



OPEN Teacher involvement in developing sustainable education materials for AI integration in green energy education

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The integration of Artificial Intelligence (AI) in education holds transformative potential, particularly in advancing Education for Sustainable Development (ESD) and green energy literacy. However, empirical evidence is lacking on how teacher involvement in ESD material development influences their capacity to integrate AI into pedagogical contexts. This study aims to examine the relationships among AI knowledge, attitudes toward AI, involvement in material development, and teachers' ability to apply AI in green energy education. Employing a quantitative correlational design, data were collected from 122 in-service teachers engaged in professional development programs. A structured questionnaire measured five constructs, which were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results indicated that teachers' practical use of AI in science and green energy learning ($\beta = 0.391$, $p < 0.01$, $f^2 = 0.180$) and their involvement in developing ESD-based teaching materials ($\beta = 0.236$, $p < 0.05$, $f^2 = 0.127$) significantly influenced their AI integration capabilities. In contrast, AI knowledge and attitudes toward AI did not show statistically significant effects. These findings suggest that experiential engagement with AI and active participation in sustainability-focused content development are stronger predictors of AI pedagogical readiness than cognitive or affective factors alone. This study underscores the importance of shifting teacher training toward context-based, practice-oriented models to enhance technological competence in sustainability education.

Keywords Artificial intelligence, Continuing education, Sustainable education, Green energy, Technological competence

The rapid advancement of Artificial Intelligence (AI) technology is transforming multiple sectors, including education, by enabling automation, personalization, and innovative learning methods^{1–3}. AI offers a wide range of potentials, including improving learning personalization, automating administrative tasks, and driving innovation in pedagogical approaches^{4–6}. In educational contexts, AI is considered a catalyst for achieving the Sustainable Development Goals (SDGs), particularly SDG 4 (Quality Education) and SDG 7 (Affordable and Clean Energy), by expanding access and improving quality (Bachmann et al., 2022; Leal Filho et al., 2024). Given the accelerating digital transformation, the need to adopt advanced technologies in continuing education is becoming increasingly urgent.

Education for Sustainable Development (ESD) aims to equip students with the knowledge, skills, and values that support sustainability (UNESCO, 2017). In this regard, teachers play a central role in integrating sustainability principles into their teaching practices. The integration of AI in green energy education requires not only technical skills but also pedagogical and content expertise, which can be systematically understood through the Technological Pedagogical Content Knowledge (TPACK) framework. The TPACK model provides a valuable structure for understanding how these three elements interact to create effective and sustainable teaching.

TPACK synthesizes technological knowledge (e.g., AI applications), pedagogical knowledge (teaching approaches), and content knowledge (e.g., energy sustainability), forming a holistic foundation for effective

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and context-sensitive teaching^{7–9}. These three elements work synergistically to create a relevant and adaptive learning experience, which supports the achievement of SDG 4 (Quality Education) and SDG 7 (Affordable and Clean Energy). Therefore, integrating AI in continuing education, especially in relation to green energy, requires a deep understanding of TPACK to ensure effective use of technology in the context of sustainable learning.

Although the potential of AI to enhance sustainability education is acknowledged, there remains a lack of empirical research exploring how teachers' engagement in ESD material development contributes to their capacity to integrate AI. Most studies have focused on AI's impact on student learning and institutional systems rather than on its role in teacher professional development. Therefore, this study investigates the relationship between teachers' AI knowledge, their involvement in designing ESD-based instructional materials, their attitudes towards AI, and their ability to apply AI in green energy education settings.

Anchored in the TPACK model, this study aims to identify key enabling factors for teacher readiness in AI-enhanced sustainable education by understanding the relationship between technological knowledge, pedagogy, and content.

The findings are expected to contribute both theoretically and practically: by advancing literature at the intersection of AI, teacher development, and sustainability; and by informing more targeted and forward-looking teacher training initiatives aligned with global sustainability goals^{10–12}.

Literature review

The integration of Artificial Intelligence (AI) in education has been widely explored over the past decade, with increasing attention to its role in supporting personalized, inclusive, and sustainable learning approaches. Milićević et al.¹³ emphasize AI's transformative potential to promote educational equity by enabling individualized learning pathways, particularly for underserved populations. Such advancements align directly with the objectives of Sustainable Development Goal 4 (SDG 4), which seeks to ensure inclusive and equitable quality education for all.

In the realm of Technical and Vocational Education and Training (TVET), Subrahmanyam (2025) highlights the importance of AI integration for equipping learners with “green skills” essential for navigating sustainability-driven labor markets. This alignment of AI with sustainability not only enhances learners' technological fluency but also fosters heightened awareness of global environmental issues. The application of Green AI in institutional management contributes to resource optimization and operational efficiency, thereby fostering a more sustainable education ecosystem.

Curriculum innovation also emerges as a key area where AI demonstrates pedagogical promise. Mzwiri and Turcsányi-Szabó¹⁴ introduce the Dynamic Course Content Integration (DCCI) model, which connects Learning Management Systems (LMS) with generative AI to continuously update curricular content with relevant materials in fields such as renewable energy. This approach enhances curriculum responsiveness and relevance. Similarly, Aggarwal et al.¹⁵ note that AI integration in sustainability-focused education can foster collaborative learning models between teachers and students, promoting active engagement through project-based approaches aimed at real-world environmental challenges.

While these studies underscore AI's contributions to educational equity, institutional effectiveness, and curricular innovation, most have primarily focused on student-oriented outcomes or administrative applications. A significant research gap remains regarding the intersection of AI and teacher professional development—particularly how it informs sustainable pedagogy in green energy education. Few empirical studies have examined how AI-informed teacher training influences pedagogical capacity to deliver sustainability content, or how teachers' engagement in developing Education for Sustainable Development (ESD)-based materials enhances their readiness to utilize AI tools.

Addressing this gap is crucial. Teachers serve as the linchpin in integrating sustainability principles into classroom practices, especially in emerging disciplines such as green energy. Their involvement in instructional material development and familiarity with AI-supported strategies is foundational for cultivating pedagogical innovation aligned with SDG 7 (Affordable and Clean Energy).

The Technological Pedagogical Content Knowledge (TPACK) framework provides a valuable lens for understanding this complex interaction. TPACK conceptualizes effective teaching at the intersection of technological knowledge (e.g., AI tools), pedagogical knowledge (instructional methods), and content knowledge (subject matter expertise). Within the context of ESD and green energy education, TPACK offers a theoretical foundation for evaluating how AI use by teachers must be coupled with appropriate pedagogical and content integration to achieve sustainable learning outcomes. To visually synthesize the reviewed literature and position the current research, Fig. 1 presents a conceptual mapping of AI's opportunities and challenges in sustainable education, particularly from the perspective of teacher engagement and professional capacity-building.

