|Jurnal Ilmu Komputer dan Sistem Informasi |JIKSI|Vol. 7| No. 1|May|Year 2026|
This is an Open Access article, published by Institute of Information Technology and Social Science (IITSS), Indonesia
|ISSN: 2721-1193|https://iitss.or.id/ojs/index.php/jiksi/index

Modeling AI readiness in a faith-based educational context: Evidence from Adventist schools in Western Indonesia using a hierarchical PLS-SEM approach

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Abstract

This study examines the influence of AI literacy and AI ethics awareness on teachers' readiness to adopt artificial intelligence in educational practice. As AI technologies become increasingly integrated into teaching and learning processes, understanding the factors that shape teachers' preparedness is essential. Data were collected from 204 teachers in Adventist schools in Western Indonesia and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that AI literacy significantly predicts AI readiness ($\beta = 0.491$, $p < 0.001$), while AI ethics awareness shows a positive but weaker effect ($\beta = 0.313$, $p < 0.001$). The model explains 53.1% of the variance in AI readiness, indicating moderate to substantial explanatory power. AI readiness is conceptualized as a multidimensional construct comprising confidence, intention, and digital self-learning. These findings suggest that cognitive competence plays a more dominant role than ethical awareness in shaping readiness. This study contributes by providing empirical evidence within a faith-based educational context and by advancing the conceptualization of AI readiness as a hierarchical construct. The results highlight the importance of AI-specific professional development and ethical awareness to support responsible AI integration in education.

Keywords

AI literacy, AI readiness, AI ethics awareness, PLS-SEM, digital self-learning, AI in Education

Article History

Received 01 February 2026
Accepted 28 May 2026

How to Cite

Pandia, H., & Chen, W. (2026). Modeling AI readiness in a faith-based educational context: Evidence from Adventist schools in Western Indonesia using a hierarchical PLS-SEM approach. *Jurnal Ilmu Komputer dan Sistem Informasi, 9*(1), 17-35. https://doi.org/10.61346/jiksi.v7i01.336

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Introduction

Artificial intelligence has become a key determinant in learning in the 21st century. Artificial Intelligence (AI) plays a significant role in educational practice through its various applications, including intelligent tutoring systems (Lin & Chen, 2024), automated assessment, learning analytics (Zhai et al., 2021), and personalized learning environments (Fortuna et al., 2025). The advancement of generative AI and conversational agents offers additional support to instructors and enhances learner engagement (Crompton & Burke, 2023; Dwivedi et al., 2023). Policy agendas feature growing evidence of this. Kurikulum Merdeka in Indonesia highlights new suggestions for digital competence, emphasizing computational thinking and adaptive learning pedagogy. Nonetheless, the availability of technology and teachers' readiness to adopt AI are factors that can lead to meaningful AI use (Holmes & Tuomi, 2022; Silva et al., 2024). Studies show that teachers' readiness and self-efficacy are critical determinants of technology integration (Scherer et al., 2019; Sihombing et al., 2025). In the realm of artificial intelligence (AI), two competency domains stand out: AI literacy and AI readiness.

AI literacy refers to the ability to understand artificial intelligence, to read and interpret the output of artificial intelligence systems, and to incorporate them into the classroom (Long & Magerko, 2020; Ng et al., 2021; Mills et al., 2024; Hershkovitz et al., 2025). According to Holmes and Tuomi (2022), UNESCO (2024), and Yan et al. (2025), ethical awareness towards privacy, bias, transparency, and accountability is central to the use of AI. Teachers' skills and competencies will influence AI interaction.

Despite this progress, four gaps remain. The studies conducted have focused only on technological performance and student outcomes, with teacher readiness not being the main enabling condition (Zawacki-Richter et al., 2019; Adewale et al., 2024). Secondly, competence typically draws upon digital literacy models with ethical and cognitive requirements that may differ from those of AI. Scherer et al. (2019) and Dolah et al. (2025) present this as validation. AI literacy and ethical awareness have generally been studied in isolation, and so their joint effects are underexplored. Finally, readiness is often viewed as a unidimensional construct (e.g., intention), which may neglect its behavioral aspect (Gao & Liu, 2023; Dwivedi et al., 2023). These gaps encourage a more nuanced and integrated framework. In practice, readiness means more than just intending. It entails a process of continuous capability development in one's self-directed learning (Chapman et al., 2026; Kohnke et al., 2025). It is necessary to adopt a multidimensional conceptualization that considers both motivation and behavior (Ng et al., 2021; Bozkurt et al., 2021).

The study aims to develop and test a hierarchical model of AI readiness in a specific institutional context, teachers in Adventist schools in Western Indonesia, to avoid overgeneralization. The study looks at AI literacy and awareness of AI ethics in relation to the individual's AI readiness. AI readiness is defined as a second-order construct comprising confidence, intention, and digital self-learning. Due to its predictive orientation and hierarchical component modeling capabilities, Partial Least Squares Structural Equation Modeling (PLS-SEM) is employed. The study contributes in three ways. First of all, reconceptualizing AI readiness as a multidimensional, hierarchical construct that encompasses motivational and behavioral dimensions. As a second contribution, we provide empirical evidence on the joint effects of AI literacy and ethical awareness, as prior work assumes they are independent. To begin with, it will be particularly useful for further studies as it is based in an educational institution of faith.

