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Artificial intelligence literacy and the use of educational technology: A structural modeling study in the context of mathematics teachers

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Abstract

This study aims to examine the relationship between mathematics teachers' artificial intelligence literacy (AIL) and their levels of educational technology use. A quantitative research approach was adopted to model and test the relationships among the variables. Structural equation modeling (SEM) was employed to determine the predictive effect of mathematics teachers' AIL levels on their use of educational technologies. The study was conducted with 183 mathematics teachers, and the model fit indices, the validity of the measurement model, and the relationships among the variables were examined in detail. The factor loadings related to the measurement model indicated that the indicators of both AIL and educational technology use were statistically significant and at acceptable levels. The findings revealed that mathematics teachers' AIL has a significant and strong effect on their levels of educational technology use. The measurement model was supported in terms of validity and reliability, while the structural model demonstrated a moderate yet acceptable level of fit. The results suggest that policies and practices aimed at technology integration in education should focus not only on the use of technological tools but also on the development of comprehensive technology literacy.

Keywords: artificial intelligence literacy, educational technology use, mathematics teachers, SEM

INTRODUCTION

The rapid development in the field of artificial intelligence (AI) technologies has greatly impacted the field of education, particularly in the field of mathematics education. Thus, the perceptions of mathematics teachers, the artificial intelligence literacy (AIL) level of teachers, and the pedagogical practices have become important areas in the field of education in recent years (Li et al., 2025; Tashtoush et al., 2024).

Chiu et al. (2024) defined AIL as an individual's capacity to understand and explain how AI technologies operate and influence society, to use these technologies ethically and responsibly, and to interact, communicate, and collaborate effectively across different contexts. Building on this conceptualization, AIL has come to be regarded as an important area that shapes pedagogical practices in mathematics education. Zhao et al. (2022) conceptualized AIL as a multidimensional construct and showed that teachers' AIL is an important predictor of teachers' technology integration efficacy through structural equation modeling (SEM).

LITERATURE REVIEW

The following review synthesizes the literature relevant to the present study under three interrelated strands. It first considers how AIL relates to technology adoption in mathematics education, then examines teachers' perceptions, competencies, and concerns regarding the use of AI, and finally addresses the broader technological competence that underpins effective technology integration. Together, these strands situate mathematics teachers' AIL within the wider context of educational technology use and clarify the gap that this study seeks to address.

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Contribution to the literature

- This study demonstrates, through SEM, that mathematics teachers' AIL is a significant and strong predictor of their educational technology use.
- The study conceptualizes AIL as a multidimensional construct comprising awareness, use, evaluation, and ethics, and examines how these dimensions are associated with educational technology use.
- The findings indicate that effective educational technology use depends not only on teachers' ability to use AI tools but also on their evaluative and ethical competencies, thereby contributing to the existing literature on AIL and technology integration.

AIL and Technology Adoption in Mathematics Education

Understanding how mathematics teachers adopt AI-based tools requires attention to the perceptions and competencies they bring to this process. Recent work has linked technology perceptions, teacher beliefs, and AIL to teachers' willingness to adopt AI technologies in mathematics education (Lin et al., 2025). The following subsection therefore reviews the evidence on teachers' perceptions and competencies regarding the use of AI.

Teachers' Perceptions and Competencies Regarding the Use of AI

Research on teacher readiness for adoption of AI in education has further stressed the significance of pedagogical theories. Yue et al. (2024) studied the readiness of K-12 teachers' technology pedagogical content knowledge and their attitude towards AI education. The research found that it was not sufficient for teachers to have positive attitudes for AI education to be successful; they must be given pedagogical guidance to match AI education with specific teaching objectives for each subject.

Overall, these research studies suggest that mathematics teachers are considered to be early adopters of AI technology due to their digital competence (Pörn et al., 2024), but they face many challenges with balancing the two (Li et al., 2025; Tashtoush et al., 2024).

Existing research has shown that, in general, math teachers tend to have positive yet cautious attitudes towards the integration of AI in education. Tashtoush et al. (2024) have found that math teachers are aware of the potential of AI in increasing the efficiency of instruction and student engagement, yet they are also concerned about issues of ethics, privacy, and overdependence on technology. Likewise, Pörn et al. (2024) have found that math teachers in K-12 schools who are proficient in using digital tools are aware of the potential of AI yet are also aware of its potential risks and dangers.

AIL, Trust, and Dependency

While teachers have a natural inclination towards using AI technologies, they also stress the danger of "a focus of instruction moving from the development of fundamental mathematical reasoning capabilities to the manipulation of AI systems themselves" (Pörn et al., 2024). This danger again points to the tension between technological advancement and the maintenance of fundamental learning objectives in mathematics education.

