International Journal of Evaluation and Research in Education (IJERE)
Vol. 15, No. 3, June 2026, pp. 1986~2000
ISSN: 2252-8822, DOI: 10.11591/ijere.v15i3.36999

Artificial intelligence literacy and adoption among basic education teachers

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Article Info

Article history:

Received Sep 21, 2025
Revised Mar 29, 2026
Accepted May 7, 2026

Keywords:

AI adoption
AI literacy
Artificial intelligence
Basic education teachers
Structural equation modeling

ABSTRACT

Despite growing interest in artificial intelligence (AI) integration, a gap in AI literacy and adoption among teachers limits the benefits of AI-enhanced learning and widens the digital divide. This study explored AI literacy and adoption among basic education teachers in Butuan City, Philippines, using the technological pedagogical content knowledge (TPACK) framework and social cognitive theory (SCT). It examined factors influencing readiness to integrate AI tools into teaching. Using a quantitative descriptive-causal design, data from 243 randomly selected teachers were analyzed through structural equation modeling (SEM) with the adopted research instruments. Results show that AI literacy and positive affective-cognitive variables strongly predict AI adoption, with behavioral intention (BI) mediating the link between self-esteem (SE) and AI literacy. Findings underscore the need for targeted professional development and institutional support to bridge the AI literacy gap and ensure the responsible and effective integration of AI in primary education.

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1. INTRODUCTION

The increasing integration of artificial intelligence (AI) in education has transformed traditional teaching and learning processes, making it essential for educators to develop AI literacy and adopt AI-driven tools effectively. However, many teachers face challenges in understanding, applying, and evaluating AI applications (EAIA) technology in their classrooms, which may affect its adoption [1]. For basic education teachers, understanding and adopting AI technologies is essential to prepare students for a future where AI plays a pivotal role. Despite this, AI literacy levels and adoption rates vary significantly across educational settings, influenced by factors such as technological infrastructure, training opportunities, and teachers' perceptions of AI's role in education [2].

According to Yang and Banks [3], AI literacy among elementary educators is crucial in determining how effectively they integrate AI-driven technologies into their classrooms, fostering better teaching practices and student engagement. Teachers who possess a solid understanding of AI concepts and applications are more likely to leverage its benefits to support student learning and administrative tasks [4]. AI encompasses tools such as adaptive learning platforms, automated grading systems, and intelligent tutoring applications that enhance the teaching and learning processes. AI literacy among teachers goes beyond basic familiarity with these tools; it involves four key dimensions: knowledge, which includes understanding AI concepts, capabilities, and limitations; ethics, which addresses responsible use, fairness, privacy, and data protection; application, which focuses on the ability to integrate AI tools effectively into instructional practices; and evaluation, which entails critically assessing AI outputs and their impact on learning outcomes. Mastery of these dimensions enables educators to make informed decisions about AI integration and ensures that its use aligns with pedagogical goals and ethical standards [5].

Additionally, many research works indicate that teachers' behavioral intentions (BI) to teach AI literacy particularly knowledge, ethics, application, and evaluation, are influenced by factors such as the perceived relevance of AI, attitudes towards its use, and confidence in implementing AI tools. However, while AI promises to enhance learning experiences and improve teaching methodologies, research shows that educators' knowledge and attitudes towards these technologies are still in the developmental stage [6]. Despite the advancements and interest in AI integration, there exists a notable gap in AI literacy and adoption among basic education teachers. Many educators lack sufficient training and confidence to implement AI technologies effectively in their classrooms [7]. This deficiency not only hinders the potential benefits of AI-enhanced learning but also exacerbates the digital divide, limiting students' exposure to essential AI competencies. Additionally, there is a gap in understanding the factors that influence educators' willingness to adopt AI, including institutional support, training availability, and perceived usefulness [8].

To address the gap, the present study aims to fill this gap by examining the level of AI literacy among basic education teachers and understanding the factors influencing their adoption of AI tools. By focusing on teacher perceptions, preparedness, and the challenges they face in integrating AI into their teaching, this research seeks to offer insights that could guide professional development and policy decisions regarding AI in education. Previous studies have shown that teachers' knowledge and attitudes toward AI significantly impact its adoption [9]. The study intends to provide insights into how AI literacy could be improved and how educators could be better supported in adopting AI technologies effectively.

The study is anchored on the technological pedagogical content knowledge (TPACK) and the social cognitive theory (SCT) framework. TPACK explains how technology, pedagogy, and content shape teachers' readiness and competence. Teachers with strong TPACK can meaningfully incorporate AI tools by aligning technological capabilities with instructional goals. SCT complements this by emphasizing the role of self-efficacy, attitudes, BI, and environmental factors in technology adoption, where confidence and positive expectations drive actual use. In this study, AI literacy reflects TPACK's technological knowledge dimension, while factors such as self-esteem (SE), ease of utilization (EU), and expected benefits (EB) align with SCT principles. Together, these frameworks inform a structural model that views AI adoption as a function of both technical knowledge and psychological readiness, offering a holistic perspective on successful integration.

Furthermore, this study assessed the level of AI literacy and AI adoption among faculty members and basic education teachers in Butuan City, Philippines, providing insights into their readiness and attitudes toward integrating AI into educational practices. Specifically, the descriptive phase of this study aims to: i) describe the teachers' demographic profile in terms of gender, teaching experience, generational age group, and highest educational attainment; ii) determine the level of AI literacy, AI applications, and AI ethics (AIE); iii) measure the level of AI adoption based on SE, ease of use, stress and anxiety, attitude toward using AI (ATUA), BI, and EB; and iv) investigate whether significant differences exist in participants' perceptions of AI literacy and adoption when categorized by demographic profile. Its causal phase endeavored to: v) establish the mediating role of BI in the relationship between SE and AI literacy; and vi) develop and validate a structural model that best explains the interplay among demographic variables, AI literacy, and AI adoption, offering a comprehensive framework for understanding and promoting effective AI integration in education. The study hopes to provide recommendations for fostering a better understanding of AI among teachers, thereby enhancing their ability to effectively incorporate these technologies into their teaching practices.

2. METHOD

This study adopted a quantitative research design, combining both descriptive and causal approaches to explore AI literacy and adoption among basic education teachers in Butuan City, Philippines. The descriptive aspect focused on assessing the levels of AI literacy and adoption, while the causal component employed structural equation modeling (SEM) to analyze the relationships and predictive influences among AI literacy, AI adoption, and behavioral factors. Additionally, mediation analysis was conducted to examine the indirect effects of AI literacy on adoption behavior. These analyses aimed to provide deeper insights into how AI knowledge, application, and ethics shape teachers' readiness to integrate AI into their educational practices.

The research was conducted across three educational institutions in Butuan City: Obrero Central Elementary School, Butuan Central Elementary School, and Libertad Central Elementary School. Each school was selected to represent diverse teaching environments and ensure a comprehensive perspective on

AI literacy and adoption. Obrero is located approximately 3 kilometers from the city center, Butuan Central is about 2 kilometers, and Libertad is around 2.5 kilometers. These varied locations helped capture a broad range of experiences and attitudes among educators.