Methodology

Research design

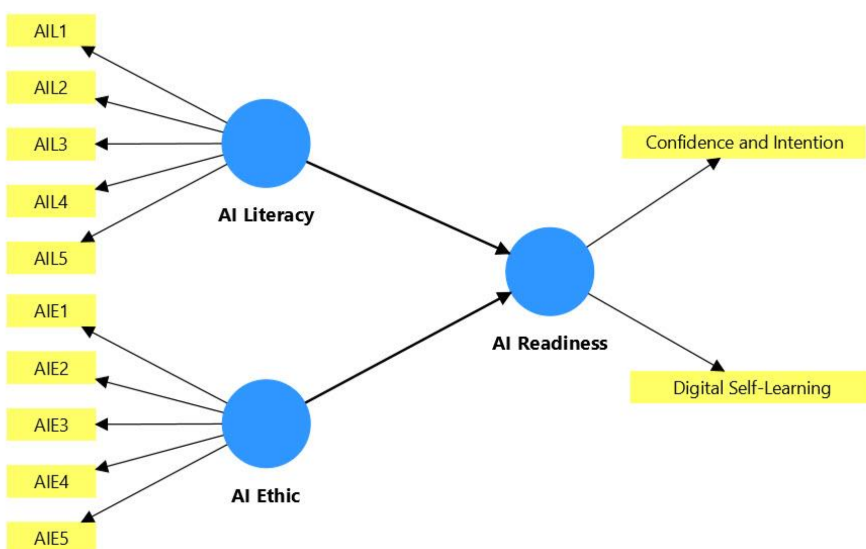
This section describes the overall research design employed to address the study's objectives. It outlines the proposed research model, sampling and data collection procedures, instrument development, and data analysis techniques.

Research model

This study proposes a hierarchical structural model to explain AI readiness among teachers in Adventist schools in Western Indonesia. AI readiness is conceptualized as a multidimensional capability that integrates both motivational and behavioral components. Accordingly, the study draws on competency-based perspectives and technology adoption theories to examine readiness within this specific context.

The hierarchical model is shown in Figure 1. In this model, AI Readiness (Y) is conceptualized as a second-order construct formed by two first-order dimensions: Confidence and Intention, and Digital Self-Learning. Confidence and Intention reflect teachers' motivational readiness and willingness to adopt AI, whereas Digital Self-Learning represents their autonomous behavioral engagement in acquiring AI-related skills.

Figure 1. *Research model*



(Source: Developed by the authors)

AI Literacy (X1) and AI Ethics Awareness (X2) are specified as exogenous constructs that directly influence AI Readiness. Teachers with stronger cognitive understanding of AI and greater ethical awareness are expected to demonstrate higher levels of confidence, intention, and self-directed learning, which together constitute overall readiness. Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed to analyze the model, as it is well-suited for handling complex hierarchical component structures and prediction-focused research.

Sample and Data Collection

The Data were collected during a national conference organized by the Yayasan Pendidikan Advent Indonesia (YPAI). The YPAI operates under the educational system of the Seventh-day Adventist Church, integrating Christian values into curriculum design, school culture, and teaching practices. As such, the participating schools represent a faith-based educational context. YPAI oversees a network of primary and secondary schools across multiple regions in Indonesia. These schools operate under a relatively consistent institutional framework, including similar governance structures, curriculum implementation, and professional development systems. This context provides a controlled environment for examining teachers' AI readiness while minimizing variability across institutional factors.

Therefore, the findings of this study should be interpreted within this specific institutional context or in educational settings with similar characteristics, and may not be fully generalizable to the broader population of teachers in Indonesia. The total number of conference participants was 712 teachers. Data collection was conducted using a paper-based questionnaire distributed randomly to 350 participants during the conference sessions. This approach ensured a structured and supervised environment, thereby supporting a relatively high response quality. Respondents were notified that the collected data would be used solely for academic research, with assurances of anonymity and confidentiality to encourage truthful, unbiased responses. Of the 350 questionnaires distributed, 258 were returned, yielding a response rate of approximately 73.7%. Following data screening procedures—including checks for incomplete responses, patterned answers, and inconsistencies—204 questionnaires were deemed valid and suitable for further analysis.

The final sample size was considered adequate for Partial Least Squares Structural Equation Modeling (PLS-SEM) based on the "10-times rule." In addition, the sample size meets the power requirements for detecting medium effect sizes at a 5% significance level, as recommended in the PLS-SEM literature (e.g., Hair et al., 2021). Therefore, the dataset is deemed sufficient to ensure robust estimation and reliable hypothesis testing. The demographic profile of the respondents is presented in Table 1. In terms of gender, the sample was predominantly female, consisting of 162 female teachers (79.4%) and 42 male teachers (20.6%). Regarding age distribution, most respondents belonged to Generation X (45–60 years), accounting for 104 teachers (51.0%), followed by Millennials or Generation Y (29–44 years) with 62 teachers (30.4%), Generation Z (13–28 years) with 26 teachers (12.7%), and Baby Boomers (61–79 years) with 12 teachers (5.9%).