Although the importance of AIL and trust is considered to produce desirable educational results, recent studies suggest that the relationship is more intricate than initially thought. There is a growing body of research that points to the potential adverse effects of the overuse of AI tools. Zhang et al. (2025) conducted a study that proved the negative impacts of the dependency of preservice mathematics teachers on generative AI on essential 21st century skills, including problem-solving skills, critical thinking skills, creative thinking skills, collaboration skills, communication skills, and self-confidence. Wijaya et al. (2024) used latent profile analysis to establish the differences in mathematics teachers based on their levels of AIL and trust. The results of the study pointed to the fact that the two variables did not always produce desirable results in mathematics teachers. There were instances where the two variables were associated with AI dependency. These profiles were further associated with a decline in self-confidence and higher-order thinking skills among teachers who were highly dependent on AI.

Likewise, in the case of preservice mathematics teachers, Zhang et al. (2025) observed that there was a strong relationship between AIL, AI trust, and AI dependency. The research indicates that the higher the teachers' familiarity with AI tools, the higher the dependency that might develop on the tools, especially generative AI tools, thereby diminishing the extent of independent cognitive activities.

Tashtoush et al. (2024) carried out a research with 580 mathematics teachers in Abu Dhabi. The research observed that the teachers acknowledged the potential of AI in motivating students, differentiating teaching content, and engaging students. However, the teachers also observed that AI could create pressure and risk in teaching. The teachers observed that students might develop dependency on AI tools to carry out homework and assessments, thereby diminishing independent problem-solving abilities.

Likewise, studies on teacher perceptions of the broader use of AI systems suggest that the use of AI systems might limit students' opportunities for productive struggle—a vital feature of mathematical learning—as it might offer immediate answers instead of supporting students' reasoning process (Alwaqdani, 2024). Such issues are critical in assessment situations where it is becoming increasingly hard to differentiate students' mathematical thinking from AI-produced results.

Teachers also questioned the reliability of AI-generated information, noting that such outputs are not consistently accurate (Erdoğdu & Çakır, 2024).

Ethical and Privacy Concerns Regarding the Use of AI in Mathematics Education

Moreover, while mathematics teachers nowadays recognize the importance of AI in the teaching process, the literature indicates that there are significant ethical concerns with regard to fairness, privacy, academic integrity, and student dependency. These concerns can be considered critical in the formation of the cautious attitude that mathematics teachers exhibit with regard to the use of AI in mathematics education. Indeed, mathematics teachers express apprehension about the use of AI systems, especially generative AI tools that enable students to cheat, plagiarize, and avoid the actual process of problem-solving (Tashtoush et al., 2024). In mathematics education, where the use of mathematical reasoning, procedures, and conceptual justifications is essential, the use of AI in the generation of mathematical solutions can be considered a direct threat to the authenticity of student learning outcomes.

Apart from the issue of academic integrity, other ethical concerns raised by the teachers in the study conducted by Alwaqdani (2024) include the issue of fairness, data privacy, and trust in AI systems. For instance, the study indicated that the teachers were not comfortable with the use of AI systems due to the unclear nature of the algorithms used in the systems. For example, the teachers were not aware whether the AI systems were giving any biased or inaccurate information. The issue is even more critical in the field of mathematics education since any minor inaccuracy in the information provided may result in major misconceptions.

The issue of privacy is also an ethical concern that contributes to the teachers' negative attitudes towards AI systems. For example, the study conducted by Tashtoush et al. (2024) indicated that the teachers were not comfortable with the collection of data by AI systems due to the unclear institutional policies regarding the use of data for ethical purposes. Although the teachers were aware that AI systems have the potential to contribute to the development of the field of mathematics education, they were not aware of the transparency in the way the data collected is processed.

Ethical issues also arise in relation to the perceived effects of AI on the cognitive development and quality of education of students. Alwaqdani (2024) revealed that teachers believe that overdependence on AI could have a negative effect on students' creativity, critical thinking, and conceptual understanding. These views are consistent with the findings of mathematics education literature, which suggests that uncritical use of AI could lead to a shift in the learning goals of mathematics from reasoning to efficiency and answer-getting.

While teachers express optimism about the potential of AI to save time, assist in lesson planning, and facilitate personalized learning, this optimism is qualified by concerns about the potential negative consequences of AI, such as reduced student autonomy and participation in complex mathematical tasks (Alwaqdani, 2024; Tashtoush et al., 2024). Therefore, teachers take a balanced and prudent stance, promoting the controlled and ethical use of AI.