This framework highlights how the development of ESD-based teaching materials serves not only as an end product but also as an active process reflecting teachers' involvement in improving AI- and sustainability-oriented pedagogical competencies. The model covers three interrelated domains: (1) AI for Equity and Efficiency, emphasizing AI's role in expanding access, personalizing learning, and improving the operational efficiency of sustainable education institutions; (2) Curriculum and Instructional Innovation, encompassing AI-based dynamic content (e.g., DCCI), and collaborative learning between teachers and students in the context of green education; and (3) teacher Capacity and Professional Development—Emphasizing the importance of teacher involvement in designing teaching materials supported by the TPACK construct—namely, mastery of technology, pedagogical strategies, and relevant content.

This framework aims to identify factors that enable teachers to effectively integrate AI into sustainable energy education, in alignment with SDG 4 (Quality Education) and SDG 7 (Affordable and Clean Energy).

Based on the previous literature review and identified research gaps, a conceptual model was developed to describe the relationship between knowledge about AI, attitudes toward AI, the use of AI in green energy

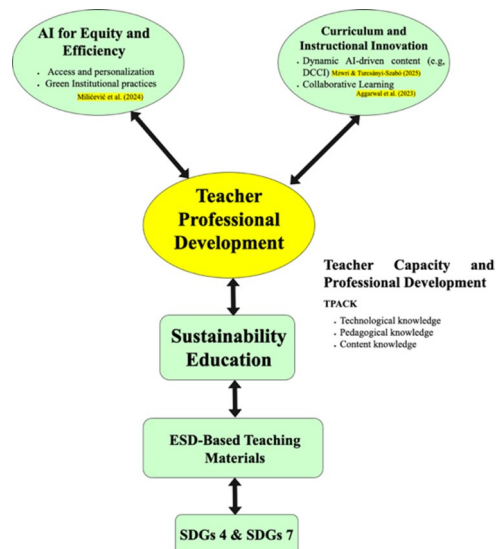


Fig. 1. Conceptual Mapping of AI in Education: Challenges and Opportunities.

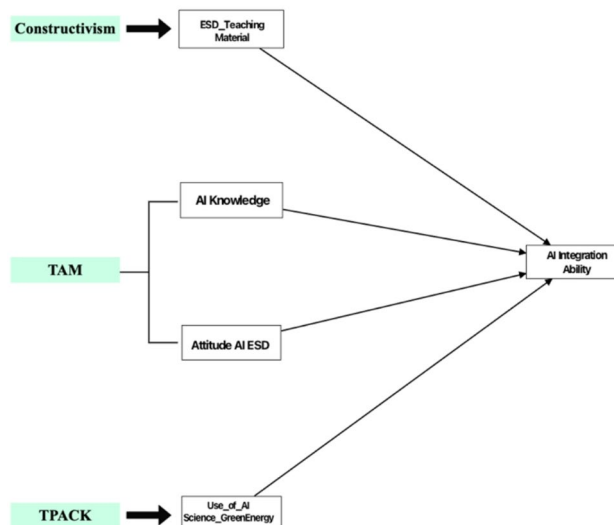


Fig. 2. Conceptual model of the relationship between variables in AI integration in green energy education.

education, teacher involvement in the development of ESD teaching materials, and perceived TPACK related to AI integration capabilities in sustainable pedagogical practices. This model combines elements from the TPACK framework, the Technology Acceptance Model (TAM), and constructivist theory, as shown in Fig. 2.

Figure 2 presents a revised conceptual model that integrates three main theoretical frameworks: Constructivism, Technology Acceptance Model (TAM), and Technological Pedagogical Content Knowledge (TPACK). This model was developed to explain the factors that influence teachers' ability to integrate Artificial Intelligence (AI) into green energy education.

Constructivism underlines the importance of teacher involvement in developing Education for Sustainable Development (ESD)-based teaching materials. This process is framed as a reflective and collaborative practice within authentic learning environments that support sustainability goals^{16,17}. Such involvement is believed to not only result in quality instructional resources but also enhance teachers' pedagogical readiness to address technological challenges such as AI.

TAM contributes by explaining how AI Knowledge and Attitudes toward AI reflect teachers' cognitive and affective readiness to adopt emerging technologies^{18,19}.

TPACK is represented in the Perceived TPACK construct, which reflects teachers' self-assessed ability to integrate technology, pedagogy, and content effectively^{20,21}. This construct encapsulates the multifaceted knowledge required to implement AI in meaningful and pedagogically sound ways.

These five constructs are theoretically predicted to have a direct influence on the main dependent variable: AI Integration Ability. With a solid theoretical foundation and clearly defined inter-variable relationships, this model addresses previous critiques that it lacked specificity and theoretical rigor.

Methodology

This section presents the study's design and context, including the participants and the activities implemented. It also describes the data collection and analysis methods and procedures.

Research design

This study employed a quantitative, correlational survey design to explore the relationships among constructs related to the use of Artificial Intelligence (AI) and sustainable pedagogical practices among teachers. A quantitative approach was chosen for its ability to systematically collect numerical data and analyse relationships among variables with a high degree of objectivity^{22,23}, (Lincoln, 2024).

To enhance analytical rigour, Partial Least Squares Structural Equation Modelling (PLS-SEM) was adopted, given its suitability for exploratory models with small to moderate sample sizes and multiple latent constructs. Although the indicators were dichotomous (yes/no), this method was retained for its robustness in handling non-normal distributions. This limitation is acknowledged as part of the study's methodological scope.

The survey method was used to collect data from a large number of teachers efficiently and to identify patterns in the relationships among the constructs being studied. The questionnaire was developed with attention to content validity and item clarity to measure teachers' knowledge about AI, their use of AI in science and green energy education, their involvement in developing Education for Sustainable Development (ESD)-based teaching materials, their attitudes toward AI, and their ability to integrate AI into sustainable pedagogical practice^{24–26}.

This study was designed as an exploratory baseline assessment, in which participants were not provided with specific AI training before completing the survey. This approach aimed to naturally capture teachers' existing levels of AI-related knowledge, attitudes, and competencies within their professional contexts, without external intervention. However, it is recognised that participants' prior exposure to ESD-based professional development may have indirectly influenced their responses, a limitation addressed in the discussion. The general framework of this research design can be seen in Fig. 3 below.

Figure 3 provides a visual overview of the research design, summarizing the sequence of activities from conceptual framework development to data analysis. This diagram clarifies the study's flow by integrating the key components: problem identification, instrument development, data collection via Google Forms, and PLS-SEM analysis. Rather than repeating methodological details, the figure supports transparency and illustrates the study's structure in a concise, systematic format.

Population and sampling

This research involved 122 in-service teachers who were participating in a professional development program (TPD) focused on science, green energy, and pedagogical innovation. Participants were selected using purposive sampling techniques targeting individuals with specific characteristics aligned with the study's focus (Etikan & Bala, 2017). The selected teachers had real-world experience in continuing education and workplace technology integration but had not received specialized training in artificial intelligence (AI).

All participants voluntarily agreed to take part in the study after receiving a detailed explanation of its objectives, procedures, and implications. There was no element of coercion in the recruitment process, in accordance with ethical research principles that respect the rights and autonomy of human subjects. All procedures were approved by the Ethics Commission of Universitas Muhammadiyah Sukabumi under approval number IRB-2024–185 and were conducted in compliance with the Declaration of Helsinki and CIOMS 2016 guidelines.