With respect to school level, respondents represented all major educational stages: 103 teachers (50.5%) taught at Elementary School (SD), 52 teachers (25.5%) at Junior High School (SMP), and 49 teachers (24.0%) at Senior High School/Vocational School (SMA/SMK). In terms of teaching experience, the largest group had more than 21 years of experience (72 teachers; 35.3%), followed by those with 0–5 years (46 teachers; 22.5%), 6–10 years (34 teachers; 16.7%), 16–20 years (27 teachers; 13.2%), and 11–15 years (25 teachers; 12.3%).

Instrument development

The survey instrument was adapted from validated measures in prior studies and aligned with the UNESCO AI Competency Framework for Teachers (UNESCO, 2024) and established research on AI literacy (Ng et al., 2021; Long & Magerko, 2020). All constructs were modeled as reflective and measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The constructs of this study were defined based on the literature and the existing competency framework. The AI Literacy of teachers was measured through 5 indicators that assessed their understanding of AI concepts, the application of AI in daily life and education, and their ability to explain AI concepts. This construct aligns with the "Knowledge and Understanding of AI" dimension proposed by UNESCO (2024) and is conceptually supported by Ng et al. (2021).

The AI ethics awareness construct was operationalized using five indicators based on teachers' awareness about algorithmic bias, data privacy, copyright issues, transparency, and responsible use of AI. This construct aligns with UNESCO's 'Ethical and Responsible Use of AI' dimension and other global AI ethics principles (UNESCO, 2024).

Table 1. *Respondent demography*

No	Descriptions	Respondents
A	**Jenis Kelamin**	
1	Male	42
2	Female	162
B	**Generation (Age in years)**	
1	Baby Boomers (61-79)	12
2	Gen X (45-60)	104
3	Millennial (Gen Y) (29-44)	62
4	Gen Z (13-28 tahun)	26
C	**School Level**	
1	Elementary School (SD)	103
2	Junior High School (SMP)	52
3	Senior High School/Vocational School (SMA/SMK)	49
D	**Teaching Experience (years)**	
1	0 - 5	46
2	6 - 10	34
3	11 - 15	25
4	16 - 20	27
5	21 and above	72
	Total	**204**

(Source: Developed by the authors)

The measurement of Digital Self-Learning by teachers was based on five indicators, encompassing self-directed activities, experiential learning, and continuous professional development. This dimension demonstrates UNESCO's commitment to ongoing continuous professional learning and is conceptually similar to the Professional Engagement area of DigCompEdu (UNESCO, 2024; Redecker, 2017). Finally, to measure Confidence and Intention, four indicators were used, including assessments of teachers' preparedness, confidence, intention, and effectiveness in using AI for teaching. This concept is anchored on the earlier literature on technology readiness and AI adoption (Ng et al., 2021). The research instrument underwent expert review to evaluate its content validity and clarity, resulting in several minor revisions based on the experts' recommendations. Table 2 summarizes the constructs, measurement items, and sources of the theoretical framework adopted in this study.

Data analysis

A two-stage analysis followed the study. In the first step, the measurement model evaluates the reliability and validity of the first-order constructs. Internal consistency was evaluated using Cronbach's Alpha and Composite Reliability (CR). Convergent validity was assessed using the Average Variance Extracted (AVE), which indicated that the indicators measuring each construct did so at the respective significance levels. Discriminant validity was assessed using the Fornell–Larcker criterion and the Heterotrait–Monotrait (HTMT) ratio, as best practices, to ascertain construct distinctiveness. After validating the first-order constructs, the higher-order construct of AI Readiness was assessed using the repeated-indicator approach in SmartPLS. This approach enables the indicators of the lower-order constructs (Confidence and Intention, Digital Self-Learning) to represent the higher-order construct, helping to estimate the hierarchical relationships in the model.

Table 2. *Constructs, measurement items, and framework sources*

Construct	Measurement Items	Framework/ Source
AI Literacy	AIL1: I understand the difference between AI, machine learning, and data science. AIL2: I know how AI is used in daily life. AIL3: I know AI tools that support teaching. AIL4: I understand how AI can assist in student assessment. AIL5: I can explain AI concepts in simple terms to students.	(UNESCO, 2024) (Ng et al., 2021) (Long & Magerko, 2020)
AI Ethics Awareness	AIE1: I understand the importance of protecting students' personal data when using AI. AIE2: I am aware that AI systems may produce biased outcomes. AIE3: I am cautious about copyright when using AI-generated content. AIE4: AI should be used responsibly and transparently. AIE5: I consider ethical aspects before using AI tools in class.	(UNESCO, 2024)
Confidence and Intention	CI1: I feel ready to use AI tools in teaching. CI2: I am confident in evaluating AI-generated outputs. CI3: I plan to integrate AI into my teaching methods. CI4: I believe AI can improve learning effectiveness.	(Ng et al., 2021) (UNESCO, 2024)
Digital Self-Learning	DSL1: I actively search for information about AI tools. DSL2: I participate in AI-related webinars or training. DSL3: I experiment with AI applications in my work. DSL4: I learned to use AI tools independently. DSL5: I am enthusiastic about learning new AI developments.	(UNESCO, 2024) (Redecker, 2017)