Teachers' Technological Competence

Aside from specific competencies in AI, technological and digital capabilities of mathematics teachers are a basic prerequisite that underpins their ability to successfully integrate technology in their teaching practices. The literature has consistently shown that technological and digital capabilities of mathematics teachers are generally at a basic and moderate level in various educational contexts, although this has been improving over time due to professional development efforts. Mathematics teachers are generally able to use various types of digital tools, such as computers and other Internet platforms, although few have been shown to have the ability to successfully integrate specific types of mathematics technologies in their teaching practices (Tran et al., 2020).

Agyei et al. (2022) found that there was a considerable expression of confidence and self-efficacy in technology use by many in-service mathematics teachers, but their actual information and communications technology skills and willingness to use technology effectively in class were much lower. This discrepancy is especially true for teachers who completed their teacher education programs more than a decade ago, as their programs might not have provided them with the necessary skills for technology-enhanced mathematics instruction (Agyei et al., 2022). Knowledge of mathematics-specific technology seems to be another important shortcoming. Joshi (2016) pointed out that mathematics teachers lack adequate knowledge of specialized software like GeoGebra, Geometer's Sketchpad, and Graphmatica. Although this finding predates the current generation of AI-based tools, it remains relevant to the present study because the same gap in mathematics-specific technological knowledge is likely to constrain teachers' ability to integrate AI applications meaningfully into instruction. In other words, limited familiarity with established educational software signals a broader competence gap that AIL must build upon rather than replace.

There are different contextual and demographic factors that affect the technological capability level of teachers. For example, Fitrah et al. (2024) indicated that the technological capability level of teachers is higher for junior teachers, teachers working in full-time or government institutions, and teachers at the upper secondary level. However, the overall technological capability level of mathematics teachers in advanced digital competence is still very low. For example, Manaban et al. (2025) indicated that the transformation level in the technological capability of mathematics teachers is very limited in the context of communication technologies, collaborative practices, and the use of software. However, the study identified the technological capability level of teachers in the context of digital empowerment as an important predictor for the communication behaviors of students. Thus, the study emphasized the need to develop digitally competent mathematics teachers through technological empowerment to meet the needs of the contemporary education system (Manaban et al., 2025).

In summary, the literature shows that mathematics teachers acknowledge the tremendous potential of AI, on one hand, and, on the other, face the challenge of the limitations of technology, pedagogy, and ethical considerations. Although the levels of AIL and trust are on the rise, the existing gaps in digital competence and ethical considerations might lead to superficiality, dependency, and the loss of 21st century skills.

Although the literature on AIL, trust, dependency, and teachers' perceptions is extensive, there is still room for further studies on the ways in which mathematics teachers can develop critical AIL, which incorporates technological, ethical, and pedagogical considerations.

The Aim of This Study

Today, rapid technological developments in the field of education have made the use of educational technologies in teaching processes inevitable. Educational technologies encompass tools, methods, and applications that support teaching and learning processes and play an important role in improving the quality of teaching. In this context, teachers' ability to use educational technologies effectively and in line with pedagogical objectives is considered one of the fundamental requirements of contemporary education.

The integration of educational technologies into teaching processes is closely related to teachers' knowledge, skills, and competence levels regarding technology. Arpa (2017), in his study examining the impact of educational technologies on educational programs, emphasized that when contemporary educational policies and plans and programs do not make sufficient use of educational technologies, it becomes difficult to respond to today's individual and social needs. Therefore, the effective, meaningful, and ethical application of technologies used in educational settings is directly linked to teachers' competencies regarding these technologies.

In recent years, AI applications that have come to the fore in the field of educational technologies have provided teachers with new opportunities in the planning, implementation, and evaluation of teaching processes. AI-supported educational technologies, especially in mathematics education, make significant contributions in terms of personalized learning, instant feedback, and monitoring student performance. This situation makes the role of mathematics teachers' AIL levels in their use of educational technologies even more important. Accordingly, this study aims to examine the relationship between mathematics teachers' AIL and their use of educational technologies. Rather than treating this relationship as a simple question of whether AIL matters—an issue that prior work on teachers' internalization of digital tools has already addressed—the present study approaches AIL as a multidimensional construct (awareness, use, evaluation, and ethics) and asks how these competencies are reflected in the educational applications of technology in mathematics teaching, such as personalized learning, formative feedback, and the monitoring of student performance. The hypothesis developed in this study is presented below.