Research variables

This study was designed to examine the relationships among five main variables, developed based on the Technological Pedagogical Content Knowledge (TPACK) framework, which is relevant to the integration of Artificial Intelligence (AI) in continuing education and green energy contexts. Each variable represents a critical aspect of teachers' readiness and capacity to implement AI in their instructional practices.

The five variables measured are: (1) Knowledge of AI, which describes teachers' understanding of basic concepts, functions, and the potential of AI in education; (2) Use of AI in Green Education, reflects teachers' experience in integrating AI into science and green energy learning; (3) development of ESD-Based Teaching Materials, Indicates the extent of teachers' involvement in creating instructional materials aligned with Education for Sustainable Development (ESD) principles; (4) Attitudes Toward AI, Assesses teachers' perceptions both positive and negative of AI's use in continuing education; and (5) Ability to Use AI, Measures teachers' self-reported ability to apply AI in sustainability-oriented teaching practices.

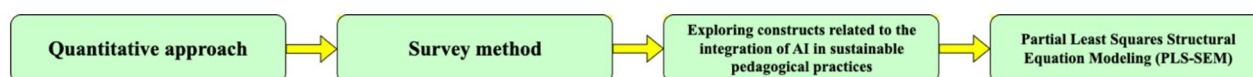


Fig. 3. Research design visualization.

These five variables were operationalised into questionnaire indicators and are further detailed in the Instrument Development section (see Table 1).

Ethical considerations

All procedures in this study received ethical approval from the Research Ethics Committee of Universitas Muhammadiyah Sukabumi, in accordance with the actual data collection timeline. A revision to the ethics approval letter was made to ensure compliance with research principles for the transparent and ethical conduct of research involving human participants.

The most recent ethics approval is documented in the official letter numbered 185/IV.1/A/2024, dated January 8, 2024. This revision reflects the institution’s commitment to responsible research conduct while aligning with the field data collection schedule.

Instrument development

The instrument used in this study was a structured questionnaire designed to measure five primary constructs relevant to the integration of Artificial Intelligence (AI) into green energy education, aligned with the Technological Pedagogical Content Knowledge (TPACK) framework. The five constructs are: Knowledge of AI, Use of AI in Green Education, Development of ESD-Based Teaching Materials, Attitudes Toward AI, and Ability to Use AI.

Instrument development was guided by recent literature^{8,25,26} and designed to reflect the real conditions of teachers participating in professional development programs. Each construct was represented by five dichotomous items (Yes = 1, No = 0). This binary format was intentionally selected to accommodate varying levels of technological familiarity among participants, most of whom had not received formal AI training. The simplified response scale also aimed to reduce respondent burden and improve data completeness.

Although dichotomous scales are sometimes considered limited in capturing nuanced attitudes or competencies, their use in this study is methodologically sound and compatible with the PLS-SEM approach. PLS-SEM is robust in handling categorical and binary data through dummy-variable standardisation, as supported by Henseler & Fassott²⁷. Furthermore, SmartPLS, the software used in this study, explicitly supports modelling binary indicators within structural equation modelling procedures²⁸. Therefore, the measurement approach is aligned with recommended practices for exploratory SEM research in educational contexts.

The instrument underwent content validation by three experts in science education and learning technology. These experts assessed each item for clarity, alignment with the construct, and contextual relevance. After incorporating their feedback, minor revisions were made before the questionnaire was distributed online via Google Forms to eligible participants.

Table 1 outlines the five primary research constructs measured in this study, along with their operational definitions, sample indicators, the number of items per construct, and their corresponding domains within the TPACK framework. Each construct aligns with a distinct domain of teacher knowledge, providing a comprehensive foundation for analysing how AI integration relates to teachers’ pedagogical and technological readiness.

The indicators were constructed to reflect the professional realities of in-service teachers participating in the study. By using examples rooted in science and sustainability education, the questionnaire ensures contextual relevance and facilitates more accurate self-assessment. The alignment with the TPACK domains also strengthens the instrument’s theoretical validity by clarifying the intersections among technology, pedagogy, and content knowledge.

Data collection flow and procedure

Data collection for this study was conducted through an online survey using Google Forms, allowing for broad and efficient distribution to participants. The procedure followed several systematic stages to ensure clarity, validity, and ethical compliance throughout the process.

The research team first developed the questionnaire instrument, which had been validated by experts in technology and science education. The instrument was then distributed to teachers actively participating in training programs related to green energy and science education. The survey was administered between August and September 2024.

Research Construct	Operational Definition	Example Indicator	Number of Items	TPACK Domain
Knowledge of AI	Teachers’ understanding of basic concepts, applications, and educational potential of AI	“I know how AI is used to personalize learning.”	5	Technological Knowledge
Use of AI in Green Science and Energy Education	Teachers’ experience in using AI tools to teach science and green energy topics	“I have used AI-based tools in teaching renewable energy topics.”	5	Technological & Content Knowledge
ESD-Based Teaching Material Development	Teachers’ involvement in designing instructional materials aligned with Education for Sustainable Development	“I actively develop teaching modules with sustainability (ESD) principles.”	5	Pedagogical & Content Knowledge
Attitudes toward AI in ESD	Teachers’ perceptions, beliefs, and acceptance of AI use in supporting sustainability education	“I believe AI can support the achievement of sustainability education goals.”	5	Pedagogical Knowledge
Ability to Use AI	Teachers’ self-reported ability to integrate AI in the design and delivery of sustainable teaching practices	“I am able to use AI to design interactive learning activities on environmental topics.”	5	Technological Pedagogical Content Knowledge (TPACK)

Table 1. Construct, description, and number of items in the research instrument.

Before completing the questionnaire, participants were provided with comprehensive information regarding the study's objectives, benefits, and confidentiality protocols. Informed consent was explicitly obtained from all respondents.

Each participant completed the questionnaire independently, without intervention or additional training. This approach was chosen to capture their authentic perceptions and capabilities related to AI adoption in educational contexts.

To clarify the steps involved, the data collection flow is illustrated in Fig. 4.