Participants in the study included teachers from the three schools, with a total population of 311 educators. Specifically, there were 90 teachers from Obrero, 152 from Butuan Central, and 69 from Libertad. Using stratified random sampling, 243 teachers were selected to participate, 74 from Obrero, 110 from Butuan Central, and 59 from Libertad. This sample size, according to Kenny [10], supports adequate power, model stability, and valid SEM results. The sampling method used ensured fair representation across institutions and enhanced the reliability of the study's findings.

To select participants, all teachers were listed and assigned codes, then randomly chosen from each group based on the required sample size. This approach helped maintain objectivity and ensured that the sample accurately reflected the population. The stratified random sampling technique also allowed the researchers to account for differences in school size and demographics, making the results more generalizable to the broader teaching community in Butuan City.

Figure 1 shows the hypothesized path diagram of this study. It is primarily anchored on TPACK since it informed the measurement of AI literacy through four dimensions: knowing and understanding AI (KUA) captured technological knowledge, focusing on familiarity with AI concepts, capabilities, and limitations; applying AI (AAI) reflected technological-pedagogical knowledge by assessing teachers' ability to integrate AI tools into instructional practices; EAIA measured critical assessment skills, while AIE addressed ethical awareness related to fairness, privacy, and responsible use.

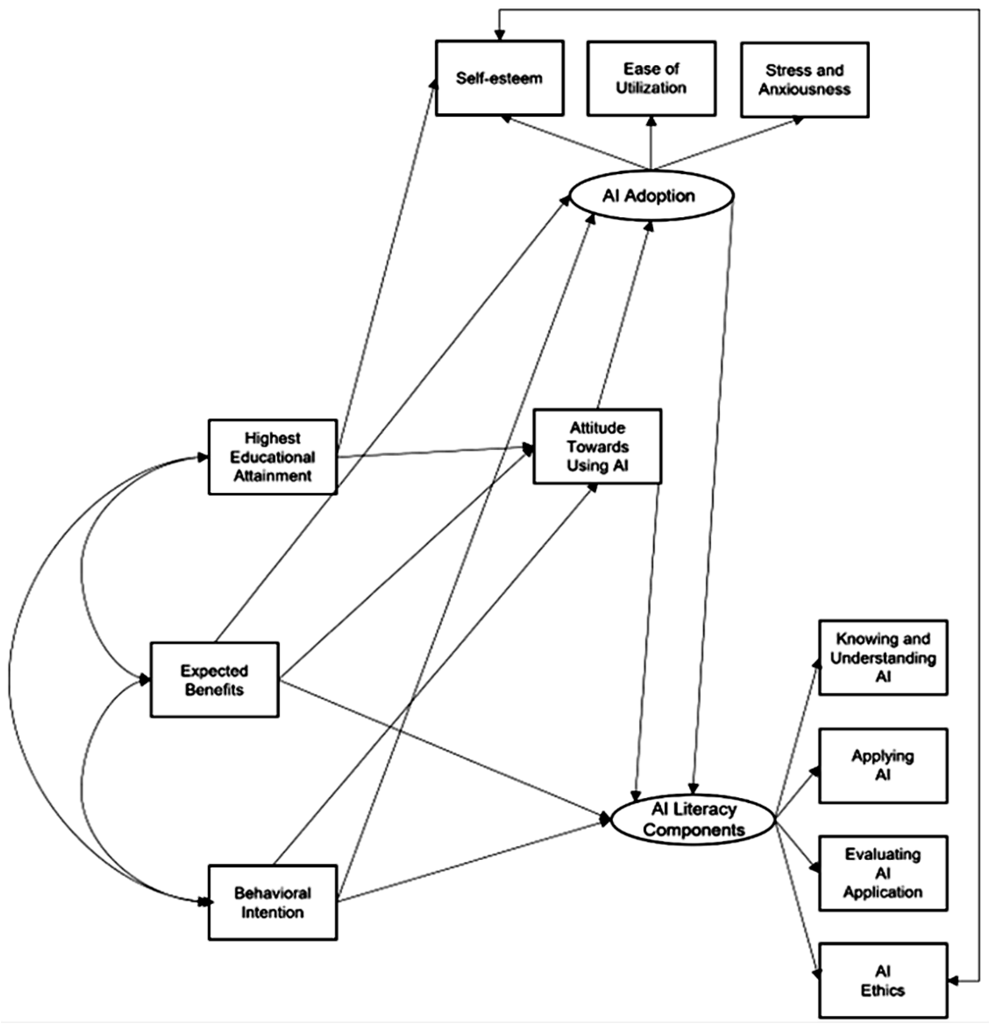

Figure 1. Hypothesized model of the study

The model reflects the interplay among AI literacy components (ALC), individual cognitive–affective factors, and adoption outcomes, consistent with the TPACK and SCT frameworks. In this model, the four AI literacy dimensions (KUA, AAI, EAIA, and AIE), adoption factors (SE, EU, stress and anxiousness or SA, and ATUA), and outcome constructs (BI and EB) are the latent variables. Observed variables consisted of the questionnaire items corresponding to each latent construct. Path directions as shown in the figure were specified as: AI literacy → attitude; AI literacy → BI; attitude → BI; and AI literacy → attitude → BI (indirect effect). These pathways operationalize how knowledge-based competencies (TPACK's technological knowledge dimension) shape adoption-related beliefs and behaviors, while SCT's emphasis on personal factors (self-efficacy), affective states (stress, anxiety), and behavioral expectations is reflected in the mediating mechanisms between literacy and intention.

The study utilized an adapted questionnaire that combines AI literacy (four subscales from [11], 20 items) and AI adoption factors (three subscales from [12], 15 items). Sample items demonstrate face validity, while reliability is solid to excellent across subscales, supporting a coherent measurement foundation for SEM. Table 1 summarizes the instruments used to assess AI-related constructs, including their sources, number of items, sample statements, and reliability, indicating generally acceptable to high internal consistency.

Table 1. Summary of instruments used in AI constructs

Source	Constructs	Number of items	Sample item	Reliability (Cronbach's alpha)
Zhao *et al.* [11]	ALC (KUA, AAI, EAIA, and AIE)	20	I can explain what AI means.	0.732–0.961
Nja *et al.* [12]	AI adoption factors (SE, SA, ease of use, EB, attitude towards AI)	15	Using AI tools will improve my teaching effectiveness.	0.78–0.89

Internal consistency was evaluated using McDonald's Omega and Cronbach's alpha, both of which showed strong reliability across all scales. For estimation, no machine learning (ML) robustness corrections were applied; instead, bias-corrected bootstrapping provided confidence intervals (CI) and p-values to bolster inference under mild departures from normality. There were 243 participants in this study hence, considered sufficient for ML estimation as discussed in Hair *et al.* [13]. All indicators were collected on a 5-point Likert scale and were treated as continuous in the latent variable analyses, consistent with common practice for multi-item psychometric scales.

Table 2 presents the results of the effect analysis, including the total, direct, and indirect effects of ALC on BI. It shows the estimated coefficients, bias-corrected confidence intervals, and p-values, indicating that all examined effects are statistically significant. Bootstrapping was applied to SEM estimates to generate bias-corrected CI and robust significance levels for direct, indirect, and total effects. The results indicate that all paths are statistically significant, with CI that do not cross zero, confirming the stability of the hypothesized relationships.

