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Teachers' Readiness and Perceptions of Augmented Reality for Sustainable STEM Education

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Abstract: This study explores teachers' readiness and perceptions regarding the integration of Augmented Reality (AR) in STEM education. The research, conducted with 250 teachers from Indonesia and Malaysia, uses an explanatory survey design and Structural Equation Modeling (SEM) to analyze a framework combining Teacher Readiness, the Technology Acceptance Model (TAM), and Deep Learning Orientation. The results reveal that Teacher Readiness significantly influences Perceived Ease of Use (β = 0.48) and Perceived Usefulness (β = 0.42), which in turn affect Attitude Toward Use (β = 0.31) and Behavioral Intention (β = 0.52). Behavioral intention strongly predicts Deep Learning Orientation (β = 0.57). The model explains 56% of the variance in Behavioral Intention and 32% in Deep Learning Orientation. Multi-group analysis shows that these findings are consistent across countries, genders, education levels, and age groups, demonstrating the robustness and generalizability of the model. This research highlights the importance of teacher readiness in adopting AR technology, which fosters deeper learning in STEM education.

Keywords: Augmented Reality; Deep Learning; STEM Education; Teacher Readiness; Technology Acceptance Model

Introduction

The The acceleration of digital technology in the last decade has significantly transformed education, expanding learning from traditional face-to-face interactions to online platforms, Learning Management Systems (LMS), and various digital tools that enhance learning flexibility (Jamrus & Razali, 2021; Liu & Liu, 2025; Perifanou et al., 2023). This shift, amplified by the adoption of distance and hybrid learning models, demands that teachers not only master technology but also integrate it effectively into their teaching. However, many schools, particularly in developing countries like Indonesia, face a gap between available technology and teachers' readiness to use it effectively. This gap highlights the need for a deeper understanding of how prepared teachers are to integrate technology into their daily classroom practices (Lee & Hwang, 2022; Schmidt & Stumpe, 2025).

Previous research frameworks have applied the Technology Acceptance Model (TAM) to explain technology adoption by teachers, focusing on the key constructs of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). These studies suggest that when technology is perceived as easy to use and beneficial, teachers are more likely to adopt it (Bhattacharya et al., 2025; Kulkarni & Harne, 2024; Mcnerney et al., 2023). However, there is a significant research gap in integrating the TAM framework with a deeper pedagogical orientation, especially regarding

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teachers' commitment to fostering deep learning. Most prior studies primarily focus on external factors such as infrastructure, technical capability, and basic pedagogical skills, treating readiness as an operational prerequisite without considering how teachers' deeper pedagogical orientation impacts their adoption of technology. This gap highlights the need for a conceptual link between TAM constructs and deep learning, which has been minimally explored in existing literature.

Deep learning, which emphasizes critical thinking, problem-solving, and conceptual understanding, encourages teachers to view technology not just as a tool for presenting information but as a medium to enrich meaningful learning experiences (Mundy et al., n.d.; Mystakidis & Christopoulos, 2022; Ripsam & Nerdel, 2024). However, this pedagogical orientation remains underexplored in quantitative models, particularly in how teachers' behavioral intention to adopt technology, as modeled in TAM, can influence their commitment to deep learning. Previous studies typically treat deep learning as a student achievement outcome or as an antecedent to perceptions, rather than as a distinct teacher-level outcome influenced by their technology adoption intentions.

This study bridges these gaps by offering an integrative approach that combines the TAM framework with a multidimensional view of teacher readiness and explicitly positions deep learning orientation as an outcome variable. This study's novel approach integrates TAM constructs (PEOU, PU, attitude, and behavioral intention) with teacher readiness indicators (technical, pedagogical, and psychological readiness) and examines how these factors influence teachers' deep learning orientation. Unlike previous research, which focuses on external factors or technical readiness, this study positions deep learning orientation as a critical outcome, influenced by teachers' behavioral intention to use technology (Aida et al., 2025; Rowe et al, 2020; Buraiki et al., 2025; Dawana et al., 2024). By focusing on AR (Augmented Reality) in STEM learning, which requires in-depth and contextual exploration of concepts, this research tests the relationship between teacher readiness and deep learning orientation, offering a fresh perspective on how these constructs interact in meaningful technology integration.

The specific objectives of this study are to measure elementary school teachers' perceptions of AR integration in STEM learning, using the TAM framework, focusing on PEOU, PU, attitude, behavioral intention, and deep learning orientation; to analyze the influence of teacher readiness (technical, pedagogical, and psychological) on PEOU and PU, and how the TAM pathway (PEOU → PU → attitude → behavioral intention) leads to an enhanced deep learning orientation.