H1: Mathematics teachers' AIL affects their use of educational technology.

In addition to testing this hypothesis, the study addresses the following research question: How are the components of mathematics teachers' AIL reflected in the way they apply educational technology, and what does this association imply for educational practice in teaching mathematics?

METHODOLOGY

This is a quantitative, cross-sectional study in which data were collected at a single point in time and analyzed using statistical modeling techniques. Quantitative methods were used in this study to model and evaluate the relationship between variables. Quantitative research is an approach that aims to reveal the relationships between variables or the differences between groups through data obtained from measurable variables and thereby test theoretical constructs. In such research, data is collected in numerical form and analyzed using appropriate statistical analysis techniques, with the aim of generalizing the findings to broader populations (Creswell & Creswell, 2023). The

Table 1. Descriptive statistics of participants' demographic variables

Variable	F	P (%)
Gender		
Female	135	74
Male	48	26
Field of study		
High school mathematics teaching	60	33
Primary school mathematics teaching	123	67
Years of professional experience		
1-5 years	44	24
6-10 years	26	14
11-15 years	43	24
16-20 years	22	12
21 years and above	48	26

Note. F: Frequency & P: Percentage

structures addressed in the study were collected using different measurement tools, and the data obtained was evaluated using quantitative analysis methods.

The study employed SEM to determine the effect of mathematics teachers' AIL levels on their levels of educational technology use. SEM is a powerful statistical analysis method that allows for the testing of multidimensional and complex relationships between variables, including latent variables, within the same model (Heck & Thomas, 2020). In this respect, SEM ensures that the relationships between observed and latent variables are presented in a comprehensive manner within the proposed theoretical framework (Schumacker & Lomax, 2004).

Various fit indices are used to determine the extent to which a SEM fits the data when evaluating such models. In this study, the χ^2/df, SRMR, Root mean square error of approximation (RMSEA), comparative fit index (CFI), and Tucker-Lewis index (TLI) were considered in assessing model fit. As suggested in the relevant literature, χ^2/df values below 5, SRMR and RMSEA values below 0.08, and CFI and TLI values above 0.90 were considered acceptable fit criteria (Kline, 2016).

Although the sample size (N = 183) is below the threshold of 200 that is sometimes recommended for stable estimation of indices such as RMSEA and TLI, the adequacy of a sample in SEM is more appropriately judged by the ratio of cases to the number of freely estimated parameters (the N:q ratio) than by an absolute cutoff (Kline, 2016). The model tested in the present study estimates 17 free parameters; with 183 participants, this yields an N:q ratio of approximately 10.8:1, which satisfies the commonly cited 10:1 criterion and clearly exceeds the minimum 5:1 ratio. Relative to the eight observed indicators, the ratio of participants to indicators is approximately 23:1. In addition, maximum likelihood estimation (MLE) is generally regarded as relatively robust at this sample size, and indices that are less sensitive to sample size (e.g., SRMR and CFI) are reported alongside RMSEA so that model fit is not evaluated on the basis of a single, sample-size-dependent index. These considerations support the adequacy of the sample for the model tested, although the comparatively modest sample size is acknowledged as a limitation when interpreting the fit indices.

Participants

The sample group for this study consisted of a total of 183 mathematics teachers working at different school levels. In the study, convenience sampling was preferred in the sampling process. This method, also known as eligibility sampling, is based on the selection of individuals who are accessible to the researcher, willing to participate in the study, and reachable (Dörnyei, 2007). Accordingly, participants who agreed to participate in the study on a voluntary basis from a specific population were included in the sample group (Saumure & Given, 2008).

The data collection process was conducted online. The data collection tools used in the study were created using Google Forms and distributed to participants digitally. Teachers responded to the research forms individually and entirely of their own volition. In line with the ethical principles of the research, approval was obtained from the relevant ethics committee and the necessary institutional permissions were secured before proceeding to the data collection stage. Participation in the research was voluntary for all participants. The distribution of participants' demographic characteristics is presented in **Table 1**.

Data Collection Tools

Data was collected using the artificial intelligence literacy scale (AILS) and the educational technology usage levels scale (ETULS). Using the data collected in the study, reliability coefficients were recalculated for each scale and are presented below.

