., Tripepi, G., Dekker, F. W., & van Diepen, M. (2021). Conducting correlation analysis: Important limitations and pitfalls. *Clinical Kidney Journal*, *14*(11), 2332–2337. https://doi.org/10.1093/ckj/sfab085

JASP Team. (2025). *JASP* (Version 0.95.4) [Computer software]. https://jasp-stats.org/

Kamath, A., Poojari, S., & Varsha, K. (2025). Assessing the robustness of normality tests under varying skewness and kurtosis: A practical checklist for public health researchers. *BMC Medical Research Methodology*, *25*(1), 206. https://doi.org/10.1186/s12874-025-02641-y

Knezek, G., & Christensen, R. (2015, October). The will, skill, tool model of technology integration: Adding pedagogy as a new model construct. *International Association for Development of the Information Society*. 12th International Conference on Cognition and Exploratory Learning in Digital Age (CELDA 2015). https://eric.ed.gov/?id=ED562193

Kwak, S. G., & Kim, J. H. (2017). Central limit theorem: The cornerstone of modern statistics. *Korean Journal of Anesthesiology*, *70*(2), 144–156. https://doi.org/10.4097/kjae.2017.70.2.144

Lodge, A. (2024). Teachers' perceptions of artificial intelligence in the classroom [Dissertation, The Chicago School of Professional Psychology]. In *ProQuest Dissertations and Theses*. (3106949059). https://www.proquest.com/dissertations-theses/teachers-perceptions-artificial-intelligence/docview/3106949059/se-2?accountid=210494

Lucas, M., Zhang, Y., Bem-Haja, P., & Vicente, P. N. (2024). The interplay between teachers' trust in artificial intelligence and digital competence. *Education and Information Technologies*, *29*, 22991–23010. https://doi.org/10.1007/s10639-024-12772-2

Lynn, M. R. (1986). Determination and quantification of content validity. *Nursing Research*, *35*(6), 382–386. https://journals.lww.com/nursingresearchonline/citation/1986/11000/determination_and_quantification_of_content.17.aspx

Magat, R. J. B., & Sangalang, E. M. (2024). Teachers' familiarity, perceptions, and training needs on the use of ChatGPT in mathematics instruction. *International Journal of Education in Mathematics, Science and Technology*, *12*(6), 1471–1487. https://eric.ed.gov/?id=EJ1465795

Manczka, J. (2024). A phenomenological study: Teacher perceptions of generative artificial intelligence and its impact on teaching and learning in high schools [Dissertation, Point Park University]. In *ProQuest Dissertations and Theses*. Publicly Available Content Database (3116914866). https://www.proquest.com/dissertations-theses/phenomenological-study-teacher-perceptions/docview/3116914866/se-2?accountid=210494

Metsämuuronen, J. (2023). Artificial systematic attenuation in eta squared and some related consequences: Attenuation-corrected eta and eta squared, negative values of eta, and their relation to Pearson correlation. *Behaviormetrika*, *50*(1), 27–61. https://doi.org/10.1007/s41237-022-00162-2

Meylani, R. (2024). Artificial intelligence in the education of teachers: A qualitative synthesis of the cutting-edge research literature. *Journal of Computer and Education Research*, *12*(24), 600–637. https://doi.org/10.18009/jcer.1477709

Miao, F., & Cukurova, M. (2024). *AI competency framework for teachers*. UNESCO. https://doi.org/10.54675/ZJTE2084

Miao, F., & Holmes, W. (with Giannini, S.). (2023). *Guidance for generative AI in education and research*. UNESCO. https://doi.org/10.54675/EWZM9535

Mills, G. E., & Jordan, A. W. (2022). *Educational research: Competencies for analysis and applications* (13th ed.). Pearson.

Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology and a professional development program to improve it. *British Journal of Educational Technology*, *53*(4), 914–931. https://doi.org/10.1111/bjet.13232

Ng, D., Leung, J., Su, J., Ng, R., & Chu, S. (2023). Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. *Educational Technology Research and Development*, *71*, 137–161. https://doi.org/10.1007/s11423-023-10203-6

Nueva, M. G. (2022). *Adoptive environment on teachers' technology acceptance and digitized pedagogy among selected schools in Metro Manila* [Dissertation, De La Salle University]. https://animorepository.dlsu.edu.ph/etdd_behsc/2

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill Companies, Inc.

OECD. (2019). *TALIS 2018 results (volume I): Teachers and school leaders as lifelong learners*. https://doi.org/10.1787/1d0bc92a-en

OECD. (2023). *PISA 2022 results (Volume I & II): Country note—Philippines*. https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/11/pisa-2022-results-volume-i-and-ii-country-notes_2fca04b9/philippines_dbf92b65/a0882a2d-en.pdf

OECD. (2025a). *Empowering learners for the age of AI: An AI literacy framework for primary and secondary education (Review draft)*. OECD. https://ailiteracyframework.org

OECD. (2025b). What should teachers teach and students learn in a future of powerful AI? In *OECD Education Spotlights*. OECD Publishing. https://doi.org/10.1787/ca56c7d6-en

Opesemowo, O. (2024). Artificial intelligence in mathematics education: The pros and cons. In M. Khosrow-Pour (Ed.). In *Encyclopedia of Information Science and Technology* (6th ed., pp. 1–18). Advance online publication. https://doi.org/10.4018/978-1-6684-7366-5.ch084

Phillips, K. N. (2025). Artificial intelligence: Diffusion of innovation and generational considerations in a higher education institution [Dissertation, Marymount University]. In *ProQuest Dissertations and Theses*. Publicly Available Content Database (3176518399). https://www.proquest.com/dissertations-theses/artificial-intelligence-diffusion-innovation/docview/3176518399/se-2?accountid=210494

Polit, D. F., & Beck, C. T. (2006). The content validity index: Are you sure you know what's being reported? Critique and recommendations. *Research in Nursing & Health*, *29*(5), 489–497. https://doi.org/10.1002/nur.20147

Raosoft, Inc. (2004). *Sample size calculator* [Computer software]. http://www.raosoft.com/samplesize.html

Rodgers, C. (2002). Defining reflection: Another look at John Dewey and reflective thinking. *Teachers College Record*, *104*, 842–866. https://doi.org/10.1111/1467-9620.00181

Rogers, E. M. (1962). *Diffusion of innovations*. Free Press.

Samundeeswari, D. (2024). Teacher professional development: Effective strategies and evaluation methods. *Educational Administration: Theory and Practice*, *30*, 1726–1733. https://doi.org/10.53555/kuey.v30i6.5578

Sasota, R. S., Cristobal, R. R., Sario, I. S., Biyo, J. T., & Magadia, J. C. (2021). Will–skill–tool (WST) model of technology integration in teaching science and mathematics in the Philippines. *Journal of Computers in Education*, *8*(3), 443–464. https://doi.org/10.1007/s40692-021-00185-w

Schofield, L., & Zhou, X. (2025). Rethinking teaching approaches to integrating AI in teaching and learning. In M. Kremantzis, A. Essien, & E. Pantano (Eds.), *Intelligent Technologies in Education*. Advance online publication. https://open-publishing.org/journals/index.php/ited/article/view/1352

Shatz, I. (2024). Assumption-checking rather than (just) testing: The importance of visualization and effect size in statistical diagnostics. *Behavior Research Methods*, *56*(2), 826–845. https://doi.org/10.3758/s13428-023-02072-x

Shi, L. (2025). Assessing teachers' generative artificial intelligence competencies: Instrument development and validation. *Education and Information Technologies*, *30*, 23365–23384. https://doi.org/10.1007/s10639-025-13684-5