This research departs from previous studies by treating behavioral intention as a core outcome of TAM rather than a component of teacher readiness. It positions teacher readiness as an antecedent to teachers' perceptions, which subsequently shapes their attitudes and intentions, culminating in their commitment to deep learning. This new perspective challenges the conventional approach of focusing solely on technical capability, emphasizing that the success of technology integration depends on teachers' pedagogical orientation and their ability to connect technology to deeper learning experiences.

The novelty of this study lies in three aspects. First, it extends TAM by integrating a multidimensional teacher readiness construct (technical, pedagogical, and psychological) that shapes perceptions of AR. Second, it conceptualizes and tests deep learning orientation as a distinct outcome variable influenced by teachers' behavioral intention to use AR, linking TAM to a deeper pedagogical commitment. Third, it offers cross-country evidence from Indonesia and Malaysia, contributing insights into how readiness, TAM constructs, and deep learning orientation relate across different educational contexts. This study represents a significant contribution to both academic theory and educational practice, offering empirical evidence on how technology acceptance is integrated with teachers' deeper pedagogical commitment, which sets it apart from previous studies that primarily focus on operational readiness or usage intention alone.

Method

This study uses a quantitative approach with an explanatory survey design to test the causal relationship between constructs in an integrative model that combines Technology Acceptance Model (TAM), Teacher Readiness, and teacher deep learning orientation in Augmented Reality (AR) assisted STEM learning. The explanatory survey design was chosen because it allows testing of direct and indirect influences between variables simultaneously through Structural Equation Modeling (SEM) (Sukmawati et al., 2024; Umam et al., 2024; Wahjusaputri et al., 2024; Sukmawati et al., 2021).This design was chosen because it enables simultaneous estimation of the direct and indirect effects between variables and provides empirical evidence of how strongly each construct influences teachers' acceptance and readiness to integrate Augmented Reality (AR) into STEM learning. The AR experience referred to in this study is a real experience based on standardized exposure, not just hypothetical assumptions. Before filling out the questionnaire, all respondents were given the same stimulus in the form of demonstration videos and simulations of the use of AR in the context of STEM learning. This stimulus aims to equalize respondents' perception of the features, flow of use, and benefits of AR in teaching and learning activities. To ensure that respondents really understand the stimulus given, a manipulation check was carried out through short questions related to video/simulation content. Respondents who do not meet the minimum criteria of understanding can be excluded from the analysis so that the quality of the data and interpretation of the measured constructs are maintained. The proposed structural model is illustrated in Figure 1 (Model Flow): Teacher Readiness (Technical, Pedagogical, Psychological) → PEOU, PU → ATU → BI → Deep Learning Orientation. See Figure 1.