Table 2. Results of the effect analysis of ALC on BI

Effect type	Path	Estimate	Lower CI (bias-corrected)	Upper CI (bias-corrected)	p-value
Total effect	AI literacy → BI	0.62	0.48	0.73	0.001
Indirect effect	AI literacy → attitude → BI	0.35	0.22	0.49	0.002
Direct effect	Attitude → BI	0.41	0.29	0.54	0.001

Assumptions were examined prior to structural modeling: linearity via residual patterns and component-plus-residual plots (no problematic nonlinearity detected); multicollinearity via variance inflation factor (VIF) and condition indices (no problematic levels observed); and multivariate normality via Mardia's coefficient (minor deviations addressed through the bootstrap procedure). In sum, the scales exhibit strong internal consistency, the estimation approach is appropriate for the data, and diagnostics do not indicate violations that would compromise SEM results. The results underscore the importance of both direct and mediated pathways in explaining BI.

The researchers added a section for the demographic profile to the final questionnaire consisted of three sections: demographic profile, AI literacy, and AI adoption. The demographic section gathered data on gender, teaching experience, age group, and educational attainment. Furthermore, data collection followed a structured and ethical process. Formal approval was obtained from the division office and school administrators, followed by participant orientation to explain the study's purpose and ensure informed consent. Questionnaires were distributed both physically and electronically, with built-in checks to prevent missing responses. After collection, the data were reviewed, encoded, and analyzed using statistical tools such as frequency counts, percentages, mean, standard deviation (SD), t-tests, analysis of variance (ANOVA), Spearman Rho correlation, multiple regression, and SEM. Confidentiality was strictly maintained throughout the study to protect participant privacy and uphold research integrity.

3. RESULTS AND DISCUSSION

3.1. Demographic profile of the participants

Table 3 displays the demographic profile of the participants, including gender, teaching experience, age by generation, and highest educational attainment. As shown, the sample was predominantly female. This gender distribution aligns with national trends in the Philippine education sector, where female educators comprise over 85% of the elementary teaching workforce [14]. Similarly, Sebastian *et al.* [15] found that the elementary teaching profession remains female-dominated, raising concerns about limited exposure to male role models in early education. This demographic imbalance may influence the interpretation of the study's results, particularly if gender is a relevant variable in AI literacy and adoption.

Table 3. Demographic profile of the basic education teachers

Demographic profiles		Frequency	Percentage (%)
Gender	Female	204	83.951
	Male	39	16.049
Teaching experience	1-5 years	29	11.934
	6-10 years	65	26.749
	11-15 years	43	17.695
	More than 15 years	106	43.621
Age group	Baby boomer	21	8.642
	Generation X	105	43.210
	Millennial	102	41.975
	Generation Z	15	6.173
Educational attainment	Bachelor's degree	59	24.280
	Master's degree (with units)	125	51.440
	Master's degree	53	21.811
	Doctorate degree (with units)	6	2.469

As for teaching experience, the most significant proportion of participants had more than 15 years of experience which indicates that over 70% of participants have been teaching for more than a decade, suggesting a sample composed primarily of seasoned educators. This finding is consistent with the World Bank's 2020 report, which highlights that many public school teachers in the Philippines possess extensive teaching. In terms of age distribution, the majority of participants belonged to Generation X and Millennials, with smaller percentages from Baby Boomers and Generation Z. This generational composition reflects similar findings in Villanueva *et al.* [16], where younger and mid-career teachers dominated the sample in public schools. The generational makeup is significant, as prior studies suggest that Millennials and Gen X educators may differ in their attitudes toward technology adoption, with Millennials generally more receptive to digital tools in the classroom experience. The presence of experienced educators may influence perspectives on AI integration, as they may have established pedagogical routines and varying levels of openness to technological change.

Educational attainment among participants showed that more than half had earned academic units toward a master's degree. This finding suggests a highly educated sample, which may positively influence AI literacy and adoption. Lumanlan *et al.* [17] similarly reported that most teachers in their study held bachelor's degrees or were pursuing graduate studies, indicating a trend toward professional advancement in the teaching workforce.

Taken together, these demographic characteristics like gender, experience, age, and education provide important context for interpreting the study's findings on AI literacy and adoption. The predominance of female, experienced, and highly educated teachers may shape the overall readiness and attitudes toward integrating AI into educational practice. These insights are supported by existing literature and highlight the importance of considering demographic variables in technology adoption research.

3.2. Artificial intelligence literacy of the participants

Table 4 exhibits the level of AI literacy in terms of ALC. As shown, participants demonstrated a generally high level of AI literacy across all four components. The highest mean score was observed in KUA indicating that participants are highly likely to possess a solid understanding of AI concepts. This was followed by AIE suggesting that participants are also highly aware of ethical considerations related to AI use.

The results on the component AAI and EAIA suggest that participants are confident in their ability to apply and critically evaluate AI tools and systems.

The findings emphasize the importance of strengthening educators' knowledge in AI and its ethical considerations, supporting previous research that highlights the role of comprehensive AI education in fostering responsible use in educational settings [18]. While participants showed competence in AAI and EAIA, the slightly lower scores in these areas suggest the need for further development in practical application and critical evaluation skills. These findings suggest that targeted professional development programs incorporating hands-on AI tools and real-world evaluations could further enhance teachers' ability to effectively integrate and assess AI technologies in their classrooms [18].

Table 4. Level of AI literacy in terms of knowledge, application, evaluation, and ethics

Literacy	Valid	Mean	STD. Deviation
KUA	243	4.261	0.605
AAI	243	4.141	0.695
EAIA	243	4.069	0.742
AIE	243	4.216	0.739

3.3. AI adoption among the participants

Table 5 showcases the level of AI Adoption among the participants in terms of AI Adoption components. Participants demonstrated generally high levels of AI adoption across most components. The highest mean score was observed for EB, followed closely by BI, indicating that participants perceived strong benefits from AI and expressed a clear intention to integrate it into their practices. The results reveal that SE in relation to AI adoption and ATUA suggest a positive self-concept and attitude regarding participants' ability to use AI technologies.

EU scored slightly lower, but still reflects a favorable perception toward the usability of AI systems. In contrast, SA related to AI adoption scored the lowest among the components, suggesting that while some participants may experience discomfort or uncertainty when using AI, this concern is not dominant across the group. This implies that while they find AI systems generally easy to use, targeted support is needed to reduce residual anxiety and build confidence for effective adoption.

The study indicates that teachers' perceptions of AI's EB and BI are key drivers for AI adoption. With high mean scores for EB and BI, the findings suggest that recognizing AI's potential benefits is associated with stronger intentions to adopt it, consistent with prior research [19]. Although SE and ATUA were positively correlated with adoption, SA were lower, implying that addressing emotional readiness and providing support could ease teachers' concerns. This suggests that fostering positive SE and attitudes, along with proper training, can reduce anxiety and enhance AI adoption, which is consistent with the results of previous study [20].