Data analysis procedure

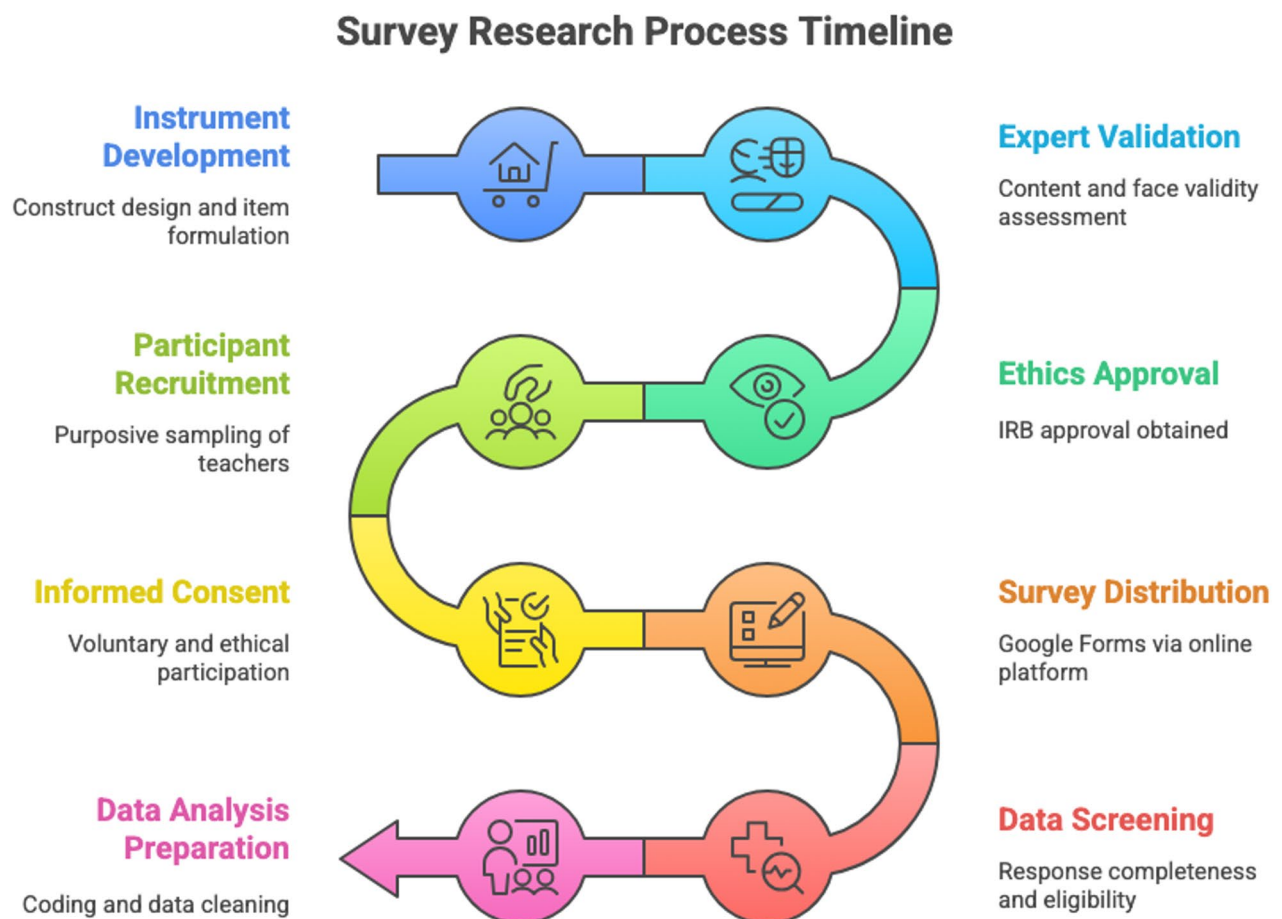
The data collected in this study were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM) with the latest version of SmartPLS. PLS-SEM was selected for its suitability for exploratory research examining relationships among latent constructs in complex models, particularly when working with moderate sample sizes. Additionally, PLS-SEM does not require normally distributed data and is effective at addressing multicollinearity, making it ideal for educational and social research contexts.

The data analysis process consisted of two main stages:

- (1) Evaluation of the Measurement Model (Outer Model).

This stage aimed to assess the validity and reliability of the latent constructs. Convergent validity was evaluated through the Average Variance Extracted (AVE), while construct reliability was measured using Composite Reliability (CR). A construct was considered valid if $AVE \geq 0.50$ and $CR \geq 0.70$. Discriminant validity was further tested using the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT), ensuring that each construct was distinct from the others.

- (2) Evaluation of the Structural Model (Inner Model).



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Fig. 4. Flowchart of the Data Collection Procedure.

This stage focused on examining the strength and significance of the relationships between latent constructs. It involved assessing path coefficients, R^2 values (as indicators of model explanatory power), and the significance of these relationships using bootstrapping with a minimum of 5,000 subsamples. A path was considered statistically significant if the t -value was ≥ 1.96 and the p -value < 0.05 .

This two-stage approach enabled the researchers to assess not only the direct and indirect relationships between constructs but also the overall adequacy and predictive power of the model. The findings from this analysis formed the empirical basis for addressing the research questions and testing the proposed hypotheses.

The structure of the tested model is illustrated in Fig. 5.

Figure 5 shows the revised structural model, tested using Partial Least Squares Structural Equation Modelling (PLS-SEM). This model was updated based on reviewers' input to improve conceptual clarity, theoretical relevance, and the accuracy of its construct representation. This model consists of five primary latent constructs, namely: Knowledge of AI, Attitudes towards AI in the context of ESD, Use of AI in Science and Green Energy Learning, Teacher Involvement in the Development of ESD Teaching Materials, and AI Integration Capabilities. This structure is built based on the theoretical frameworks of Constructivism, Technology Acceptance Model (TAM), and Technological Pedagogical Content Knowledge (TPACK).

As part of the measurement model revision process, several indicators were removed because they exhibited low or negative outer loadings, which could compromise overall construct validity. The indicators that were eliminated include Knowledge_AI_1 (AK_1), Knowledge_AI_2 (AK_2) (with a loading of -0.406), and Knowledge_AI_4 (AK_4) in the Knowledge of AI construct; Attitude_AI_ESD_1 (AAE_1) in the Attitudes towards AI in ESD construct; and ESD_Teaching_Material_2 (ETM_2) in the Development of ESD-Based Teaching Materials construct. The removal of these indicators was carried out in accordance with methodological recommendations in PLS-SEM^{28,29}, which emphasise the importance of convergent validity and construct reliability to support the validity of structural model results.

Based on the theoretical foundations of Constructivism, TAM (Technology Acceptance Model), and TPACK (Technological Pedagogical Content Knowledge), as well as a conceptual model that has been adjusted according to reviewer input, the hypotheses proposed in this study are as follows:

H1 Teacher involvement in the development of ESD-based teaching materials has a positive effect on the ability to integrate AI into sustainable learning practices.

H2 Teachers' knowledge of AI has a positive effect on their ability to integrate AI into learning.

H3 Teachers' attitudes toward AI in the context of sustainable education have a positive effect on their ability to integrate AI into learning.