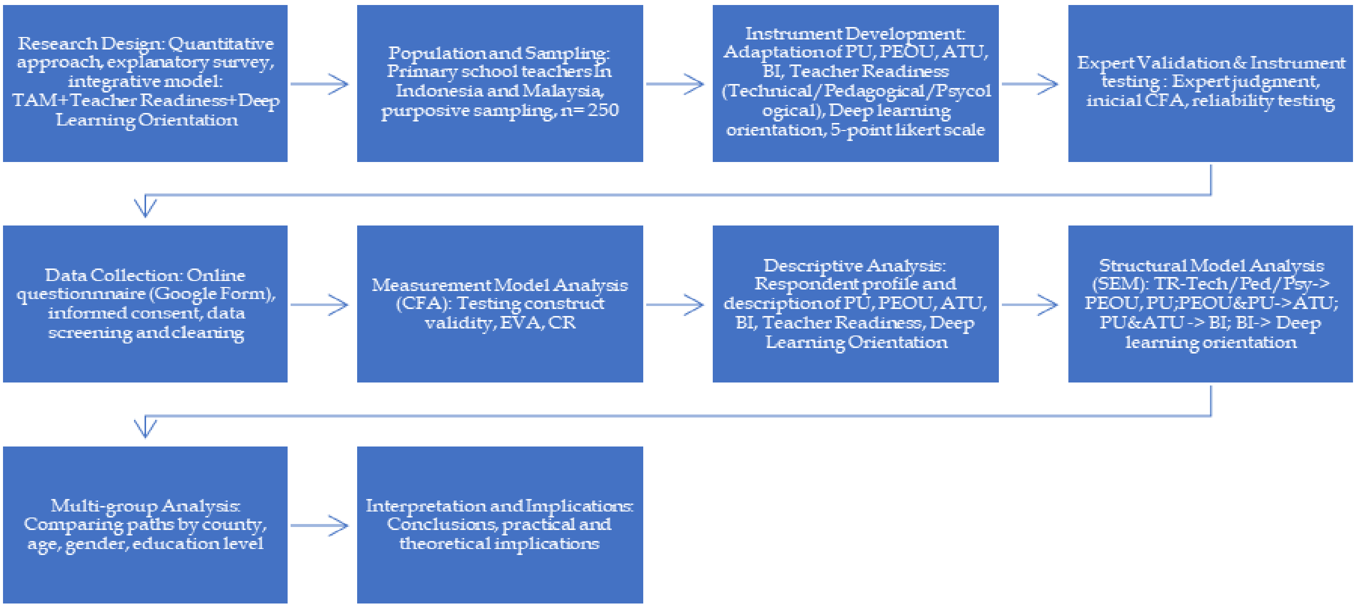

Figure 1. Research Flowchart

Population and Sample

The research population consists of teachers in Indonesia and Malaysia who have participated in training or demonstrations on the use of AR for STEM learning. The sampling technique used was purposive sampling, with the following criteria: (1) active primary school teachers, (2) have used or participated in AR technology demonstrations, and (3) understand the context of STEM learning. The research population is teachers who teach STEM-related subjects at the level set in the study (junior high school/high school or equivalent) in Indonesia and Malaysia. The sampling technique uses purposive sampling with inclusion criteria: (1) teachers are actively teaching in the current year, (2) teaching STEM-related subjects, (3) willing to participate in AR stimulus exposure and filling out complete questionnaires, and (4) having device access to watch AR videos/simulations. Due to the cross-border scope of the research, differences in access to technology and school policies were recognized as limitations, so the generalization of results was limited to the characteristics of respondents that matched the inclusion criteria. The sample size is determined by taking into account the SEM analysis recommendations. In general, SEM requires an adequate sample size to obtain a stable parameter estimate. Therefore, the sample size is set to meet the minimum thresholds recommended in the SEM methodological literature, taking into account the number of constructs, indicators, and the complexity of the path in the model. In addition, sample sufficiency checks are carried out to ensure that every key parameter in the model can be reliably estimated. The total number of respondents was 250 teachers, with the distribution by country, age group, gender, and education level presented in Table 1.

Table 1. Respondent Data

Code	Country	Age	Gender	Education	Sum
ID-M-P-S1	Indonesia	Young	Woman	S1	80
ID-T-P-S1	Indonesia	Old	Woman	S1	20
ID-T-L-S1	Indonesia	Old	Man	S1	20
ID-T-L-S2	Indonesia	Old	Man	S2	35
ID-T-L-S3	Indonesia	Old	Man	S3	5
MY-M-P-S1	Malaysia	Young	Woman	S1	40
MY-T-P-S1	Malaysia	Old	Woman	S1	12
MY-T-L-S1	Malaysia	Old	Man	S1	12
MY-T-L-S2	Malaysia	Old	Man	S2	26
				Sum	250

Table 1 shows dataset contains information about individuals from two countries, Indonesia and Malaysia, categorized by their age, gender, education level, and a numerical value labeled as "Sum." In Indonesia, multiple entries are provided for both "Young" and "Old" individuals across different educational levels (S1, S2, and S3). The "Sum" values vary for each group, with the highest value observed in the "Old Man S1" category, which has a sum of 80. In Malaysia, the dataset shows fewer entries, with the majority being "Old" individuals who have an S1 education. The "Sum" values in Malaysia are generally lower compared to those in Indonesia, with the highest sum being 40. The total value of the "Sum" for all entries in the dataset is 250, representing the overall sum of the "Sum" values across all rows. This dataset is structured to analyze the distribution of a specific metric (represented by "Sum") across different demographic categories such as age, gender, education level, and country.

Research Instruments

The A research instrument in the form of a closed questionnaire using a Likert scale (e.g. 1 to 5) to measure the main constructs in the model. TAM constructs are measured through perceived ease of use and perceived usefulness, which theoretically affect the attitude of using technology. The measured constructs refer to the core variables of TAM, Teacher Readiness, and Deep Learning Orientation: Perceived Usefulness (PU): teachers' perception that AR improves learning effectiveness and performance. Perceived Ease of Use (PEOU): teachers' belief that AR is easy to learn and operate. Attitude Toward Use (ATU): teachers' positive evaluation and affective response toward using AR in learning. Behavioral Intention (BI): teachers' intention and commitment to use AR in future STEM lessons. Teacher Readiness (TR): teachers' readiness in three dimensions: technical, pedagogical, and psychological, related to AR integration in STEM. Deep Learning Orientation (DLO): teachers' orientation to promote deep learning in their teaching, including critical thinking, conceptual understanding, problem solving, and connecting concepts to real contexts.