Table 5. Level of AI adoption in terms of SE, usability, emotional response, attitude, intention, and perceived benefits

Adoption	Valid	Mean	STD. Deviation
SE	243	4.025	0.799
EU	243	3.949	0.844
SA	243	2.891	0.903
ATUA	243	3.981	0.693
BI	243	4.201	0.68
EB	243	4.240	0.630

3.4. Significant difference in AI literacy and AI adoption when grouped according to profile

Table 6 presents the summary of participants' perceptions of AI adoption as grouped by their teaching experience. It shows the mean scores and variability of AI adoption across four teaching experience groups: 1–5 years, 6–10 years, 11–15 years, and more than 15 years. Participants with 1–5 years of teaching experience reported the highest mean level of AI adoption, followed by those with 6–10 years, 11–15 years, and over 15 years of experience. The standard error values indicate that the estimates of the group means are relatively precise, especially in the larger sample groups.

Additionally, the coefficient of variation (CV), which expresses the SD relative to the mean, was lowest for the 1–5 years group, suggesting that this group not only had the highest AI adoption but also the most consistent responses. In contrast, the highest variability was observed in the group with more than 15 years of experience, indicating more diverse perceptions of AI adoption within that group. Moreover, these findings align with studies that suggest younger, less experienced teachers tend to adopt technology more readily [21], whereas those with more experience may be more resistant to such changes [11]. The CV further emphasizes the variability in AI adoption perceptions across teaching experience groups. Teachers with more than 15 years of experience exhibited greater diversity in their responses, reflecting a mix of openness and resistance to AI adoption.

Table 6. Descriptive statistics for AI adoption by teaching experience

Teaching experience	N	Mean	SD	Standard error	CV
1-5 years	29	4.123	0.403	0.075	0.098
11-15 years	43	3.828	0.581	0.089	0.152
15 years above	106	3.795	0.608	0.059	0.160
6-10 years	65	3.950	0.447	0.055	0.113

Note: Descriptive statistics include mean, standard deviation (SD), standard error, and coefficient of variation (CV) for AI adoption by teaching experience

The results highlight the influence of teaching experience on the willingness to integrate new technologies into the classroom. Moreover, prior research has shown that less experienced teachers are often more comfortable with AI tools due to their familiarity with technology, while more seasoned educators may need additional support to overcome resistance and fully embrace AI [22]. The variation in responses across different groups suggests that targeted interventions could help address specific concerns and enhance AI adoption, especially among the more experienced teachers.

Table 7 exhibits descriptive statistics for participants' AI adoption scores grouped according to their age group (Baby Boomer, Generation X, Generation Z, and Millennial). It presents the mean scores and variability of AI adoption across four generational cohorts: Baby Boomers, Generation X, Millennials, and Generation Z. The mean scores indicate variation in AI adoption based on age group, suggesting that generational affiliation may influence participants' perceptions and engagement with AI technologies.

Table 7. Descriptive statistics for AI adoption by age group

Age group	N	Mean	SD	Standard error	CV
Baby Boomer	21	3.974	0.499	0.109	0.126
Generation X	105	3.762	0.603	0.059	0.160
Generation Z	15	4.126	0.417	0.108	0.101
Millennial	102	3.950	0.497	0.049	0.126

Note: Descriptive statistics include mean, standard deviation (SD), standard error, and coefficient of variation (CV) for AI adoption by age group.

Moreover, Generation Z reported the highest mean AI adoption score, followed closely by Baby Boomers and Millennials. Generation X reported the lowest mean score, suggesting relatively lower levels of perceived or practiced AI adoption among that cohort. The standard error values show that the estimates of group means are relatively precise, particularly for Millennials and Generation X, which had large sample sizes. Generation Z, while the smallest group (n=15), showed the highest adoption mean and lowest CV (CV=0.101), indicating both a high level of AI adoption and relatively consistent responses within that group.

The results are consistent with previous studies indicating that younger generations are generally more open to adopting new technologies [23], [24]. The standard error values show that the estimates of group means are relatively precise, especially for Millennials and Generation X, which had large sample sizes. Although Generation Z was the smallest group (n=15), it demonstrated the highest level of AI adoption and the lowest CV (CV=0.101), indicating consistent responses within this cohort. Additionally, these findings further support the notion that generational differences significantly impact the adoption of AI, with younger generations showing higher levels of familiarity and comfort with such technologies [24]. Moreover, the variation in AI adoption scores across age groups suggests that tailored interventions may be needed to enhance AI adoption, particularly among older generations [11].

Table 8 presents a statistical summary of scores by highest educational attainment. The groups represented are bachelor's degree, doctorate units, master's degree, and master's units. The data provide insight into the variability and central tendency of scores across these educational categories. The table displays the mean scores and variability in AI adoption among participants grouped by their highest educational attainment: bachelor's degree, master's units, master's degree, and doctorate units.

Table 8. Descriptive statistics for AI adoption by highest educational attainment

Highest educational attainment	N	Mean	SD	Standard error	Coefficient of variative
Bachelor’s degree	59	3.910	0.642	0.084	0.164
Doctorate units	6	3.882	0.603	0.246	0.155
Master’s degree	53	3.967	0.436	0.060	0.110
Master’s units	125	3.832	0.545	0.049	0.142

Note: Descriptive statistics include mean, standard deviation (SD), standard error, and coefficient of variation (CV) for AI adoption by highest educational attainment.

Participants with a master’s degree reported the highest mean AI adoption score, followed closely by those with a bachelor’s degree. Despite these differences in mean scores, the SD across the groups were relatively similar. The standard error values indicate precise estimates for larger groups, particularly for the master’s units, while the estimate for doctorate units is less reliable due to the small sample size. As a result, the CV was lowest for the master’s degree group, indicating more consistent responses within this group, and highest for the bachelor’s degree group (CV=0.164), suggesting greater variability in responses.

The master’s degree group’s CV is relatively low. On the other hand, the bachelor’s degree group exhibited more diverse levels of AI literacy and adoption behaviors, indicating a wider range of experiences and perceptions regarding AI integration in education. This result aligns with previous studies suggesting that higher levels of education tend to be positively correlated with greater technology adoption, including AI tools [12], [21]. However, while the mean scores show a trend, the SD across the groups were relatively similar, ranging from 0.44 to 0.64, indicating that there is consistent variability in AI adoption within these educational categories. These findings suggest that education level may play a role in shaping AI adoption among teachers, with individuals holding master’s degrees showing more consistency in their perceptions and behaviors towards AI adoption, while those with a bachelor’s degree exhibited greater variability in responses [21].

Table 9 presents the means, SD, standard errors, and coefficients of variation for the perception of AI literacy, categorized by the participants’ years of teaching experience. The table reveals that the mean scores for AI literacy perceptions indicate that participants with 1-5 years of teaching experience reported the highest perception of AI literacy, followed by those with 6-10 years, 11-15 years, and 15+ years. Results reveal that variability in responses, as reflected by the SD, was highest in the group with 11-15 years of experience and lowest in the 1-5 years group. Additionally, the CV, which represents the relative variability in the data, was lowest for the 1-5 years group, suggesting a more consistent perception of AI literacy, and highest for the 11-15 years group, indicating greater variability in perceptions.