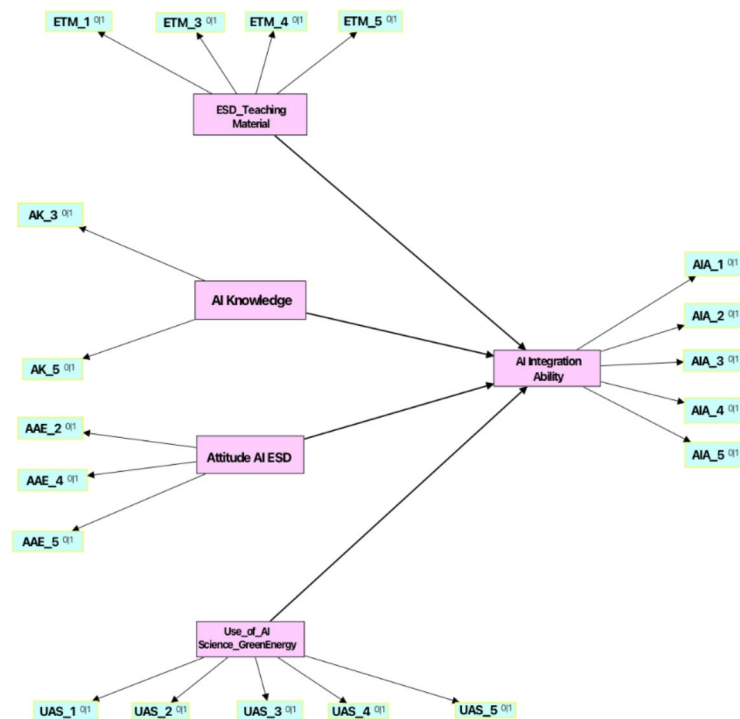


Fig. 5. The PLS-SEM model in the present study.

H4 The use of AI in science and green energy learning has a positive effect on the ability to integrate AI into learning.

These hypotheses reflect the assumed direction of causal relationships between exogenous and endogenous variables as described in the structural model and serve as the basis for empirical testing using the PLS-SEM approach. If necessary, further testing can be conducted to examine mediation or moderation effects in the model.

Result and discussion

Results

Demographic profile

This study involved 122 in-service teachers who participated voluntarily. The demographic characteristics of respondents include four main aspects: gender, age range, teaching experience, and educational qualifications. A complete summary of the demographic distribution is presented in Table 2.

Based on gender, the majority of respondents were female (55.74%), while male respondents accounted for 44.26%, indicating relatively balanced representation. In terms of age, most respondents were in the 36–40 age group (27.05%), followed by those above 45 (25.41%) and 41–45 (21.31%). This distribution suggests that the majority of participants are in the mid-to-late stages of their teaching careers.

Regarding teaching experience, the highest proportion had between 11 and 15 years of experience (36.07%), with 18.85% having 16–20 years, and 10.66% with 21–25 years. Only 6.56% had less than 5 years of experience, indicating that most participants are seasoned educators. In terms of educational qualifications, 62.30% of the respondents held a Bachelor’s degree in Education, and 27.05% held a Master’s degree in Education. Only a small portion had non-educational backgrounds, either at the undergraduate (7.38%) or postgraduate (2.46%) levels. One respondent held a Doctorate in Education (0.82%). These demographics indicate that the respondents are predominantly experienced educators with formal academic backgrounds in teaching, an essential profile for examining AI adoption and professional development in sustainable education contexts.

Measurement model testing

The measurement model in this study was tested to ensure construct validity and reliability through three main approaches: outer loadings, convergent validity (via Average Variance Extracted and Composite Reliability), and discriminant validity (via HTMT and the Fornell-Larcker criterion).

Figure 6 illustrates the structural model derived from the PLS-SEM analysis, showing the relationships among latent variables along with indicator loadings and path coefficients.

The structural model in Fig. 6 shows the contribution of each construct to AI Integration Ability in the context of ESD-based science and green energy education. Most indicators demonstrated strong outer loadings (≥ 0.60), indicating substantial contributions to their respective latent constructs. Additionally, the Use of AI in Science and Green Energy and ESD Teaching Material constructs showed the most substantial positive contributions to AI integration capability. This visual representation supports the statistical estimates and clarifies the strength and direction of relationships within the conceptual model.

Respondent’s Demographic Profile	Variables	Usable Responses	Percentage (%)
Gender	Female	68	55.74
	Male	54	44.26
Age Range	25—30	9	7.38
	31—35	23	18.85
	36—40	33	27.05
	41—45	26	21.31
	above 45	31	25.41
Teaching experience	1—5	8	6.56
	6—10	20	16.39
	11—15	44	36.07
	16—20	23	18.85
	21—25	13	10.66
	above 25	14	11.48
Education qualification	Bachelor—Education	76	62.3
	Masters—Education	33	27.05
	Bachelor non- Education	9	7.38
	Masters non- Education	3	2.46
	Doctor—Education	1	0.82

Table 2. Respondent’s demographic profile.