From data Table 2, teacher readiness (TR) is assessed through key dimensions such as pedagogical, technological, psychological/self-confidence, and environmental support readiness, using validated question items from previous studies. This ensures comprehensive measurement of TR constructs. Teachers' deep learning orientation and concept exploration in STEM, reflects their preference for in depth learning experiences (Alfeo B. Tulang, 2025; Lyu, 2024; Ramanujan et al., 2023; Zhang & Li, 2022; Zhao et al., 2025).

To ensure validity across countries, instruments undergo forward-back translation and expert judgment. A pilot test on a small sample assesses clarity, reliability, and estimated time. The instrument, adapted from previous studies on TAM, teacher readiness, and AR in education, was validated for content, construct validity (using Confirmatory Factor Analysis), and reliability (using Cronbach's Alpha and Composite Reliability), with all constructs meeting the >0.70 threshold.

Table 2. Construct Instruments

Construct	Dimension	Number of items	Item code
Perceived Usefulness (PU)	–	5	PU1–PU5
Perceived Ease of Use (PEOU)	–	5	PEOU1–PEOU5
Attitude Toward Use (ATU)	–	5	ATU1–ATU5
Behavioral Intention (BI)	–	5	BI1–BI5
Teacher Readiness (TR)	Technical, Pedagogical, Psychological	6	TR-T1–2 TR-P1–2 TR-Psy1-2
Deep Learning Orientation (DLO)	–	4	DLO1–DLO4

Data Collection Procedure

Data collection was conducted online using Google Forms to accommodate respondents in Indonesia and Malaysia. Respondents independently filled out the questionnaire after receiving a brief explanation of the study objectives (Sukmawati et al., 2023). Prior to completing the questionnaire, they were presented with an informed consent statement, ensuring voluntary participation, confidentiality, and adherence to research ethics. The data collection process included submitting research information, exposure to AR stimuli (video/simulation), and checking answer completeness while guaranteeing anonymity. The conceptual model of the research, based on TAM constructs, Teacher Readiness, and deep learning orientation, examines relationships between these variables and outcomes like AR usage intention or implementation, with hypotheses grounded in theoretical foundations and previous research findings, including both direct and indirect effects.

Data Analysis Techniques

Data collection was conducted online using Google Forms to accommodate respondents in Indonesia and Malaysia. After receiving a brief explanation of the study objectives (Sukmawati et al., 2023), respondents independently filled out the questionnaire, with informed consent ensuring voluntary participation and confidentiality. The data were then screened and cleaned before analysis. Data analysis was carried out in several stages: 1) Descriptive analysis to summarize teachers' profiles and levels of PU, PEOU, ATU, BI, Teacher Readiness (technical, pedagogical, psychological), and Deep Learning Orientation. 2) Measurement model evaluation using CFA to test the validity and reliability of each construct and ensure TAM, Teacher Readiness, and Deep Learning Orientation are distinguishable. 3) Structural Equation Modeling (SEM) to test the integrative model, including the effects of Teacher Readiness dimensions on PEOU and PU, and TAM pathways from PEOU and PU to ATU, from ATU and PU to BI, and from BI to Deep Learning Orientation. 4) Multi-group analysis to examine whether the structural relationships are invariant across groups based on country, age, gender, and education level. The evaluation included model fit indices and thresholds for CB-SEM or PLS-SEM, and mediation was tested using bootstrapping. Structural models were assessed through path coefficients, significance, effect size, explainability, and predictive relevance, with results interpreted for implications in AR implementation in STEM learning and teacher readiness (Blatti et al., 2019; Duan, 2022; English, 2023; Jiang et al., 2024; Lyu, 2024; Qablan et al., 2025; Ramanujan et al., 2023; Zhou et al., 2023). Methodological limitations include purposive sampling, online response bias, and differences in school policies and technology access between Indonesia and Malaysia, which are addressed in the discussion and recommendations for further research.

Result and Discussion

Descriptive Analysis

In general, the results of the descriptive analysis show that all the constructs studied are in the category of quite high to high. This is illustrated by the average value on the radar diagram. See Figure 2.