The SD of the group with 11-15 years of experience indicates a high level of variability in their responses. This means that teachers in this group had diverse perceptions and experiences regarding AI literacy, with responses spread out widely around the mean. In contrast, the group with 1-5 years of experience had a much lower SD, showing that their responses were more clustered around the mean, reflecting more uniform perceptions of AI literacy.

Overall, teachers with 1-5 years of experience had more consistent perceptions of AI literacy, while those with 11-15 years of experience exhibited more diverse views. These findings support the idea that teaching experience may be associated with the perceptions of AI literacy, as more recent educators (with 1-5 years of experience) show a stronger and more consistent view of AI’s role in education [12], [21]. Previous studies have emphasized that teacher perceptions of emerging technologies, such as AI, are often shaped by their level of exposure and engagement with such tools [22].

Table 9. Descriptive statistics of AI literacy perception by teaching experience

Teaching experience	N	Mean	SD	Standard error	CV
1-5 years	29	4.569	0.332	0.062	0.073
11-15 years	43	4.107	0.680	0.104	0.165
15 years above	106	4.030	0.649	0.063	0.161
6-10 years	65	4.268	0.461	0.057	0.108

Note: Descriptive statistics include mean, standard deviation (SD), standard error (SE), and coefficient of variation (CV) for AI adoption by teaching experience.

3.5. Significant relationship between AI literacy and adoption

Table 10 shows that the analysis yielded a Spearman’s $\rho=.749$, $p<.001$, indicating a strong positive correlation. This result suggests that higher levels of AI literacy are associated with increased likelihood of AI adoption. The 95% CI for Spearman’s rho ranges from 0.688 to 0.800, further confirming the strength of the relationship, as the correlation value falls well above the threshold of 0.7, which is generally considered a strong correlation. This finding highlights that AI literacy is a key factor in AI adoption among teachers, emphasizing the importance of increasing AI literacy in fostering greater adoption and effective use of AI technologies [23], [24].

Table 10. Spearman's correlation between ALC and AI adoption

Model	N	Spearman's rho	P	Lower 95% CI	Upper 95% CI
ALC and AI adoption	243	0.749	<0.001	0.688	0.800

In view of these results, Ngoveni [25] emphasizes the critical role of AI literacy in modern organizations in his study. Bridging the AI knowledge gap is essential for organizations to thrive and remain relevant in today's rapidly evolving technological landscape. Accordingly, AI literacy is not just about operating AI tools but involves a deeper understanding and the ability to integrate AI technologies effectively into daily workflows.

Table 11 explains the results in Table 10. As shown, the results of the Shapiro-Wilk test indicated that the data for both ALC and AI adoption significantly deviate from a normal distribution, with $p<0.001$ for both variables. This means that the assumption of normality was not met. The Shapiro-Wilk test is a widely used statistical procedure for assessing whether data follow a normal distribution, and a significant result suggests that the data are not normally distributed. The Shapiro-Wilk test is efficient for small to medium-sized datasets. It is considered one of the most sensitive tools for detecting deviations from normality.

The violation of the normality assumption is a critical factor when selecting appropriate statistical analyses. In cases where the assumption of normality is not satisfied, the use of parametric tests such as Pearson's correlation may be associated with misleading conclusions due to their reliance on normally distributed data. Applying parametric methods to non-normal data can distort statistical outcomes and reduce the reliability of inferential conclusions, especially in behavioral and educational research contexts [26]. Given these results, the researchers opted to use Spearman's rank-order correlation, a non-parametric test that does not require the assumption of normality. Using a non-parametric method, such as Spearman's correlation, ensures the robustness and validity of the findings despite the non-normal distribution of the data. This approach is particularly appropriate for ordinal or skewed data and provides a reliable means of evaluating the strength and direction of the association between AI literacy and AI adoption.

Table 11. Relationship between AI literacy and AI adoption

Model	Shapiro-Wilk	P
ALC and AI adoption	0.971	<0.001

Note: Shapiro-Wilk is used to test for normality, and p indicates the significance level.

3.6. AI Adoption with direct influence on AI literacy of the participants

Table 12 demonstrates whether the factors under the level of AI adoption have direct influence on the participants in terms of ALC. As shown, the baseline model (M_0), which included no predictors, resulted in an R^2 of 0.000 and a root mean square error (RMSE) of 0.602, indicating no explanatory power. In contrast, the full model (M_1), which included six predictors—SE, EU, SA, ATUA, BI, and EB—showed a substantial improvement.

The full model yielded an R of 0.856 and an R^2 value of 0.732, indicating that approximately 73.2% of the variance in ALC can be explained by the combined influence of the six AI adoption factors. The adjusted R^2 of 0.726 accounts for model complexity and still demonstrates a strong explanatory capacity. The RMSE decreased to 0.315, further reflecting improved model accuracy and predictive performance.

These findings suggest that teachers' AI literacy is strongly influenced by multiple adoption factors, indicating that comprehensive support addressing technical, cognitive, and affective dimensions can significantly enhance their readiness to integrate AI into classroom practice. Table 13 presents the regression of the ALC. Given the use of a large sample size ($n=243$) and robust procedures, it is worth noting that the impact of minor deviations from normality is minimized in this study. Therefore, the assumptions were considered adequately addressed through corrective measures.

The results reveal that the ANOVA test for the regression model was significant, $F(6, 236)=107.61$, $p<.001$, indicating that the model accounts for a statistically significant amount of variance in ALC. The regression sum of squares (SS=64.232) reflects the portion of variance explained by the predictors included in the model—namely SE, EU, SA, ATUA, BI, and EB. The residual sum of squares (SS=23.477) represents the variance not accounted for by the model.

Table 12. Model summary for the influence of AI adoption factors on ALC

Model	R	R^2	Adjusted R^2	RMSE
M_0	0.000	0.000	0.000	0.602
M_1	0.856	0.732	0.726	0.315

Notes: M_1 includes SE, EU, SA, ATUA, BI, EB

Table 13. ANOVA summary for the regression model predicting ALC

Model		Sum of squares	Df	Mean square	F	p
M_1	Regression	64.232	6	10.705	107.613	<0.001
	Residual	23.477	236	0.099		
	Total	87.709	242			

Note: M_1 includes SE, EU, SA, ATUA, BI, EB

The high F-ratio and extremely low p-value confirm that the regression model provides a significantly better fit compared to a model with no predictors. This supports the conclusion that the factors under AI adoption, when considered collectively, have a meaningful and direct influence on ALC among the participants. The significant ANOVA results indicate that teachers' AI literacy is strongly shaped by SE, ease of use, attitudes, BI, perceived benefits, and stress levels, suggesting that holistic interventions targeting these factors can substantially improve their capacity to adopt AI in teaching.

In consonance with the results, Liu [27] stated that enhancing ALC, such as confidence and readiness, can positively influence AI adoption. This aligns with the notion that increasing AI literacy is crucial for fostering greater adoption and effective use of AI technologies. Table 14 reveals the coefficients of the regression model used to assess the direct influence of AI adoption factors on ALC. The unstandardized coefficients (B), standardized beta coefficients (β), standard errors, t-values, p-values, and collinearity statistics (tolerance and VIF) are reported for each predictor.