Shreffler, J., & Huecker, M. R. (2025). Types of variables and commonly used statistical designs. In *StatPearls [Internet]*. StatPearls Publishing. http://www.ncbi.nlm.nih.gov/books/NBK557882/

Sibug, V. B., Vital, V. P., Miranda, J. P. P., Fernando, E. Q., Gamboa, A. B., Hernandez, H. E., Bansil, J. A., Penecilla, E. M., & Gonzales, D. D. (2024). Teachers' perspectives on integrating AI tools in classrooms: Insights from the Philippines. In A. Kashihara (Ed.), *International Conference on Computers in Education*. Asia-Pacific Society for Computers in Education. https://doi.org/10.58459/icce.2024.4964

Sidoti, O., Park, E., & Gottfried, J. (2025, January 15). About a quarter of U.S. teens have used ChatGPT for schoolwork – double the share in 2023. *Pew Research Center*. https://www.pewresearch.org/short-reads/2025/01/15/about-a-quarter-of-us-teens-have-used-chatgpt-for-schoolwork-double-the-share-in-2023/

Silagan, B. L., & Tumapon, T. (2025). Technological competence, training and support, attitude towards AI, and teachers' acceptance. *Psychology and Education: A Multidisciplinary Journal*, *36*(8), 941–964. https://doi.org/10.70838/pemj.360809

Sun, F., Tian, P., Sun, D., Fan, Y., & Yang, Y. (2024). Pre-service teachers' inclination to integrate AI into STEM education: Analysis of influencing factors. *British Journal of Educational Technology*, *55*(6), 2574–2596. https://doi.org/10.1111/bjet.13469

Tan, X., Cheng, G., & Ling, M. H. (2025). Artificial intelligence in teaching and teacher professional development: A systematic review. *Computers and Education: Artificial Intelligence*, *8*, 100355. https://doi.org/10.1016/j.caeai.2024.100355

Tomczyk, Ł., & Majkut, A. (2025). Integrating AI in education: An analysis of factors influencing the acceptance, concerns, attitudes, competencies and use of generative artificial intelligence among Polish teachers. *Human Behavior and Emerging Technologies*, *2025*. https://doi.org/10.1155/hbe2/5599169

UNESCO. (2018). *ICT competency framework for teachers*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000265721

University of Iowa. (2024). *The role of AI in modern education*. University of Iowa. https://onlineprograms.education.uiowa.edu/blog/role-of-ai-in-modern-education

UP NISMED. (2022, August 18). *UP NISMED conducts training on GeoGebra for the Division of Albay*. UP NISMED News. http://news.nismed.upd.edu.ph/2022/08/up-nismed-conducts-training-on-geogebra.html

Wang, J. (2025). Survey study on college student's acceptance and attitude towards generative AI to their learning [Dissertation, Long Island University, C. W. Post Center]. In *ProQuest Dissertations and Theses*. Publicly Available Content Database (3175897399). https://www.proquest.com/dissertations-theses/survey-study-on-college-student-s-acceptance/docview/3175897399/se-2?accountid=210494

Younis, B. (2025). The artificial intelligence literacy (AIL) scale for teachers: A tool for enhancing AI education. *Journal of Digital Learning in Teacher Education*, *41*, 37–56. https://doi.org/10.1080/21532974.2024.2441682

Yue, M., Jong, M. S.-Y., & Ng, D. T. K. (2024). Understanding K–12 teachers' technological pedagogical content knowledge readiness and attitudes toward artificial intelligence education. *Education and Information Technologies*, *29*(15), 19505–19536. https://doi.org/10.1007/s10639-024-12621-2

Zhou, T., Tondeur, J., & Howard, S. (2025). AI competency frameworks for teachers: A systematic review. In T. Bastiaens (Ed.), *Proceedings of EdMedia + Innovate Learning* (pp. 648–654). Association for the Advancement of Computing in Education (AACE). https://www.learntechlib.org/primary/p/226198/