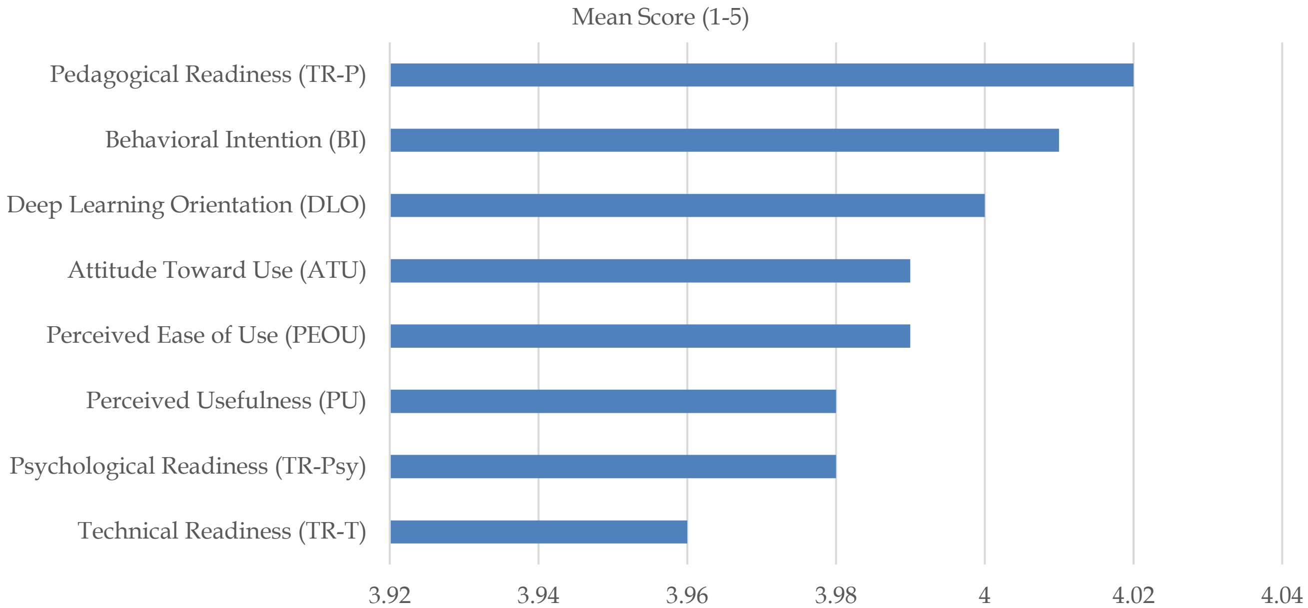

Figure 2. Mean Scores of Key Construct AR with a Deep Learning Approach

Figure 2 shows the descriptive analysis indicates that the study involved a sufficiently large and diverse sample of 250 teachers, providing a strong basis for generalizing the findings. Overall, the composite scores across all constructs fall within the moderate to high range (3.0–5.0), suggesting that teachers generally hold positive perceptions toward technology integration, although some variability among individuals remains. High mean scores for Perceived Usefulness and Perceived Ease of Use reflect that teachers largely view educational technology as both beneficial and manageable, which supports the subsequent SEM findings showing the importance of these perceptions in shaping attitudes and intentions (Jamrus & Razali, 2021; Mundy et al., 2022).

Teachers' positive attitudes toward technology and their strong behavioral intentions to continue using it indicate a readiness to sustain and possibly expand technology-based practices in teaching (Aguilos & Fuchs, 2024; Al-Dokhny et al., 2021; Chiriacescu et al., 2023; Darwish et al., 2024; Lim et al., 2025; Sondakh et al., 2023). The high level of pedagogical readiness suggests that teachers feel confident integrating technology into instructional strategies, while the slightly wider variation in technical and psychological readiness highlights the presence of a subgroup of teachers who may still require additional technical training or motivational support(Carrillo Ros, 2023; Sabourianzadeh & Ahmadi, 2024).

The high mean score for Deep Learning Orientation demonstrates that teachers are inclined to promote higher order cognitive processes, aligning well with the goals of deep learning and sustainable STEM education (Amores Valencia et al., 2022; Jamrus & Razali, 2021; Perifanou et al., 2023). Taken together, these findings suggest that teachers are generally well positioned to adopt advanced educational technologies, although targeted support remains important to address individual differences in readiness(Zhao et al., 2025). Below is the correlation among key construct, See Figure 3.