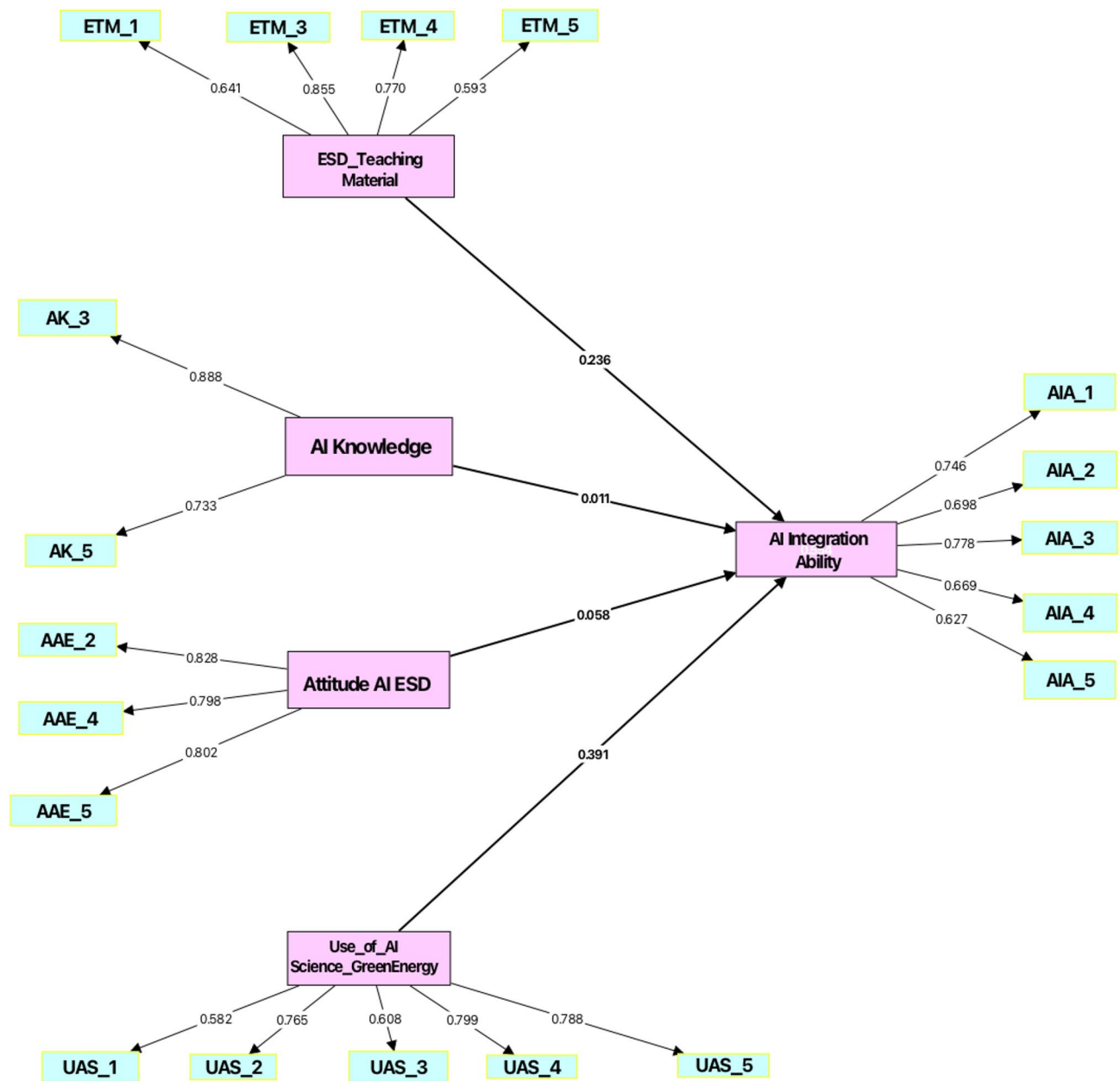


Fig. 6. PLS-SEM structural model.

Outer loading

Most indicators had outer loading values above the acceptable threshold of 0.70, indicating strong relationships with their corresponding constructs. However, a few indicators, ETM_5 (0.593), UAS_1 (0.582), and AIA_5 (0.627), were slightly below this threshold. These items were retained due to their theoretical relevance and minimal impact on construct consistency.

Table 3 presents the outer loading values for all indicators across the five latent constructs.

The results show that all indicators have adequate outer loading values, above the general threshold of 0.60, indicating acceptable indicator reliability. Several indicators, such as AAE_2 (0.828), ETM_3 (0.855), and AK_3 (0.888), show robust correlations with their respective constructs: Attitudes toward AI in ESD, ESD Teaching Materials, and AI Knowledge. Although indicators such as AIA_5 (0.627) and ETM_5 (0.593) are close to the lower limit, they are retained for their contribution to construct validity and their alignment with the theoretical basis. Overall, this measurement model demonstrates convergent validity because all indicators load higher on their respective constructs than on other constructs.

Convergent reliability and validity

Table 4 presents the results of construct reliability and convergent validity testing, using three key metrics: Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).

Construct	Indicator	Loading
Attitude AI ESD	AAE_2	0.828
	AAE_4	0.798
	AAE_5	0.802
AI Integration Ability	AIA_1	0.746
	AIA_2	0.698
	AIA_3	0.778
	AIA_4	0.669
	AIA_5	0.627
AI Knowledge	AK_3	0.888
	AK_5	0.733
ESD Teaching Material	ETM_1	0.641
	ETM_3	0.855
	ETM_4	0.770
	ETM_5	0.593
Use of AI Science Green Energy	UAS_1	0.582
	UAS_2	0.765
	UAS_3	0.608
	UAS_4	0.799
	UAS_5	0.788

Table 3. Outer Loading.

Construct	Cronbach's Alpha	CR (rho_a)	CR (rho_c)	AVE
AI Integration Ability	0.762	0.804	0.831	0.498
AI Knowledge	0.504	0.505	0.795	0.662
Attitude AI ESD	0.746	0.846	0.851	0.655
ESD Teaching Material	0.697	0.720	0.810	0.522
Use of AI Science Green Energy	0.782	0.842	0.837	0.511

Table 4. Cronbach's Alpha, Composite Reliability, and Average Variance Extracted (AVE) Values.

The results indicate that most constructs exhibit acceptable levels of reliability and convergent validity. For Attitude Toward AI in ESD, Use of AI in Science Green Energy, and AI Integration Ability, both Cronbach's Alpha and Composite Reliability (CR) exceed the recommended thresholds (≥ 0.70), indicating strong internal consistency.

However, the AI Knowledge construct shows lower values for Cronbach's Alpha (0.504) and rho_a (0.505), suggesting weak internal consistency. Nonetheless, its Composite Reliability (0.795) and AVE (0.662) remain above the minimum criteria, allowing it to be cautiously retained in the analysis.

Regarding AVE, all constructs surpass the recommended threshold of 0.50, indicating that each construct explains more than 50% of the variance in its indicators—except for AI Integration Ability, which falls slightly below at 0.498. Despite this, it is considered tolerable due to the construct's overall reliability and theoretical relevance.

Discriminant validity

HTMT ratio

To assess discriminant validity, the Heterotrait-Monotrait Ratio (HTMT) was calculated. All HTMT values fall below the conservative threshold of 0.85, indicating no significant concerns about discriminant validity. The results are presented in Table 5.

Although the highest HTMT value was 0.886 (Use of AI ↔ ESD Teaching Material), it remains within acceptable limits (below the liberal threshold of 0.90). This confirms that each construct captures a unique conceptual domain, thereby supporting the model's discriminant validity.

Fornell-Larcker criterion

The Fornell-Larcker criterion further confirms discriminant validity by comparing each construct's AVE with its correlations with other constructs. The square root of each AVE (shown in bold on the diagonal in Table 6) is greater than the inter-construct correlations, indicating satisfactory discriminant validity.

As seen in Table 6, each construct's AVE square root exceeds its correlations with other constructs in the model, thereby confirming discriminant validity according to Fornell-Larcker criteria.

Construct Relationships	HTMT
AI Knowledge ↔ AI Integration Ability	0.503
Attitude AI ESD ↔ AI Integration Ability	0.321
Attitude AI ESD ↔ AI Knowledge	0.237
ESD Teaching Material ↔ AI Integration	0.834
ESD Teaching Material ↔ AI Knowledge	0.656
ESD Teaching Material ↔ Attitude AI ESD	0.328
Use of AI ↔ AI Integration	0.697
Use of AI ↔ AI Knowledge	0.783
Use of AI ↔ Attitude AI ESD	0.230
Use of AI ↔ ESD Teaching Material	0.886

Table 5. HTMT Ratio.

Construct	AI_Integration	AI_Knowledge	Attitude_AI	ESD_Material	Use_of_AI
AI Integration Ability	0.706	0.348	0.295	0.669	0.684
AI Knowledge		0.814	0.127	0.387	0.443
Attitude AI ESD			0.810	0.243	0.191
ESD Teaching Material				0.722	0.702
Use of AI Science GreenEnergy					0.715

Table 6. Fornell-Larcker Matrix for Discriminant Validity between Constructs.

Indicator	VIF	Indicator	VIF
AAE_2	1.303	AIA_1	2.784
AAE_4	1.745	AIA_2	2.188
AAE_5	1.690	AIA_3	1.719
AK_3	1.128	AIA_4	1.518
AK_5	1.128	AIA_5	1.474
ETM_1	1.218	UAS_1	1.580
ETM_3	1.538	UAS_2	2.834
ETM_4	1.579	UAS_3	1.879
ETM_5	1.215	UAS_4	1.390
		UAS_5	1.520

Table 7. Inner VIF Value of Latent Construct.