Source: Adapted from UNESCO (2024), Ng et al. (2021), Long and Magerko (2020), and Redecker (2017)

An assessment of the structural model was carried out in the second stage to test the relationships between the two exogenous constructs (AI Literacy and AI Ethics Awareness) and the higher-order construct, AI Readiness. The bootstrapping procedure of 5,000 resamples was used to estimate the strength and statistical significance of path coefficients.

Using the coefficient of determination (R^2), the model's explanatory power was assessed, and effect sizes (f^2) were calculated to quantify each predictor's contribution to the endogenous construct. To evaluate the model's out-of-sample predictive power, PLSpredict was used (Shmueli et al., 2019). This method compares the PLS model's prediction accuracy with benchmark linear regression models and provides further support for the model's relevance.

Conceptual framework and hypotheses development

This study develops a conceptual framework to examine the relationships among AI Literacy, AI Ethics Awareness, and teachers' AI Readiness. AI Readiness is conceptualized as a multidimensional construct integrating both motivational and behavioral dimensions. The hypotheses are grounded in competency-based perspectives and technology adoption theories.

AI literacy and AI readiness

AI literacy refers to teachers' understanding of AI concepts, applications, and limitations, including their ability to interpret outputs and evaluate pedagogical implications. Prior research shows that higher levels of digital and AI competence are associated with greater confidence and stronger intentions to adopt emerging technologies (UNESCO, 2024; Ng et al., 2021). These findings suggest that foundational AI knowledge is essential for meaningful integration in education.

In educational contexts, readiness reflects teachers' psychological preparedness and capability to adopt new technologies (Luttrell et al., 2020), which is strongly influenced by their technical and pedagogical competence (Ngongpah & Oni, 2025). Accordingly, AI literacy provides the cognitive foundation that enables teachers to evaluate, interpret, and confidently engage with AI tools.

H1: AI Literacy positively influences AI Readiness.

AI ethics awareness and AI readiness

AI ethics awareness refers to teachers' understanding of the ethical risks associated with AI, including privacy, bias, fairness, and automated decision-making (Guilen & Oni, 2025). It is increasingly recognized as a key component of responsible AI adoption in education (OECD, 2021; UNESCO, 2024). Ethical awareness enhances teachers' ability to use AI responsibly and reduces perceived risks, thereby supporting readiness (Guilen & Oni, 2025). However, its role is likely complementary, as ethical considerations often depend on prior technical understanding.

H2: AI Ethics Awareness positively influences AI Readiness.

Hierarchical conceptualization of AI readiness

This study conceptualizes AI Readiness as a higher-order construct comprising Confidence and Intention (motivational dimension) and Digital Self-Learning (behavioral dimension). This perspective reflects the view that readiness involves both willingness and active capability development.

AI Readiness is modeled as a reflective–hierarchical component model (HCM) using PLS-SEM, with Confidence and Intention, and Digital Self-Learning as lower-order constructs. The repeated-indicator approach is applied to estimate the model (Hair et al., 2021). This hierarchical specification provides a parsimonious yet theoretically grounded representation of teachers' preparedness for AI adoption.

Results

Measurement model evaluation

The measurement model was assessed to ensure the reliability and validity of all constructs prior to testing the structural relationships. In accordance with established PLS-SEM guidelines (Hair et al., 2021), the evaluation encompassed indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

Indicator reliability

Indicator reliability was evaluated using outer loadings. Table 3 indicates that the majority of indicators surpassed the recommended cutoff value of 0.70 (Hair et al., 2021), demonstrating satisfactory item reliability. Within the AI Ethics construct, four indicators demonstrated loadings above 0.70, while one indicator (AIE2 = 0.622) fell slightly below the preferred threshold but remained above the minimum acceptable level of 0.60 (Hair et al., 2021; Chin & Marcoulides, 1998). Given its theoretical relevance and acceptable contribution to construct reliability, the item was retained.

Table 3. *Outer loadings of measurement items*

Construct	AI Ethic	AI Literacy	AI Readiness
AIE1	0,709		
AIE2	*0,622*		
AIE3	0,776		
AIE4	0,759		
AIE5	0,784		
AIL1		0,710	
AIL2		0,779	
AIL3		0,794	
AIL4		0,723	
AIL5		0,716	
Confidence and Intention			0,926
Digital Self-Learning			0,938

(Source: Developed by the authors)

All AI Literacy indicators exhibited loadings above 0.70, ranging from 0.710 to 0.794, indicating robust indicator reliability.