AILS: The scale developed by Wang et al. (2023) to determine AIL was adapted into Turkish by Polatgil and Güler (2023). The scale consists of four sub-dimensions: awareness, use, evaluation, and ethics, and contains a total of 12 items. The scale is a five-point Likert-type scale rated between strongly disagree and strongly agree. Confirmatory factor analysis confirmed a four-dimensional structure accounting for 92.24% of the total variance. The reliability analysis calculated a Cronbach's alpha (α) coefficient of 0.74 for the entire scale. The fit indices obtained from confirmatory factor analysis were found to be at an acceptable level of fit. The findings indicate that the scale is a valid and reliable measurement tool. In terms of content, the awareness sub-dimension captures the extent to which teachers recognize AI and its presence in everyday and professional contexts; the use sub-dimension addresses the practical application of AI tools to accomplish tasks; the evaluation sub-dimension concerns the ability to

Table 2. Multivariate test of normality (Mardia's coefficients)

	Coefficient	Z	χ^2	df	p
Skewness	13.38		408.0	120	< .001
Kurtosis	104.88	13.30			< .001

critically appraise the outputs and limitations of AI systems; and the ethics sub-dimension reflects awareness of the responsible, fair, and privacy-conscious use of AI.

ETULS: Developed by Bayraktar (2015) to determine the levels of educational technology usage, the scale consists of 38 items and four sub-dimensions. The four factors explain 62.895% of the total variance. When examining the sub-dimensions of the scale, the first factor is "technology literacy" with 19 items, the second factor is "technology integration into the course" with 9 items, the third factor is "social ethics and legal provisions" with 6 items, and the fourth factor is "communication" with 4 items. The α coefficient for the entire scale was calculated as 0.95. The results obtained indicate that the scale is a valid and reliable measurement tool. With respect to content, the technology literacy sub-dimension addresses teachers' basic knowledge and skills in operating digital tools; the technology integration into the course sub-dimension concerns the pedagogical use of these tools within instruction; the social ethics and legal provisions sub-dimension reflects awareness of ethical and legal considerations in technology use; and the communication sub-dimension captures the use of technology to communicate and collaborate.

Data Analysis

In SEM analyses, it is important that the observed variables exhibit a multivariate normal distribution. In this context, Mardia's multivariate skewness and kurtosis coefficients were calculated to assess this assumption, and the results are presented in **Table 2**.

The Mardia coefficients presented in **Table 2** were calculated as 13.38 (χ^2 = 408.0, df = 120, p < .001) and the kurtosis coefficient as 104.88 (z = 13.30, p < .001). These findings indicate that the data violate the assumption of multivariate normality. Because the violation is pronounced, the maximum likelihood results reported here—particularly the standard errors and the χ^2-based fit statistics—should be regarded as provisional, and re-estimation with a robust MLR is needed to confirm them. This is acknowledged as a limitation of present analysis.

FINDINGS

Table 4. AVE

Latent	AVE
AIL	0.582
LETU	0.479

In this study, a SEM was established to examine the relationships between AIL and level of use of educational technologies (LETU). MLR method was used in the analyses, and missing data were handled using the FIML method.

Model Fit Indices

The model fit indices are presented in **Table 3**. General fit statistics for the established model are presented in **Table 3**. The model's chi-square value was found to be significant, χ^2 (19) = 83.85, p < .001. Considering that the chi-square statistic is sensitive to sample size, alternative fit indices were examined.

CFI = .90 and IFI = .897 values indicate results close to the acceptable fit threshold, while TLI = .846 and NFI = .871 values indicate that the model fit is moderate. The RMSEA value is .137, with a 90% confidence interval (CI) of [.10, .17], indicating a poor fit. The SRMR = .072 value is within acceptable limits. The goodness of fit index (GFI) = .908 is also satisfactory. The contrast between the poor RMSEA and the otherwise acceptable incremental indices is partly attributable to the model's relatively small degrees of freedom (df = 19), under which RMSEA tends to be upwardly biased; the fit is therefore judged acceptable but not close and is interpreted with caution.

Taken together, the indices point to a marginal fit: the incremental indices approach the acceptable range and the SRMR is satisfactory, but the high RMSEA shows that the fit is only approximate.

Average Variance Explained

When examining the average variance explained (AVE) values calculated as a measure of convergent validity, the AVE for AIL is .582, which is above the recommended threshold value of .50. The AVE for LETU was found to be .479, yielding a result quite close to the threshold value (**Table 4**). According to **Table 4**, the values indicate strong convergent validity for the AIL latent variable and borderline acceptable convergent validity for LETU. Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio of correlations. The HTMT value between AIL and LETU was .71, which is below the conventional threshold of .85, indicating that the two latent variables are empirically distinct.