Structural model testing

Multicollinearity evaluation (VIF inner model)

To assess potential multicollinearity among the predictor variables, the Variance Inflation Factor (VIF) was calculated for each indicator. A VIF value below 5.0 indicates no serious multicollinearity issues²⁹. As shown in Table 7, all indicators meet this criterion.

All VIF values fall well below the threshold of 5.0. The highest VIF is 2.834 (UAS_2), and the lowest is 1.128 (AK_3 and AK_5), confirming that multicollinearity is not a concern in this structural model. Most indicators fall between 1.2 and 2.0, reflecting stable and independent relationships among constructs.

Model fit

The overall fit of the structural model was evaluated using several key indices, including the Standardised Root Mean Square Residual (SRMR), d_ULS, and Chi-square. An SRMR value below **0.14** indicates a good model fit in the PLS-SEM context³⁰.

Tables 8 and 9 shows the model fit index used to assess the extent to which the estimated structural model fits the data. The SRMR values for both the saturated (0.136) and estimated (0.133) models fall below the threshold, indicating acceptable model fit. Similarly, the d_ULS values for both models also fall within acceptable limits, suggesting that the discrepancy between the observed and model-implied matrices is minimal.

Although the Chi-square value is reported as infinite (∞) and the NFI is unavailable (n/a), these limitations are common in PLS-SEM, which emphasises predictive accuracy over absolute model fit. Thus, the model is considered to have adequate fit to the data.

Index	Saturated Model	Estimated Model
SRMR	0.136	0.133
d_ULS	3.510	3.354
d_G	n/a	129.981
Chi-square	∞	∞
NFI	n/a	n/a

Table 8. Model Fit Index.

Endogenous constructs	R ²	R ² Adjusted
AI Integration Ability	0.554	0.539

Table 9. Endogenous Construct R-Square Value.

Structural Pathways	f ²	Interpretation
AI Knowledge → AI Integration Ability	0.001	Very small
Attitude AI ESD → AI Integration Ability	0.036	Small
ESD Teaching Material → AI Integration Ability	0.127	Moderate
Use of AI in Science Green Energy → AI Integration	0.180	Moderate

Table 10. The f² value in the Structural Path.

Hypothesis Path	Path Coefficient (β)	t-Statistics	p-value	Significance
H1: AI Knowledge → AI Integration Ability	0.011	0.086	0.466	Insignificant
H2: Attitude AI in ESD → AI Integration Ability	0.058	0.405	0.343	Insignificant
H3: Use of AI in Science Green Energy → AI Integration	0.391	3.063	0.001	Significant ($p < 0.01$)
H4: ESD Teaching Material → AI Integration Ability	0.236	1.936	0.027	Significant ($p < 0.05$)

Table 11. Hypothesis Test Results (Path Coefficients).

Coefficient of determination (R²) and adjusted R²

The coefficient of determination (R²) was used to assess the extent to which the exogenous variables in the model explain variance in the endogenous construct (AI Integration Ability). An R² value between 0.50 and 0.75 is considered moderate to substantial²⁹.

An R² value of 0.554 indicates that approximately 55.4% of the variance in AI Integration Ability is explained by the combination of four exogenous constructs: (1) AI Knowledge; (2) Attitude Toward AI in ESD; (3) ESD Teaching Material; and (4) Use of AI in Science Green Energy. This demonstrates that the model has moderate predictive power, supporting its use for further hypothesis testing and structural interpretation.

Effect size, f²

The effect size (f²) was calculated to evaluate the relative impact of each exogenous construct on the endogenous construct (AI Integration Ability). According to Cohen (1988), the guidelines for interpreting f² are as follows: (1) 0.02 = small; (2) 0.15 = moderate; and (3) 0.35 = large.

The results (Table 10) show that the Use of AI in Science, Green Energy, and ESD Teaching Materials had the greatest effect on AI Integration Ability, with effect sizes in the moderate range. In contrast, AI Knowledge and Attitude Toward AI in ESD had small to minimal effects, indicating limited predictive influence in this context.

These findings emphasise the importance of practical and contextual engagement—such as content development and direct application of AI over purely cognitive or affective factors when predicting teachers' AI integration capacity.

Hypothesis testing

To test the proposed hypotheses, a bootstrapping analysis was conducted using 5,000 subsamples. The results include path coefficients (β), t-statistics, p-values, and significance levels, summarised in Table 11:

The results show that only two hypotheses were statistically supported:

- (1) (H3: Use of AI in science and green energy significantly influenced AI Integration Ability ($\beta = 0.391$, $p < 0.01$), with a moderate effect size.

- (2) (H4: Involvement in developing ESD teaching materials also had a significant positive effect ($\beta=0.236$, $p<0.05$).

Conversely:

H1 (AI Knowledge) and H2 (Attitude Toward AI in ESD) were not significant, with p -values well above the standard threshold of 0.05, suggesting limited predictive value in this context. These findings reinforce the idea that hands-on experience and contextual engagement are more critical predictors of AI integration capability than standalone knowledge or general attitudes.

Discussion

The results of this study indicate that of the four exogenous constructs tested as predictors of AI Integration Ability, only two were found to have a statistically significant influence: Use of AI in Science and Green Energy, and ESD Teaching Material.

In contrast, AI Knowledge and Attitude Toward AI in ESD did not have a significant effect on teachers' ability to integrate AI. These findings have several important theoretical and practical implications.

The impact of AI use in science education and green energy

Hypothesis testing revealed that the Use of AI in Science and Green Energy had a significant influence on AI Integration Ability ($\beta=0.391$, $t=3.063$, $p<0.01$), with a moderate effect size ($f^2=0.180$). This suggests that the more teachers engage with AI in applied contexts, particularly in teaching science and renewable energy, the more effectively they can integrate it into pedagogical practices.

These findings align with studies by Leal Filho et al.³¹ and Dede et al.³², who emphasised that the effective integration of AI is enhanced when implemented in applied, context-rich learning environments, such as sustainability education. First-hand experience with AI tools enables teachers to develop the technical skills and pedagogical strategies necessary for 21st-century digital learning.

This underscores the importance of practice-based approaches, where teachers apply AI in real-world, sustainability-related content areas, helping to build not only familiarity with the tools but also deeper pedagogical readiness.

The influence of teacher involvement in ESD material development

The ESD Teaching Material construct also had a significant effect ($\beta=0.236$, $t=1.936$, $p<0.05$), indicating that teachers who are actively involved in developing ESD-aligned teaching materials are more prepared to integrate AI in their classrooms.

This supports prior findings from UNESCO³³ and Gamage et al.³⁴ which highlight the value of teacher engagement in sustainability curriculum design not only as a content-creation task but also as a form of professional reflection and growth. Active participation in material development allows teachers to contextualise AI tools within their subject matter and pedagogical approaches, fostering eco-pedagogical thinking and innovation.

Insignificance of knowledge and attitudes towards AI

In contrast, AI Knowledge and Attitude Toward AI in ESD did not significantly affect AI Integration Ability ($p=0.466$ and $p=0.343$, respectively). This result is surprising, as previous literature often positions knowledge and attitudes as key predictors of technology adoption^{19,35}.