Table 14. Predictors of AI literacy based on AI adoption factors: multiple regression analysis

Model		Unstandardized	Standard error	Standardized	T	P	Collinearity statistics	
							Tolerance	VIF
M_0	(Intercept)	4.172	0.039		108.017	<0.001		
M_1	(Intercept)	1.161	0.165		7.436	<0.001		
	SE	0.228	0.047	0.303	4.826	<0.001	0.289	3.465
	EU	0.291	0.045	0.407	6.421	<0.001	0.282	3.548
	SA	-0.009	0.023	-0.014	-0.014	0.676	0.992	1.008
	ATUA	0.091	0.044	0.105	2.089	0.038	0.451	2.218
	BI	-0.038	0.051	-0.043	-0.746	0.456	0.344	2.905
	EB	0.182	0.051	0.190	3.566	<.001	0.399	2.504

The results revealed that EU (β=0.407, p<0.001), SE (β=0.303, p<0.001), EB (β=0.190, p<0.001), and ATUA (β=0.105, p=0.038) had statistically significant positive effects on ALC. These findings suggest that as teachers perceive AI as easier to use, have greater self-confidence, recognize more EB, and hold more favorable attitudes toward using AI, their level of AI literacy improves. On the other hand, SA and BI did not show significant predictive power (p=.676 and p=.456, respectively), indicating that these factors do not independently contribute to the prediction of AI literacy in this model. Collinearity statistics also confirmed acceptable levels, with all Tolerance values above 0.2 and VIF values below 5, indicating that multicollinearity is not a concern in this model. The lack of significant predictive power for SA and BI suggests that reducing anxiety alone or fostering intention may not be sufficient to improve teachers' AI literacy, emphasizing the need to focus on more influential factors such as SE, ease of use, and perceived benefits.

Fontanos and Ocampo [14] highlight that factors such as EU, SE, EB, and attitudes toward AI usage significantly impact teachers' BI to adopt AI. These factors are directly linked to ALC, suggesting that as teachers perceive AI as easier to use, have greater self-confidence, recognize more EB, and hold favorable attitudes toward AI, their AI literacy improves. Table 15 shows the descriptive statistics for ALC and the factors under AI adoption among the 243 participants. The overall mean score for ALC suggests a generally high level of AI literacy among basic education teachers. Conversely, SA recorded the lowest mean score, suggesting that while participants recognized the benefits and had positive intentions, some still experienced stress or anxiety related to AI use. The standard errors for each variable reflect reliable estimates of the population means. These descriptive results help provide context for interpreting the regression and correlation analyses, underscoring which variables are most strongly endorsed or experienced by participants. The generally high AI literacy among teachers, despite some lingering stress and anxiety, implies that while technical competence is strong, emotional support and confidence-building strategies remain essential for sustaining effective AI integration in classrooms.

Zhao [28] found that teachers who are more familiar with digital technologies and have higher confidence in their technological abilities are more likely to adopt and effectively use new technologies. Similarly, their study discusses how self-efficacy and other factors directly influence teachers' attitudes towards technology, which in turn affects their overall acceptance and usage behavior. The study concludes that improving teachers' perceptions of usability and boosting their self-efficacy can enhance their technology literacy and adoption.

Table 15. Descriptive statistics for ALC and adoption factors

ALC and adoption	N	Mean	SD	Standard error
ALC	243	4.172	0.602	0.039
SE	243	4.025	0.799	0.051
EU	243	3.949	0.844	0.054
SA	243	2.891	0.903	0.058
ATUA	243	3.981	0.693	0.044
BI	243	4.201	0.680	0.044
EB	243	4.240	0.630	0.040

Note: N=number of participants; SD=standard deviation

3.7. Mediation analysis and structural path modeling

Figure 2 shows the standardized path coefficients and variance in the mediation model. The figure displays that self-efficacy has a strong direct effect on ALC, with a standardized path coefficient of β=0.66, suggesting that higher self-efficacy is positively associated with greater AI literacy. ALC also exhibits a moderate direct effect on BI (β=0.21), indicating that AI literacy contributes to an individual's intention to engage with or use AI technologies. Additionally, SE has a direct effect on BI (β=0.64), which is considerably stronger than the path from ALC to BI. This highlights the influential role of self-efficacy in shaping BI. The squared multiple correlations (R^2) within the model provide further insight.

The variance explained in ALC by SE is 35% (R^2=0.35), while BI is influenced by both SE and ALC, together accounting for 59% of its variance (R^2=0.59). These results suggest a partially mediated pathway, where ALC serves as a mediator between SE and BI, though SE also exerts a strong direct influence on BI. The strong direct and mediated effects of SE on AI literacy and BI imply that boosting teachers' confidence and self-efficacy is pivotal for promoting both AI competence and willingness to integrate AI tools in teaching.

These findings underscore the critical role of self-efficacy in both enhancing AI literacy and directly influencing BI to use AI. This aligns with prior research, which identifies self-efficacy as a key determinant in technology adoption [12], [21]. Moreover, the moderate path from ALC to BI supports the notion that knowledge and literacy in AI can independently foster intention, though this effect may be contingent on confidence in one's abilities [29].

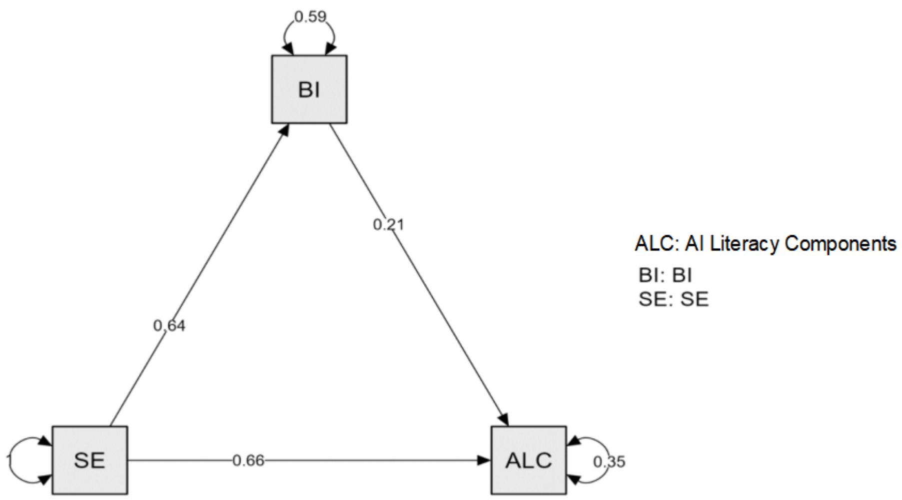

Figure 2. Standardized path coefficients and variance explain in the mediation model (SE → ALC → BI)