For the higher-order construct AI Readiness, modeled as a reflective construct. Both dimensions, Confidence and Intention, and Digital Self-Learning have very high loadings, 0.926 and 0.938, respectively. It indicates that the dimensions strongly reflect the second-order construct. These results empirically support the multidimensional structure of AI Readiness.

Construct reliability and convergent validity

Cronbach's alpha and composite reliability were used to assess internal consistency reliability. As shown in Table 4, all constructs met and exceeded the recommended threshold of 0.70, confirming adequate reliability (Hair et al., 2021). Specifically, AI Ethics (α = 0.783; CR = 0.852) and AI Literacy (α = 0.800; CR = 0.862) demonstrated strong internal consistency. The higher-order construct AI Readiness showed excellent reliability (α = 0.850; CR = 0.930), reflecting the stability of the second-order measurement model.

Table 4. *Construct reliability and validity (CA, CR, AVE)*

Constructs	Cronbach's alpha	Composite reliability (ϱA)	Composite reliability (ϱC)	AVE
AI Ethic	0,783	0,792	0,852	0,537
AI Literacy	0,800	0,804	0,862	0,555
Al Readiness	0,850	0,855	0,930	0,869

The assessment of convergent validity was conducted using the Average Variance Extracted (AVE). All constructs exceeded the recommended threshold of 0.50 (Fornell & Larcker, 1981), indicating that each construct accounts for more than half of the variance in its indicators. AI Ethics (AVE = 0.537) and AI Literacy (AVE = 0.555) demonstrated adequate convergent validity, while AI Readiness showed a substantially high AVE (0.869), further supporting the strength of the hierarchical construct.

Discriminant validity

A two-stage approach was applied to evaluate discriminant validity. In the initial stage, the Fornell–Larcker criterion (Fornell & Larcker, 1981) was examined by comparing the square root of AVE for each construct with its correlations with other constructs. As shown in Table 5, all square root AVE values exceeded the corresponding inter-construct correlations, demonstrating that each construct captures greater variance in its own indicators than in other constructs, thereby establishing discriminant validity.

Table 5. *Fornell-Larcker criterion*

Constructs	AI Ethic	AI Literacy	Al Readiness
AI Ethic	0,732		
AI Literacy	0,627	0,745	
Al Readiness	0,621	0,687	0,932

In the subsequent stage, discriminant validity was examined using the Heterotrait–Monotrait (HTMT) ratio of correlations (Henseler et al., 2015). Table 6 presents that all HTMT values fell below the conservative threshold of 0.90. The highest value (0.823, between AI Literacy and AI Readiness) remained substantially below the cutoff, confirming that the constructs are empirically distinguishable.

Table 6. *HTMT Matrix*

Construcks	AI Ethic	AI Literacy	Al Readiness
AI Ethic			
AI Literacy	0,782		
Al Readiness	0,751	0,823	

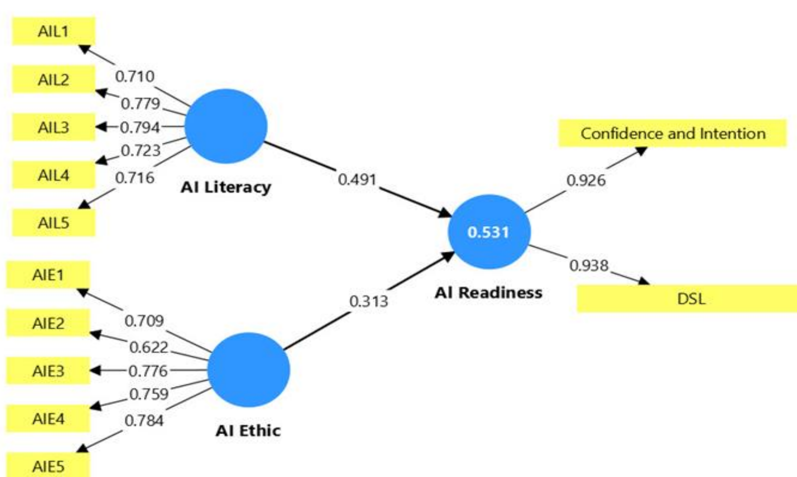
The results of the Fornell–Larcker criterion and HTMT collectively demonstrate satisfactory discriminant validity. This suggests that the constructs capture distinct dimensions of teachers' digital practices, thereby reducing the possibility of conceptual redundancy and reinforcing the robustness of the measurement model.

Structural model evaluation

The structural model was assessed by examining path coefficients, coefficient of determination (R^2), and effect sizes (f^2). Statistical significance was evaluated using a bootstrapping procedure with 5,000 resamples. The coefficient of determination (R^2) was used to assess the explanatory power of the model, while the effect size (f^2) was used to evaluate the contribution of each predictor variable. In addition, predictive relevance was assessed using PLSpredict to evaluate the model's out-of-sample predictive performance (Hair et al., 2019).