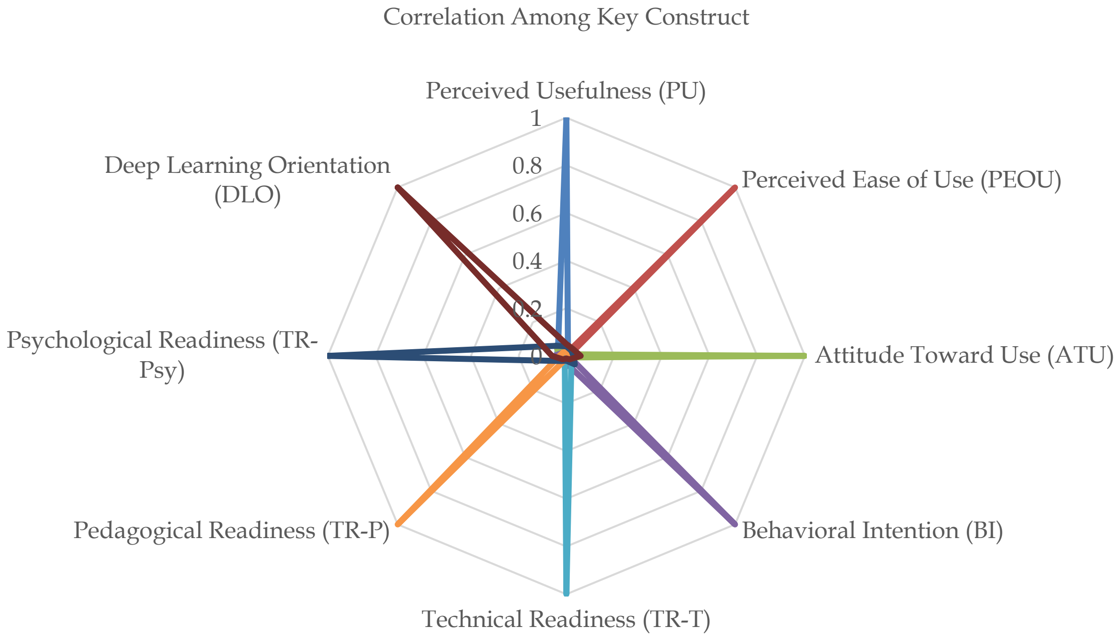

Figure 3. Correlation Among Key Construct

Figure 3 shows a correlation matrix among the eight key constructs. Most correlations are positive and moderate to high, indicating that higher perceived usefulness and ease of use tend to be associated with more favorable attitudes, stronger behavioral intentions, greater teacher readiness (technical, pedagogical, psychological), and stronger deep learning orientation (Alghamdi et al., 2022; Endot & Jamaluddin, 2023; Khan et al., 2023; Li et al., 2024; M. Li & Li, 2025; Luik & Taimalu, 2021; Marian et al., 2025; Sondakh et al., 2023; Ying et al., 2025). This pattern supports the theoretical linkage between technology acceptance and learning related outcomes (Alfeo B. Tulang, 2025).

Measurement model evaluation

Several indicators were removed due to low or negative standardized factor loadings (< 0.50), indicating insufficient contribution to their respective latent constructs. Retaining such indicators may reduce construct reliability and compromise convergent validity (Hair et al.,2021), only indicators with strong and theoretically meaningful loadings were retained, resulting in a more parsimonious and well-fitting measurement model. Specifically, the indicators removed were PU1 and PU4 for the Perceived Usefulness (PU) construct; PEOU1, PEOU4, and PEOU5 for the Perceived Ease of Use (PEOU) construct; ATU2 and ATU3 for the Attitude Toward Use (ATU) construct; and BI2, BI3, and BI4 for the Behavioral Intention (BI) construct.

From data Table 3 the proposed model is both statistically robust and theoretically coherent. All constructs demonstrate adequate measurement quality, with standardized factor loadings above 0.70, AVE values ranging from 0.59 to 0.69, and CR values between 0.79 and 0.87, confirming good validity and reliability. Teacher Readiness emerges as a key antecedent, significantly influencing Perceived Ease of Use (β = 0.48) and Perceived Usefulness (β = 0.42), highlighting the importance of teachers' technical, pedagogical, and psychological preparedness in technology integration. In line with the Technology Acceptance Model, Perceived Ease of Use positively affects Perceived Usefulness (β = 0.39) and Attitude Toward Use (β = 0.31), while Perceived Usefulness strongly predicts Attitude Toward Use (β = 0.46). Attitude Toward Use plays a central mediating role, exerting a strong effect on Behavioral Intention (β = 0.52), which in turn significantly influences Deep Learning Orientation (β = 0.57). The model explains a substantial proportion of variance in Behavioral Intention (R^2 = 0.56) and Attitude Toward Use (R^2 = 0.49), indicating strong explanatory power. Overall, these results suggest that enhancing teacher readiness and technology acceptance is critical for fostering deep learning oriented, sustainable STEM education.

Table 3. Factor Loading Construct

Construct	Item	Std. Loading	Loading²
Perceived Usefulness (PU)	PU2	0.78	0.61
	PU3	0.84	0.71
	PU5	0.76	0.58
	AVE	0.63	
	CR	0.84	
Perceived Ease of Use (PEOU)	PEOU2	0.85	0.72
	PEOU3	0.81	0.66
	AVE	0.69	
	CR	0.82	
Attitude Toward Use (ATU)	ATU1	0.72	0.52
	ATU4	0.86	0.74
	ATU5	0.80	0.64
	AVE	0.63	
	CR	0.85	
Behavioral Intention (BI)	BI1	0.83	0.69
	BI5	0.78	0.61
	AVE	0.65	
	CR	0.79	
Teacher Readiness (TR)	TRT1	0.75	0.56
	TRP2	0.83	0.69
	TRPSY	0.71	0.50
	TRPSY.1	0.79	0.62
	AVE	0.59	
	CR	0.86	
Deep Learning Orientation (DLO)	DLO2	0.82	0.67
	DLO3	0.74	0.55
	DLO4	0.88	0.77
	AVE	0.66	
	CR	0.87	

The Table 4 results demonstrate strong validity and reliability across the constructs. The standardized loadings for all indicators are above 0.7, indicating significant contributions to their respective constructs. The AVE and CR values exceed the recommended thresholds, further supporting the robustness of the measurement model.