3.8. Model that best explains the relationship of the variables

Table 16 exhibits the fit indices for the SEM that is used in this research. As displayed, the SEM analysis was performed to assess the goodness-of-fit for the hypothesized model. The results of the analysis, summarized in the table, indicate that the model demonstrates a satisfactory fit to the data. The Chi-square statistic (χ^2=40.297) with 33 degrees of freedom yielded a Chi-square to degrees of freedom ratio (χ^2/df) of 1.221, which is below the critical value of 3, suggesting an acceptable model fit. The p-value of 0.179, which is greater than the critical value of 0.05, further supports the adequacy of the hypothesized model. The goodness-of-fit indices were also evaluated. The goodness-of-fit index (GFI=0.974) and the adjusted goodness-of-fit index (AGFI=0.948) both exceeded the critical value of 0.90, indicating a good fit. The normed fit index (NFI=0.977), Tucker-Lewis index (TLI=0.993), and comparative fit index (CFI=0.996) were all greater than the critical value of 0.90, further supporting the model's suitability. Additionally, the RMSEA (RMSEA=0.030) was below the critical value of 0.05, suggesting a close fit, with the 90% CI ranging from 0.000 to 0.050. These results are consistent with Zhao *et al.* [11] who reported similar fit indices in their SEM-based study on AI tool adoption in higher education, confirming that values above 0.90 for GFI, CFI, and TLI, and RMSEA below 0.05, reflect a well-fitting model.

Table 16. Fit indices for the SEM

Model	X^2	df	X^2/df	p	GFI	AGFI	NFI	TLI	CFI	RMSEA
Hypothesized	40.297	33	1.221	0.179	0.974	0.948	0.977	0.993	0.996	0.030
Critical value		>0	<3	>0.05	>0.9	>0.9	>0.9	>0.9	>0.9	<0.05

Note: fit indices for the SEM analysis. All indices meet the required thresholds for a satisfactory model fit.

As viewed in the SEM results, AI literacy strongly influences teachers' adoption of AI technologies reflects both TPACK and SCT. AI literacy strengthens teachers' technological knowledge, enabling them to better integrate AI with pedagogy and content as emphasized in TPACK, positioning it as a foundational component of effective technology integration. According to Daher [24], enhancing educators' AI literacy is essential for responsible and effective classroom use, reinforcing this connection. At the same time, SCT highlights the role of self-efficacy in shaping behavior, and studies show that teachers' confidence mediates the relationship between AI literacy and their intention to adopt AI tools [29], demonstrating that greater AI literacy boosts both competence and confidence, thereby increasing adoption.

In addition, the SEM analysis suggests that professional development programs should focus on enhancing teachers' AI literacy. Building confidence is also crucial, as SE plays a significant role in AI adoption. Addressing attitudes towards AI is essential for its adoption. Although stress and anxiety did not show significant predictive power in this study, it is still important to provide emotional support to teachers. This recommendation is supported by the findings of Ning *et al.* [30], who found that while stress and anxiety were not direct predictors of AI adoption, emotional support and institutional encouragement significantly improved educators' willingness to engage with AI technologies. Offering resources such as counseling, stress management workshops, and a supportive community can help alleviate any concerns related to AI adoption.

4. CONCLUSION

A significant number of basic education teachers possess a strong level of AI literacy, which reflects their understanding of AI concepts, their ability to apply AI tools, and their awareness of the ethical considerations involved in AI usage within the classroom. Evidence indicates that basic education teachers exhibited a high degree of confidence in utilizing AI. They also demonstrate awareness of the ethical implications of AI, particularly in relation to student privacy, data protection, and fairness in its application and such level of AI literacy supports their readiness to adopt AI tools in their teaching practices.

Moreover, teachers with a higher understanding and familiarity with AI are more likely to integrate it into their teaching activities. The components of AI adoption—SE, ease of use, attitude towards AI, and EB are all aligned with higher AI literacy. However, some teachers still experience stress and anxiety regarding the adoption of AI, which may hinder their willingness to integrate AI into their classroom practices fully. Novice teachers (1–5 years) are more prepared and consistent in integrating AI tools, likely due to their greater exposure to technology during their training. In contrast, teachers with more than 15 years of experience exhibit lower adoption rates and higher variability, indicating mixed attitudes and possible resistance. This implies that professional development strategies cannot be one-size-fits-all; instead, they should be tailored to individual experience levels. Additionally, the consistency among less experienced teachers suggests that future teacher education programs should continue embedding AI literacy and practical applications into pre-service training, as this translates into readiness for classroom adoption.

In general, AI literacy plays a crucial role in promoting the adoption of AI among basic education teachers. As teachers become more literate and confident in using AI, they are more likely to incorporate it into their teaching strategies, which can benefit both teaching effectiveness and student learning. To ensure successful integration, it is essential to address the emotional challenges some teachers face and provide additional professional development, training, and resources to facilitate their transition into AI-enhanced teaching environments. Strengthening these areas will help create a more supportive and effective integration of AI in basic education.

It should be noted that the findings of this study may not apply to other educational contexts or geographic areas with different technological infrastructures and policies. Additionally, potential bias could arise from the use of self-reported data, which may be influenced by social desirability. While it focused on individual factors such as SE, ease of use, and ATUA, broader influences, including institutional policies, access to resources, and cultural attitudes toward technology, were beyond its scope. Future research should incorporate these dimensions to provide a more comprehensive understanding of the determinants of AI adoption and inform systemic strategies for its sustainable integration.

ACKNOWLEDGEMENTS

The authors would like to express their appreciation to the Schools Division Superintendent of Butuan City for allowing the researchers to gather data at the selected public elementary schools in the division.

FUNDING INFORMATION

The authors would like to express their gratitude to Caraga State University for granting financial support for this study through the Office of the Vice President for Research, Extension, and Innovation RAF.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
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P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This research involving human participants has adhered to all applicable national regulations and institutional policies, in line with the principles of the Helsinki Declaration, and has received approval from the authors' collegiate review board.

DATA AVAILABILITY

We confirm that the data supporting the findings of this study are available within the article.

REFERENCES

[1] A. Hazzan-Bishara, O. Kol, and S. Levy, "The factors affecting teachers' adoption of AI technologies: a unified model of external and internal determinants," *Education and Information Technologies*, vol. 30, no. 11, pp. 15043–15069, Jul. 2025, doi: 10.1007/s10639-025-13393-z.

[2] I. Tenberga and L. Daniela, "Artificial intelligence literacy competencies for teachers through self-assessment tools," *Sustainability*, vol. 16, no. 23, p. 10386, Nov. 2024, doi: 10.3390/su162310386.

[3] S. Yang and A. Banks, "Enhancing AI literacy: a collaborative self-study of elementary teacher educators," *Studying Teacher Education*, vol. 21, no. 3, pp. 297–317, Sep. 2025, doi: 10.1080/17425964.2024.2434213.

[4] J. Lademann, J. Henze, N. Honke, C. Wollny, and S. Becker-Genschow, "Teacher training in the age of AI: impact on AI literacy and teachers' attitudes," *Frontiers in Education*, vol. 10, p. 1671306, Jan. 2026, doi: 10.3389/feduc.2025.1671306.

[5] D. T. K. Ng, J. K. L. Leung, K. W. S. Chu, and M. S. Qiao, "AI literacy: definition, teaching, evaluation and ethical issues," in *Proceedings of the Association for Information Science and Technology*, vol. 58, no. 1, pp. 504–509, 2021, doi: 10.1002/pra2.487.