The PLS-SEM results, including path coefficients, R^2 values for the endogenous constructs, and outer loadings of the measurement indicators, are illustrated in Figure 2. The figure presents the model's explanatory power and the strength of relationships among constructs, followed by a statistical summary.

Figure 2. PLS-SEM results with path coefficients, R^2 values, and indicator loadings



(Source: Developed by the authors using SmartPLS 4.0.)

Collinearity assessment

Before evaluating the structural relationships, collinearity among the predictor constructs was assessed to ensure that multicollinearity did not bias the path coefficient estimates. In PLS-SEM, collinearity is commonly evaluated using the variance inflation factor (VIF). Values below 5.0 indicate the absence of critical multicollinearity issues, while a more conservative threshold of 3.3 is often recommended to ensure robust model estimation (Hair et al., 2021). The results in Table 7 indicate that both AI Readiness predictor constructs have low VIF values. Specifically, the VIF for AI Ethics → AI Readiness was 1.648, and the VIF for AI Literacy → AI Readiness was also 1.648. These values are substantially below both the 5.0 and 3.3 thresholds, suggesting that collinearity is not a concern in the structural model.

Bootstrapping-based confidence intervals further confirm the stability of these estimates, as shown in Table 8. The 95% confidence intervals for the VIF values ranged from 1.376 to 2.137. The bias-corrected confidence intervals ranged from 1.356 to 2.070, with minimal bias (0.043), indicating that the collinearity diagnostics are stable across resamples. Therefore, the study concludes that AI Ethics and AI Literacy are empirically distinct constructs and can simultaneously predict AI Readiness without inflating standard errors or distorting structural path estimates.

Table 7. *Inner model collinearity statistics (VIF)*

Predictor → Endogenous Construct	VIF (O)	Sample Mean (M)	2.5%	97.5%
AI Ethics → AI Readiness	1.648	1.691	1.376	2.137
AI Literacy → AI Readiness	1.648	1.691	1.376	2.137

Table 8. *Bias-corrected confidence intervals for VIF*

Predictor → Endogenous Construct	VIF (O)	Bias	2.5%	97.5%
AI Ethics → AI Readiness	1.648	0.043	1.356	2.070
AI Literacy → AI Readiness	1.648	0.043	1.356	2.070

Coefficient of determination (R^2) and Adjusted R^2

The coefficient of determination (R^2) was used to evaluate the explanatory power of the structural model. As presented in Table 9, the endogenous construct AI Readiness achieved an R^2 value of 0.531, indicating that AI Literacy and AI Ethics Awareness collectively explain 53.1% of the variance in AI Readiness. According to Hair et al. (2021), this value indicates moderate to substantial explanatory power. Bootstrapping results further confirm the stability of the estimate ($t = 9.943$, $p < 0.001$), with a 95% bias-corrected confidence interval ranging from 0.407 to 0.623, excluding zero.

Table 9. *Coefficient of Determination (R^2) for AI Readiness*

Endogenous Construct	Predictors	R^2	R^2 Adjusted	95% CI (BCa)
AI Readiness	AI Literacy, AI Ethics Awareness	0.531	0.527	[0.407, 0.623]

The adjusted coefficient of determination was 0.527, indicating minimal shrinkage after adjusting for the number of predictors. This proposes that the model demonstrates stable predictive accuracy and is not inflated by model complexity.

Path coefficients and hypotheses testing

The structural model results are presented in Table 10. The findings show that both AI Ethics and AI Literacy significantly predict AI Readiness. AI Ethics demonstrates a positive and statistically significant effect on AI Readiness ($\beta = 0.313$, $t = 4.629$, $p < 0.001$). The 95% bias-corrected confidence interval ranged from 0.175 to 0.436, excluding zero, thereby confirming the stability of the effect. Conversely, AI Literacy shows a stronger positive and significant effect on AI Readiness ($\beta = 0.491$, $t = 7.327$, $p < 0.001$). The 95% bias-corrected confidence interval (0.363 to 0.627) does not include zero. These findings support both hypotheses and suggest that AI Literacy exerts a greater influence on teachers' AI Readiness than AI Ethics.

Table 10. *Structural model results*

Hypothesis	Path	β	t-value	p-value	95% CI (BCa)	Result
H1	AI Ethics → AI Readiness	0.313	4.629	< 0.001	[0.175, 0.436]	Supported
H2	AI Literacy → AI Readiness	0.491	7.327	< 0.001	[0.363, 0.627]	Supported

Both predictors exhibit statistically significant positive effects, indicating that teachers with higher levels of AI literacy and stronger ethical awareness are more likely to demonstrate readiness to adopt AI in instructional practice. Notably, AI Literacy shows a larger standardized coefficient, suggesting that cognitive competence in AI may play a more dominant role in shaping readiness compared to ethical awareness alone.

Effect size (f^2)

Effect size (f^2) was assessed to examine the relative contribution of each predictor to AI Readiness. As shown in Table 11, AI Literacy demonstrates a medium effect on AI Readiness ($f^2 = 0.312$, $t = 2.681$, $p = 0.007$), indicating a meaningful substantive contribution to the explained variance. The 95% confidence interval ranged from 0.148 to 0.596, confirming the robustness of the effect.