However, this finding may be explained by limitations in instrument design. Both constructs were measured using a dichotomous scale (0/1), which may have reduced response variability and failed to capture depth of understanding or intensity of belief. A simple "yes/no" format likely lacks the sensitivity needed to detect subtle differences in teachers' knowledge or disposition toward AI.

Furthermore, the AI Knowledge construct showed low reliability (CR=0.505; Alpha=0.504), suggesting that its indicators may not have accurately represented the latent variable. This concern was also noted by reviewers, particularly regarding low or negative outer loadings on some indicators (e.g., Knowledge_AI_2 = -0.406), which were subsequently removed.

These results reinforce the importance of using more granular measurement tools (e.g., 5- or 7-point Likert scales) to assess nuanced constructs such as beliefs, knowledge, and perceptions, particularly in PLS-SEM modelling.

Academic and practical implications

Academically, these findings contribute to the growing body of research on technology integration in sustainability education by reinforcing the role of practical engagement primarily through teaching practice and material development over isolated cognitive or affective predictors. This aligns with constructivist theories of learning and adoption, which argue that understanding and skill development are most effectively achieved through authentic, situated experiences rather than abstract knowledge alone.

In practice, the study suggests that teacher training programs should prioritise applied learning experiences. It is not enough to introduce AI concepts or promote positive attitudes; programs must also give teachers opportunities to design, experiment with, and reflect on AI tools within sustainability-oriented instructional contexts.

Contextual factors affecting results

Several contextual factors may have influenced the findings: (1) Sample characteristics. Participants were all engaged in a professional development program, which may introduce a selection bias. These teachers might

already be more open to innovation than the general teacher population; (2) Measurement limitations, as noted, the use of dichotomous items may have reduced data sensitivity and the model's ability to detect actual effects; and (3) Instrument reliability, particularly in the AI Knowledge construct, limited internal consistency weakens the validity of findings related to this variable.

Despite these limitations, the results clearly highlight that hands-on use of AI and involvement in sustainability content development are key predictors of AI integration ability. In contrast, knowledge and attitudes, as measured in this study, were not sufficient to explain integration readiness.

This reinforces the need to reframe teacher training away from purely cognitive models and toward transformative, experience-based learning, particularly in the context of science and sustainability education.

Conclusions and recommendations

This study investigated the factors influencing teachers' ability to integrate Artificial Intelligence (AI) into science and green energy education within the framework of Education for Sustainable Development (ESD). Using a structural equation model based on the TPACK framework, the research examined the impact of four exogenous constructs: AI Knowledge, Attitudes Toward AI, Use of AI in Science and Green Energy, and Development of ESD-Based Teaching Materials.

The findings of the study reveal that only two constructs, Use of AI in science and green energy, and involvement in developing ESD-aligned teaching materials, had a significant influence on teachers' AI integration capabilities. These results emphasize the importance of practical engagement and contextual experience in supporting meaningful technology integration. Conversely, AI Knowledge and Attitudes Toward AI did not show significant effects, likely due to measurement limitations and the constrained role of abstract cognition when not supported by practical application.

The findings suggest that teacher readiness for AI integration is not solely determined by knowledge or beliefs, but also by active involvement with pedagogical content and AI tools within relevant teaching contexts. From a practical standpoint, this indicates the need for a shift in teacher professional development programs, from information-based training to collaborative, experience-based design activities that involve real-world sustainability content and AI-supported instruction.

Institutions aiming to promote AI-driven innovation in education must ensure that teachers are not only empowered with knowledge but also given opportunities to collaborate, experiment, and reflect on practices within dynamic learning environments.

Future research is encouraged to adopt multi-method approaches, combining qualitative insights with robust quantitative designs, and to develop more sensitive instruments to measure constructs such as knowledge and attitudes. Further investigations are also needed to explore the longitudinal effects of AI-based training and to assess how teachers' engagement with AI evolves over time and across various disciplines.

Limitations of the research

This study has several limitations that should be considered when interpreting the results. First, the characteristics of the respondents, all of whom were teachers who had participated in professional development training, may have introduced selection bias. These participants were likely more open to innovation, including the integration of Artificial Intelligence (AI) in education, which may have influenced their perceptions and attitudes toward the variables being studied.

Second, the use of a dichotomous scale (0/1) in the questionnaire limited data variability and the sensitivity of statistical analysis. This scale was insufficient in capturing the nuances or intensity of respondents' attitudes and knowledge, ultimately weakening the predictive power of the SEM-PLS model used.

Third, there are indications that some constructs, particularly the AI Knowledge construct, exhibited weak reliability and validity, as evidenced by low Cronbach's Alpha and composite reliability values. This could impact the stability of estimates and the accuracy of measurements in the structural model employed.

Future research directions

Based on the findings and limitations identified, there are several recommended research directions for future studies. First, it is recommended to involve respondents from various educational backgrounds and institutions to improve the generalization of results and reduce potential selection bias.

Second, the use of a Likert scale with a wider response range (e.g., 5 or 7 points) is highly recommended to obtain richer data, allowing for statistical analysis that is more sensitive to variations in individual perceptions and attitudes.

Third, it is necessary to revise and revalidate the instruments, especially those constructs that show low reliability. More rigorous convergent and discriminant validity tests can help ensure the quality of the measuring instruments in describing latent variables.

Fourth, future studies are recommended to use mixed-methods or longitudinal approaches to gain a more comprehensive understanding of the dynamics of AI integration in continuing education. Qualitative studies can explore teachers' experiences contextually, while longitudinal studies allow for observation of changes in behavior and competence over a period of time.

Finally, the integration of cultural aspects, institutional policies, and technological support should also be considered as additional variables that can influence the effectiveness of AI integration in ESD-based learning.

Data availability

Data will be available on request by contacting with Prof. Dr. Riandi, M.Si (rian@upi.edu) and Dr. Ismail, M.Si, M.Pd (smile.dza@upi.edu)

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Author contributions

****R.R**** : Conceptualization, Methodology, Data Collection, Writing – Original Draft Preparation, Project Administration. ****I.I**** : Investigation, Validation, Formal Analysis, Writing – Review & Editing. ****I.K**** : Data Curation, Supervision, Writing – Review & Editing. ****W.S**** : Conceptualization, Supervision, Resources, Writing – Review & Editing, Correspondence. **D.A.R.**: Visualization, Literature Review, Writing – Initial Draft Review. **D.H.**: Statistical Analysis, Data Interpretation, Writing – Methodology Review. ****S. S:** ****** Data curation, Project administration, Writing - review & editing.

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Declarations

Competing interests

The authors declare no competing interests.

Ethical approval

The research protocol of this study was reviewed and approved by the Ethics Committee of Universitas Muhammadiyah Sukabumi (LPPM-UMMI), under approval number IRB-2024-185. The approval is valid from January 6, 2024, until December 31, 2024. All procedures involving human participants were conducted in accordance with institutional guidelines, the Declaration of Helsinki, and the CIOMS 2016 guidelines. Informed consent was obtained from all participants prior to data collection.

Additional information

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