[6] K. Zogopoulos, G. Panagiotopoulos, and A. Karatzas, "Artificial intelligence in education: attitudes, knowledge and perspectives," *IOSR Journal of Research & Method in Education (IOSR-JRME)*, vol. 15, no. 1, pp. 53–60, 2025.

[7] C. N. Jatileni, I. T. Sanusi, S. A. Olaleye, M. A. Ayanwale, F. J. Agbo, and P. B. Oyelere, "Artificial intelligence in compulsory level of education: perspectives from Namibian in-service teachers," *Education and Information Technologies*, vol. 29, no. 10, pp. 12569–12596, Jul. 2024, doi: 10.1007/s10639-023-12341-z.

[8] T. K. F. Chiu, Q. Xia, X. Zhou, C. S. Chai, and M. Cheng, "Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education," *Computers and Education: Artificial Intelligence*, vol. 4, p. 100118, 2023, doi: 10.1016/j.caeai.2022.100118.

[9] L. Xue, N. Ghazali, and J. Mahat, "Artificial intelligence (AI) adoption among teachers: a systematic review and agenda for future research," *International Journal of Technology in Education*, vol. 8, no. 3, pp. 802–824, May 2025, doi: 10.46328/ijte.1191.

[10] D. A. Kenny, "Measuring model fit." Oct. 2024. Accessed: Jun. 21, 2025. [Online]. Available: https://davidakenny.net/cm/fit.htm

[11] L. Zhao, X. Wu, and H. Luo, "Developing AI literacy for primary and middle school teachers in China: based on a structural equation modeling analysis," *Sustainability*, vol. 14, no. 21, p. 14549, Nov. 2022, doi: 10.3390/su142114549.

[12] C. O. Nja *et al.*, "Adoption of artificial intelligence in science teaching: from the vantage point of the African science teachers," *Smart Learning Environments*, vol. 10, no. 1, p. 42, Sep. 2023, doi: 10.1186/s40561-023-00261-x.

[13] J. F. Hair, J. J. Risher, M. Sarstedt, and C. M. Ringle, "When to use and how to report the results of PLS-SEM," *European Business Review*, vol. 31, no. 1, pp. 2–24, Jan. 2019, doi: 10.1108/EBR-11-2018-0203.

[14] N. Fontanos and D. Ocampo, "Reframing gender disparities in basic education in the Philippines," UP CIDS Policy Brief Series 2019-14, UP Center for Integrative and Development Studies, Quezon City, Philippines, 2019.

[15] M. Sebastian, R. Banate, and M. Saquin, "Gender roles among public elementary teachers: basis for gender-responsive intervention activities," *International Online Journal of Primary Education*, vol. 11, no. 2, pp. 401–411, 2022, doi: 10.55020/iojpe.1222199.

[16] J. A. Villanueva, M. D. Suminguit, and M. S. Valdehueza, "Assessment on the implementation of gender-responsive basic education policy among public school teachers of Talakag District 2, Division of Bukidnon," *Journal of Emerging Technologies and Innovative Research*, vol. 10, no. 8, pp. 849–894, 2023.

[17] J. Lumanlan, M. R. Ayson, M. J. Bautista, J. C. Dizon, and C. M. Ylarde, "AI literacy among pre-service teachers: inputs towards a relevant teacher education curriculum," *International Journal of Multidisciplinary Educational Research and Innovation*, vol. 3, no. 1, pp. 242–253, 2025.

[18] W. Holmes *et al.*, "Ethics of AI in education: towards a community-wide framework," *International Journal of Artificial Intelligence in Education*, vol. 32, no. 3, pp. 504–526, Sep. 2022, doi: 10.1007/s40593-021-00239-1.

[19] L. Chen, P. Chen, and Z. Lin, "Artificial intelligence in education: a review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.

[20] N. Ismail and L. M. Joshy, "Exploring the role of perceived usefulness and AI anxiety in technology-driven self-directed learning: a paradox mindset perspective," *Management and Labour Studies*, vol. 50, no. 3, pp. 448–465, Aug. 2025, doi: 10.1177/0258042X251357415.

[21] E. Alieto, B. Abequibel-Encarnacion, E. Estigoy, K. Balasa, A. Eijansantos, and A. Torres-Toukoumidis, "Teaching inside a digital classroom: a quantitative analysis of attitude, technological competence and access among teachers across subject disciplines," *Heliyon*, vol. 10, no. 2, p. e24282, Jan. 2024, doi: 10.1016/j.heliyon.2024.e24282.

[22] Z. A. T. Philippakos and L. Rocconi, "AI literacy: elementary and secondary teachers' use of AI-tools, reported confidence, and professional development needs," *Education Sciences*, vol. 15, no. 9, p. 1186, Sep. 2025, doi: 10.3390/educsci15091186.

[23] I. H. Y. Yim and R. Wegerif, "Teachers' perceptions, attitudes, and acceptance of artificial intelligence (AI) educational learning tools: an exploratory study on AI literacy for young students," *Future in Educational Research*, vol. 2, no. 4, pp. 318–345, 2024.

[24] R. Daher, "Integrating AI literacy into teacher education: a critical perspective paper," *Discover Artificial Intelligence*, vol. 5, no. 1, p. 217, Aug. 2025, doi: 10.1007/s44163-025-00475-7.

[25] M. Ngoveni, "Bridging the AI knowledge gap: the urgent need for AI literacy and institutional support," *The International Journal of Technologies in Learning*, vol. 32, no. 2, pp. 83–100, 2025, doi: 10.18848/2327-0144/CGP/v32i02/83-100.

[26] F. Orcan, "Parametric or non-parametric: skewness to test normality for mean comparison," *International Journal of Assessment Tools in Education*, vol. 7, no. 2, pp. 255–265, Jun. 2020, doi: 10.21449/ijate.656077.

[27] N. Liu, "Exploring the factors influencing the adoption of artificial intelligence technology by university teachers: the mediating role of confidence and AI readiness," *BMC Psychology*, vol. 13, no. 1, p. 311, Mar. 2025, doi: 10.1186/s40359-025-02620-4.

[28] C. Zhao and L. Zhao, "Digital nativity, computer self-efficacy, and technology adoption: a study among university faculties in China," *Frontiers in Psychology*, vol. 12, p. 746292, Sep. 2021, doi: 10.3389/fpsyg.2021.746292.

[29] H. Achmadi, "The influence of AI literacy, subjective norm, attitude, and perceived usefulness on behavioral intention to learn AI with the mediating role of confidence in learning AI," *International Journal of Advanced Education and Research*, vol. 10, no. 4, pp. 47–54, 2025.

[30] Y. Ning, H. Zheng, H. Wu, Z. Jin, H. Chang, and T. T. Wijaya, "Analysis of influencing factors on teachers' AI literacy under the SOR framework: an empirical study based on PLS-SEM and fsQCA," *Education and Information Technologies*, vol. 30, no. 13, pp. 18213–18239, Aug. 2025, doi: 10.1007/s10639-025-13477-w.

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