In contrast, AI Ethics shows a small effect size ($f^2 = 0.127$, $t = 1.934$, $p = 0.053$). Although the effect size falls within the small range, its statistical support is marginal (Hair et al., 2021). The confidence interval suggests that the effect is present but comparatively weaker than that of AI Literacy.

Table 11. *Effect Size (f^2)*

Path	f^2	t-value	p-value	Effect Size
AI Ethics → AI Readiness	0.127	1.934	0.053	Small
AI Literacy → AI Readiness	0.312	2.681	0.007	Medium

Discussion

The purpose of this study is to investigate whether teachers' AI literacy and awareness of AI ethics may influence their readiness to adopt AI in educational practice. According to the study, both AI literacy and awareness of AI ethics contribute to AI readiness, though the former has a greater impact.

AI literacy and AI ethics role

The results showed that AI Literacy has the greatest impact on AI Readiness ($\beta = 0.491$, $p < 0.001$), indicating that cognitive-level understanding contributes most to teachers' readiness to adopt AI. Educators who are better acquainted with AI (in terms of concept, application, and limitations) are likely to use it in the classroom. When users become familiar with certain Artificial Intelligence tools, the uncertainty and perceived risks associated with new technology are reduced significantly. As a result, they are willing to adopt AI.

This finding supports prior studies, which claimed that domain-specific competencies have more relevance in technology adoption than general digital literacy (Chiu, 2025; Kohnke et al., 2025; Sperling et al., 2024), together with enhancing the integration of the instructional activities of AI (Holmes & Tuomi, 2022; UNESCO, 2024). Nonetheless, this study goes beyond past research by showing that AI-specific literacy has a greater role than ethical awareness in predicting readiness. It means that initially, teachers might prefer to learn to use the technology in their teaching and learning processes rather than address the ethical issues. Consequently, AI literacy can be viewed as a foundational competency that enables further development of responsible AI use. The effect of AI ethics on AI readiness ($\beta = 0.313$, $p < 0.001$) is smaller than that of ethical climate but still significant. This coincides with growing discussions about responsible AI in education (Holmes & Tuomi, 2022; UNESCO, 2024; Sperling et al., 2024; Kohnke et al., 2025) and the need for awareness of bias, privacy, transparency, and algorithmic accountability.

This finding corroborates the existing literature on technology adoption. In particular, ethical awareness plays a crucial role in data-driven, automated technology adoption contexts. In contrast to research that positions ethical concern as a primary driver of green marketing, our findings suggest that this driver has lower influence than cognitive competence. This difference may be due to the pragmatic nature of teaching circumstances, in which useful competence takes precedence over ethical considerations. This indicates that in the AI adoption in education, ethical knowledge may not influence readiness without proper technical knowledge. Consequently, this study supports the preceding literature by indicating that ethical awareness is a complementary factor that can enhance teachers' readiness.

The model achieved significant explanatory power (Hair et al., 2021), with $R^2 = 0.531$, explaining 53.1% of the variance in AI readiness. This indicates that AI literacy and AI ethics awareness together provide a meaningful framework for understanding teachers' preparedness to adopt AI in educational settings. The high explanatory power suggests that cognitive competence and ethical awareness play a significant role in explaining readiness, although other contextual factors may also affect it.

Significantly, the current study defines artificial intelligence readiness as a second-order construct comprising confidence and intention, as well as the capability for digital self-learning. The substantial loadings on these dimensions indicate that readiness is a multidimensional construct encompassing one's psychological preparedness and proactive learning behavior. This finding contradicts prior investigations that primarily frame readiness as a unidimensional construct of intention or perceived usefulness, thereby providing a more comprehensive perspective on technology adoption in education. By utilizing a reflective-reflective hierarchical component model (HCM), the current study provides a nuanced conceptualization of AI readiness that underscores the need to incorporate motivational and behavioral dimensions in teacher adoption of AI technologies. Interventions to improve AI readiness must not only increase teachers' willingness to adopt AI but also support continuous self-directed learning behaviors.

Theoretical implications

The research builds on the growing body of literature on artificial intelligence in education in several ways. To begin with, this study enhances the conceptualization of AI readiness by modeling it as a second-order hierarchical construct comprising psychological (confidence and intention) and behavioral (digital self-learning) dimensions. Earlier works conceptualized readiness or adoption as a unidimensional construct (e.g., technology acceptance or behavioral intention models). Using a reflective hierarchical component model (HCM), this study demonstrates that AI readiness is multicompartmental.

Existing technology adoption frameworks have found that readiness is determined not only by intention but also by continuous self-directed learning, especially for rapidly changing technologies like AI. The findings further highlight the distinct and dominant role of AI literacy in readiness. According to Scherer et al. (2019), general digital competence reflects technology integration, and greater competence leads to better integration. Results indicate that AI-specific literacy has a much greater influence on predicting AI readiness than ethical awareness, according to the study. The outcome does not support the premise that general digital competence alone explains technology adoption and indicates that AI literacy ought to be regarded as a competence domain with its own theoretical significance.