Table 4. Final Retained Indicators with AVE and CR Values

Construct	Retained Indicators	Standardized Loading	AVE	CR
Perceived Usefulness (PU)	PU2, PU3, PU5	0.78, 0.84, 0.76	0.63	0.84
Perceived Ease of Use (PEOU)	PEOU2, PEOU3	0.85, 0.81	0.69	0.82
Attitude Toward Use (ATU)	ATU1, ATU4, ATU5	0.72, 0.86, 0.80	0.63	0.85
Behavioral Intention (BI)	BI1, BI5	0.83, 0.78	0.65	0.79
Teacher Readiness (TR)	TRT1, TRP2, TRPSY, TRPSY.1	0.75, 0.83, 0.71, 0.79	0.59	0.86
Deep Learning Orientation (DLO)	DLO2, DLO3, DLO4	0.82, 0.74, 0.88	0.66	0.87

Structural Equation Modeling (SEM)

The factor structural path coefficients for the hypothesized relationships in the study, as assessed through Structural Equation Modeling (SEM), are presented in Table 5.

Table 5 shows the SEM results demonstrate that Teacher Readiness is the primary driver shaping teachers' perceptions of Augmented Reality (AR), as reflected in its significant effects on Perceived Ease of Use (β = 0.48; t = 7.12) and Perceived Usefulness (β = 0.42; t = 6.35). This indicates that when teachers are pedagogically, technically, and psychologically prepared, AR technologies are more likely to be perceived as accessible and beneficial for supporting sustainable STEM learning objectives aligned with the Sustainable Development Goals (SDGs). The validated TAM relationship between Perceived Ease of Use and Perceived Usefulness (β = 0.39; t = 5.98) further suggests that user-friendly AR applications enhance teachers' beliefs in their instructional value, particularly for visualizing complex STEM concepts related to sustainability. Moreover, the significant effects of Perceived Ease of Use (β = 0.31; t = 4.87) and Perceived Usefulness (β = 0.46; t = 6.91) on Attitude Toward Use indicate that positive perceptions of AR foster favorable attitudes toward its classroom integration. These attitudes, together with the perceived benefits of AR, significantly strengthen Behavioral Intention (Attitude Toward Use: β = 0.52; t = 8.14; Perceived Usefulness: β = 0.29; t = 4.56), highlighting teachers' willingness to adopt AR as a pedagogical tool for sustainable STEM education. Crucially, the strong influence of Behavioral

Intention on Deep Learning Orientation (β = 0.57; t = 9.03) confirms that teachers' intentions to use AR go beyond technological adoption and actively support deep learning processes, such as critical thinking, problem solving, and systems thinking, which are essential competencies for achieving SDG aligned sustainable STEM education (Blatti et al., 2019; English, 2023; Nagaraj et al., 2023; Yakub et al., 2025).

Table 5. Factor Structural Path Coefficients

Hypothesis	Path	Std. β	t-value	p-value	Result
H1	Teacher Readiness → PEOU	0.48	7.12	< 0.001	Supported
H2	Teacher Readiness → PU	0.42	6.35	< 0.001	Supported
H3	PEOU → PU	0.39	5.98	< 0.001	Supported
H4	PEOU → ATU	0.31	4.87	< 0.001	Supported
H5	PU → ATU	0.46	6.91	< 0.001	Supported
H6	ATU → BI	0.52	8.14	< 0.001	Supported
H7	PU → BI	0.29	4.56	< 0.001	Supported
H8	BI → Deep Learning Orientation	0.57	9.03	< 0.001	Supported

This study briefly shows that teacher readiness plays a central role in successful technology integration. When teachers are pedagogically, technically, and psychologically prepared, they tend to perceive technology more positively, develop favorable attitudes, and show stronger intentions to use it in teaching (Ekeh & Hadebe-Ndlovu, 2025; Gurer & Akkaya, 2022; Ismail Ngao, 2025; Y. Li et al., 2019; Marangi & Mauro, 2025; Ofem et al., 2025; Pongsakdi et al., 2021; Utaminingsih et al., 2023). These positive intentions are closely linked to deeper learning practices, indicating that technology adoption supports not only instructional efficiency but also meaningful learning (Cahyana et al., 2023; Listiana et al., 2025). The findings suggest that improving teacher readiness is a key strategy for promoting deep learning oriented and sustainable STEM education.