Table 3. Fit indices of the SEM

Model	χ^2	df	p	χ^2/df	CFI	TLI	RMSEA [90% CI]	SRMR	AIC	BIC
Structural model	83.85	19.00	< .001	4.41	0.90	0.84	[0.10, 0.17]	0.07	2,245.06	2,299.62

Table 5. Reliability coefficients of the scales

	Coefficient α	Coefficient ω
AIL	.816	.850
LETU	.758	.770
Total	.847	.857

Reliability Analyses

McDonald's omega (ω) and α coefficients were calculated to assess the internal consistency of the scales and are presented in **Table 5**.

When examining internal consistency coefficients, $\alpha = .816$ and $\omega = .850$ were found for AIL. For the LETU latent variable, $\alpha = .758$ and $\omega = .770$ values were obtained. The overall reliability of the scale was calculated as $\alpha = .847$ and $\omega = .857$. These values indicate a good level of reliability for all latent structures.

Factor Loadings

Findings regarding the scale's factor loadings are presented in **Table 6**.

When examining standardized factor loadings, it was observed that the loadings for the AIL latent variable ranged from .558 to .905 and were all statistically significant ($p < .001$). The highest factor loading belongs to item AIL2.

For the latent variable of LETU, factor loadings ranged from .547 to .818, and all indicators were significant ($p < .001$). These results support the construct validity of the measurement model.

Findings Related to the Structural Model

Structural path coefficients

In **Table 7**, the AIL → LETU path in the structural model was found to be positive and significant ($\beta = .662$, $SE = .057$, $z = 11.69$, $p < .001$).

This finding indicates that AIL has a strong predictive effect on levels of educational technology use.

Supplementary analysis: Contribution of AIL sub-dimensions

To examine the relationship beyond the single latent path and to address whether the four AIL components contribute differently to educational technology use, a standardized multiple regression was conducted using the observed sub-dimension scores, with the level of educational technology use as the outcome and awareness, use, evaluation, and ethics as predictors. The four sub-dimensions together explained 40% of the variance in educational technology use ($R^2 = .40$). At the bivariate level, evaluation showed the strongest correlation with educational technology use ($r = .55$), followed by ethics ($r = .40$) and awareness ($r = .39$), while use showed the weakest correlation ($r = .28$). In the multiple regression, evaluation was the strongest unique predictor ($\beta = .53$, $p < .001$), followed by awareness ($\beta = .26$, $p < .001$) and ethics ($\beta = .18$, $p = .009$). The use sub-dimension carried a small negative coefficient once the other components were controlled ($\beta = -.24$, $p = .003$), indicating that operating AI tools, on their own, did not account for higher educational technology use. These results indicate that the overall association reported above is driven mainly by the evaluative and ethical components of AIL rather than by tool use as such, and they show that the relationship is not uniform across the construct.

Table 8 presents the model's fit indices.

When examining the fit indices reported in **Table 8**, it is observed that the CFI (.895) and IFI (.897) values are close to the acceptable fit threshold. The TLI (.846) and normed fit index (NFI) (.871) values indicate that the model fit is moderate. The RMSEA value is .137, which indicates poor fit, whereas the SRMR (.072) and GFI (.908) remain within acceptable limits. As noted above, the elevated RMSEA partly reflects the small degrees of freedom of the model; overall, the model is judged to show an acceptable but not close fit.

The path diagram for the model is provided in **Figure 1**. The SEM findings shown in **Figure 1** indicate that mathematics teachers' AIL has a strong, positive,

Table 6. Factor load

Latent	Indicator	Standard estimate	Standard error	z-value	p
LETU	LETU1	0.547	0.061	8.996	< .001
	LETU2	0.710	0.048	14.739	< .001
	LETU3	0.818	0.041	19.871	< .001
	LETU4	0.569	0.059	9.645	< .001
AIL	AIL1	0.847	0.029	29.232	< .001
	AIL2	0.905	0.025	36.579	< .001
	AIL3	0.558	0.055	10.082	< .001
	AIL4	0.691	0.044	15.886	< .001

Table 7. Regression coefficients

Outcome	Predictor	Standard estimate	Standard error	z-value	p
LETU	AIL	0.662	0.057	11.69	< .001

Table 8. Fit indices

Index	Value
CFI	0.895
TLI	0.846
Bentler-Bonett non-normed fit index	0.846
NFI	0.871
Parsimony normed fit index	0.591
Bollen's relative fit index	0.809
Bollen's incremental fit index	0.897
Relative non-centrality index	0.895
RMSEA	0.137
RMSEA 90% CI lower bound	0.107
RMSEA 90% CI upper bound	0.167
GFI	0.908
McDonald fit index	0.838