This differentiation matters in theory, as AI technologies are fundamentally different from other ICT tools owing to their algorithmic logic, automation capabilities, and bias-related capabilities. Consequently, frameworks of general digital competence must not suffice to explain AI use. Finally, this study adds to responsible Artificial Intelligence literature by integrating ethical awareness into a predictive readiness framework. The literature on AI in education features more ethical discussions (Holmes & Tuomi, 2022; UNESCO, 2024). Even so, studies have not been able to relate ethical awareness to adoption readiness. This paper fills this gap by examining the effect of ethical awareness on AI readiness and providing empirical support. Discuss the essentials of AI ethics, which predicts AI readiness, and note that we have a relatively small effect size, indicating that ethical awareness is complementary rather than a main driver. This builds on previous insights by affirming that these dimensions are distinct yet interrelated, and cognitions and norms are concepts.

Practical Implications

This research can be useful to education leaders, educational policymakers, and teacher training institutes. Because AI Literacy has the greatest influence on teachers' readiness, teacher professional development should focus more on AI capacity development rather than generic digital skills. The training modules should comprise not only a generic ICT-oriented workshop but also a systematic curriculum that builds a basic understanding of algorithms, covers practical applications of AI tools, outlines steps for integrating AI into classroom activities, and, finally, includes a critique of AI-generated outputs. To use AI judiciously and actively in their classrooms and schools, teachers need to prepare.

Secondly, the AI Ethics had a smaller effect size but significantly contributed to readiness, implying that Ethics remain an important component of readiness. With this in mind, responsible AI education should be implemented in teacher training programs by ministries of education and schools. Education can help develop an understanding of data privacy and student safety, potential algorithmic bias, transparency in AI use, and responsible classroom policies regarding AI. By integrating ethical aspects with technical expertise, a balanced and trustworthy improvement of AI can be used in schools on a more social level.

The results of the hierarchical model show that readiness is not simply a function of intention to use AI but also self-directed learning behavior. Therefore, it is essential to develop policies that combine the motivational and behavioral aspects of readiness. Strategies that work might involve hands-on exposure to AI technologies, bolstering teacher confidence, fostering a mindset of continuous digital self-learning, and institutional incentives that encourage experimentation and innovation with AI tools. Policymakers should not consider AI readiness a simple "has" or "doesn't have" but rather a multidimensional, malleable concept. It is important to develop scaffolds that promote sustainable, long-term use of AI in learning.

Conclusion and Recommendations

This study investigates the influence of AI literacy and AI ethics awareness on teachers' readiness to adopt artificial intelligence in educational practice in Adventist schools in Western Indonesia. The findings indicate that both variables significantly contribute to AI readiness, with AI literacy emerging as the strongest predictor.

The results suggest that cognitive understanding of AI plays a central role in shaping teachers' readiness, as it enhances confidence and reduces uncertainty in using AI technologies. In contrast, AI ethics awareness, although significant, functions as a complementary factor that supports responsible use rather than serving as a primary driver of readiness.

This study contributes to the literature by conceptualizing AI readiness as a multidimensional construct integrating motivational (confidence and intention) and behavioral (digital self-learning) dimensions. This perspective extends existing research, which often treats readiness as a unidimensional concept, and offers a more comprehensive understanding of how teachers prepare for AI integration.

From a practical perspective, the findings highlight the importance of prioritizing AI-specific competencies in teacher professional development programs. Institutions should focus on strengthening teachers' understanding of AI while simultaneously incorporating ethical awareness to ensure responsible and effective implementation of AI in educational settings. This study has several limitations that should be acknowledged. First, the sample is limited to teachers from Adventist schools in Western Indonesia. Therefore, the findings cannot be generalized to all teachers in Indonesia or other educational contexts. Future studies should include more diverse samples across different types of schools and geographical regions to enhance generalizability. Second, this study employs a cross-sectional design, which limits the ability to draw causal conclusions. Future research may adopt longitudinal approaches to better understand how AI readiness evolves over time as teachers gain more experience with AI technologies.

Third, the proposed model focuses on cognitive and ethical factors and excludes contextual variables such as institutional support, access to technology, or leadership influence. Future studies may extend the model by incorporating organizational and environmental factors to provide a more comprehensive explanation of AI readiness. Finally, future research may explore additional mechanisms such as self-efficacy, perceived usefulness, or prior experience with AI tools as potential mediators or moderators in the relationship between AI literacy and readiness.

AI disclosure statement

The authors used generative AI tools, including ChatGPT and Grammarly, solely to assist with language refinement, grammar correction, and clarity in academic writing during manuscript preparation. All conceptual development, data collection, data analysis, interpretation of results, and final decisions regarding the content of the manuscript were conducted entirely by the authors. The authors take full responsibility for the accuracy, originality, and integrity of the work.

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