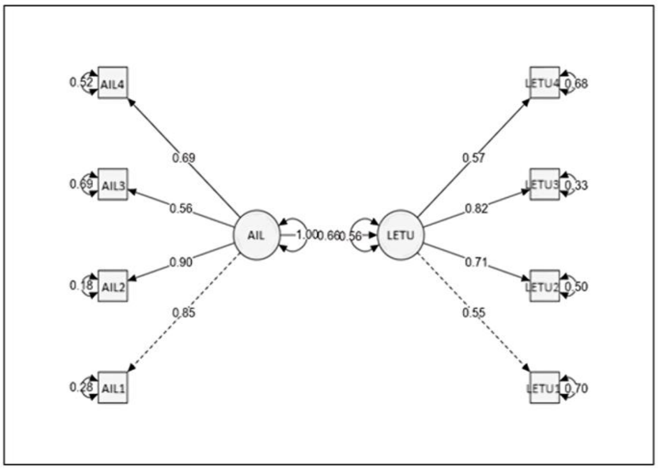

Figure 1. Path diagram of the SEM with standardized estimates (the authors' own elaboration using JASP software)

and statistically significant effect on their levels of educational technology use (β = .662, $p < .001$). This finding supports the **H1** hypothesis, which states that "mathematics teachers' AIL affects their use of educational technology."

DISCUSSION

This study examined the relationship between mathematics teachers' AIL and their use of educational technologies. Higher AIL was associated with higher reported use of educational technology (β = .66), and the supplementary analysis indicated that this association was carried mainly by the evaluative and ethical components of AIL. This finding is consistent with studies in the literature. Zhao et al. (2022) examined AIL as a multifaceted construct in their study and found that teachers' AIL is essential to their long-term professional development. In this regard, it is stated that AIL is not limited to technical skills but is also an important professional competency that supports teachers' use of pedagogical technology. The findings of the current study are consistent with these results in that they show that as mathematics teachers' AIL levels increase, they use educational technologies more consciously and effectively.

Although the model does not exhibit an excellent level of fit, it presents a theoretically meaningful and interpretable structure. High RMSEA values for complex structures in the field of educational sciences are frequently encountered in the literature, and the supporting role of indices such as CFI and SRMR becomes particularly important in higher-order structures such as multidimensional technology literacy. At the same time, the elevated RMSEA (.137) should not be dismissed: it indicates that the model only approximates the observed data, so the fit results are treated as acceptable but not strong and are interpreted with corresponding caution.

The factor loadings related to the measurement model reveal that the indicators for both AIL and the LETU are at meaningful and acceptable levels ($p < .001$). These results show that both latent variables are represented by strong indicators and support the construct validity of the measurement model. In particular, the high factor loadings for technology literacy indicate that the indicators used to measure this construct are theoretically consistent. In this regard, a review of the literature reveals that mathematics teachers generally adopt a positive but cautious approach to AI technologies. According to Tashtoush et al. (2024), math teachers show concern about concerns like ethical issues, data privacy, and an over-reliance on technology, but they also appreciate the potential advantages of AI to instructional efficiency and student participation. In a similar vein, Pörn et al. (2024) emphasize that math teachers who possess a high level of digital literacy are open to and interested in AI tools, while simultaneously cultivating a balanced understanding of the advantages and disadvantages. This implies that critical awareness coexists with the beneficial association discovered in the current study.

Together, validity and reliability results show that the technology usage level variable has strong convergent validity, whereas technology-focused learning outcomes have adequate convergent validity. The two conceptions are conceptually connected but distinct from one another, according to the HTMT results. Additionally, both latent variables show strong internal consistency based on the dependability coefficients. The scales' high ω coefficients, in particular, show that they offer accurate measures for composite structures.

The standardized path coefficient between AIL and LETU in the model created for this investigation was found to be 0.66. This suggests that the AIL variable has a positive and statistically significant impact on LETU (β = 0.662, SE = 0.057, z = 11.69, $p < .001$). This result demonstrates that technology literacy is more than just technical proficiency; it is a powerful predictor of technology-based learning outcomes when considered in conjunction with awareness, ethical assessment, and critical use characteristics. Stolpe and Hallström (2024) address technological literacy in three fundamental dimensions: the ability to use technology, knowledge and understanding of technology, and awareness of technology-society-environment interactions, noting that these dimensions can be concretized through AIL components. The study also emphasizes that technological-scientific knowledge about the functioning of AI within technological systems and socio-ethical technical understanding are priorities for students. Accordingly, an analytical framework is proposed to define AIL more explicitly in the context of technology education. It is stated that this framework can contribute to the more systematic and holistic implementation of teaching and assessment practices by guiding teachers in planning and evaluating teaching processes.

Beyond establishing that this association is statistically significant, the supplementary component-level analysis helps characterize its nature. Although the use dimension carried the strongest loading on the latent AIL construct (.905), a high loading reflects how well an indicator defines the construct, not how strongly that component predicts technology use. The component-level regression makes this distinction clear: evaluation was the strongest unique predictor of educational technology use ($\beta = .53$), whereas use did not contribute independently once the other components were controlled. In other words, the overall relationship is driven mainly by teachers' capacity to critically appraise AI rather than by their frequency of using it. The evaluative and ethical components of AIL, rather than tool use alone, are thus the most consequential aspects for how teachers apply educational technology.

These patterns also have direct implications for the educational applications of AI in mathematics teaching. The applications most often associated with AI-supported instruction—personalized learning paths, immediate formative feedback, and the monitoring of student performance—depend less on how often a teacher operates AI tools than on the capacity to judge whether an AI-generated solution or recommendation is mathematically sound. The finding that evaluation, rather than use, is the component most strongly linked to educational technology use is consistent with the view that critical appraisal is the competence that allows AI to support mathematical reasoning rather than merely deliver answers. At the same time, the negative independent contribution of the use component suggests that frequent use without evaluative judgment is not associated with more productive technology use. These results point to the evaluative and ethical components of AIL as priorities for professional development and curriculum design.

However, there are also studies in the literature showing that increased AIL does not always lead to positive outcomes. Zhang et al. (2025) found in their study of teacher candidates that dependence on generative AI can negatively affect 21st century skills such as problem solving, critical thinking, creativity, and self-confidence. Similarly, Wijaya et al. (2024) noted that AIL and the level of trust in AI can increase AI dependency in some teacher profiles and that this may be associated with a decline in higher-order thinking skills. Furthermore, Tashtoush et al. (2024) express concern that mathematics teachers worry that students' excessive use of AI systems in homework and assessment processes may weaken their independent problem-solving skills. In this context, it is important to develop AIL in conjunction with its critical, ethical, and pedagogical dimensions. On the other hand, it is emphasized that teachers' ability to use AI technologies effectively is closely related not only to AIL but also to their general digital competence levels. Tran et al. (2020) stated that mathematics teachers can use basic digital tools but may experience limitations in pedagogically integrating field-specific technologies. According to Agyei et al. (2022), instructors may have weaker practical technology integration abilities despite having strong self-efficacy beliefs in technology use. This circumstance indicates that the association found in the current study must be assessed in light of more comprehensive technological competencies.

The study's overall conclusions show that the AIL of math teachers significantly and strongly influences how much they employ instructional technology. Validity and reliability supported the measurement model, while the structural model suited the data somewhat but satisfactorily. According to the results, policies and procedures aiming at integrating technology into the classroom should prioritize the development of full technological literacy in addition to tool usage.

CONCLUSION

This study tested and supported the hypothesis that mathematics teachers' AIL predicts their level of educational technology use, with a strong and statistically significant standardized path coefficient ($\beta = .662$). Beyond confirming this relationship, the findings clarify its nature: because AIL was modeled through awareness, use, evaluation, and ethics, the result indicates that it is the combination of practical, evaluative, and ethical competencies—rather than tool familiarity alone—that is associated with more deliberate use of educational technology. This interpretation moves the discussion beyond a binary "does AI literacy matter" question toward how specific components of AIL relate to the educational applications of technology in mathematics teaching.

For practice, the pattern of results points to the evaluative and ethical dimensions of AIL, rather than basic operational skill alone, as the more useful targets for professional development, so that teachers can integrate AI-based tools in ways that protect mathematical reasoning and academic integrity. Reliable measurement of teachers' AIL is a prerequisite for such efforts, and continued refinement of teacher-focused instruments (e.g., Younis, 2025) can support this work. Several limitations should be acknowledged. The sample (N = 183) was obtained through convenience sampling and was modest relative to the conventional threshold of 200; this imprecision is reflected in the wide RMSEA CI [.10, .17], which spans poor values and indicates that the fit estimate is not precise. The non-normality of the data and the cross-sectional design further limit the conclusions and preclude causal claims. Future research could test this model with larger and more representative samples, re-estimate it with a robust estimator, incorporate the educational applications of AIL more directly (for example, through classroom observation or task-based measures), and examine potential adverse outcomes such as over-reliance.

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