Table 6. Factor Explained Variance (R^2)

Endogenous Construct	R^2	Interpretation
PEOU	0.23	Moderate
PU	0.41	Substantial
ATU	0.49	Substantial
BI	0.56	Substantial
Deep Learning Orientation	0.32	Moderate

Data Table 6 shows PEOU (R^2 = 0.23, Moderate): Approximately 23% of the variance in PEOU is explained by the exogenous constructs that lead to it, indicating moderate explanatory power based on your criteria. This means the model is adequate in explaining perceived ease of use, but there is still a significant portion of the variance influenced by other factors outside the model. PU (R^2 = 0.41, Substantial): Approximately 41% of the variance in PU can be explained by its predictor constructs, and the "substantial" category indicates the model has fairly strong explanatory power for perceived usefulness. This indicates that the exogenous variables you used are relevant and contribute significantly to shaping PU. ATU (R^2 = 0.49, Substantial): Nearly 49% of the variance in attitude toward use (ATU) is explained by the preceding constructs, so the modeled causal relationship to ATU is considered substantial. This indicates that the model is quite effective in describing how prior perceptions (e.g., PEOU, PU, etc.) shape attitudes toward use. BI (R^2 = 0.56, Substantial): Approximately 56% of the variance in behavioral intention (BI) can be explained by its predictor constructs, indicating the model's strong explanatory power in explaining technology use intentions. In technology behavior research, this value is generally considered very adequate because intentions influence many external factors. Deep Learning Orientation (R^2 = 0.32, Moderate): Approximately 32% of the variance in deep learning orientation is explained by exogenous variables in the model, and is placed in the moderate category. This means the model has captured important factors influencing deep learning (Fan & Shi, 2022; Galphade et al., 2021; Li et al., 2017; Li & Wang, 2023; Liu et al., 2022), but there is still approximately two percent of the variance that may be explained by other variables that have not been included (Alkhattabi, 2017; Castaño-Calle et al., 2022). Illustrates the TAM Integration Model, highlighting the relationship between Teacher Readiness and Deep Learning Orientation. See figure 4.

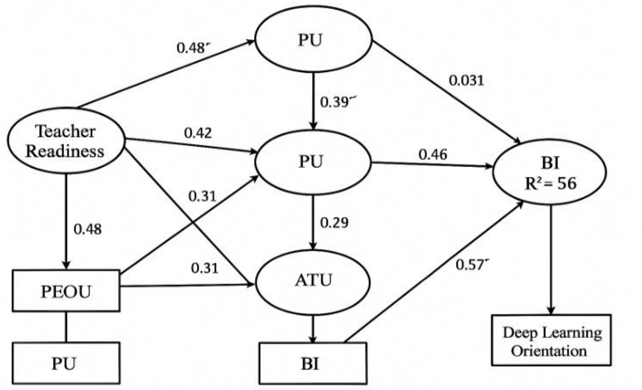

Figure 4. TAM Integration Model Teacher Redress and Deep Learning

From Figure 4 the SEM findings provide empirical evidence demonstrating how teacher readiness drives technology acceptance and deeper pedagogical outcomes. Teacher Readiness significantly influences Perceived Ease of Use (β = 0.48) and Perceived Usefulness (β = 0.42), indicating that pedagogical, technical, and psychological preparedness is a crucial foundation for teachers to positively perceive Augmented Reality (AR) in sustainable STEM contexts. In line with the Technology Acceptance Model, Perceived Ease of Use enhances Perceived Usefulness (β = 0.39), while both constructs shape Attitude Toward Use (PEOU: β = 0.31; PU: β = 0.46), highlighting that usability and instructional value are central to forming positive attitudes toward AR adoption. These attitudes, together with perceived usefulness, significantly strengthen Behavioral Intention (ATU: β = 0.52; PU: β = 0.29), with an explained variance of $R^2 = 0.56$, showing strong predictive power of the model. Most importantly, Behavioral Intention has a substantial effect on Deep Learning Orientation (β = 0.57), indicating that teachers' intentions to use AR extend beyond technical adoption and support deeper learning processes such as critical thinking, problem solving, and meaningful knowledge construction, which are essential for achieving SDG aligned sustainable STEM education (Berkova et al., 2023; Çetin, 2022; Sapta et al., 2025).

Multi Group Analysis

This analysis helps in understanding the generalizability of the model across diverse populations, with an overview of the Multi Group Analysis (MGA) results presented in Figure 5.

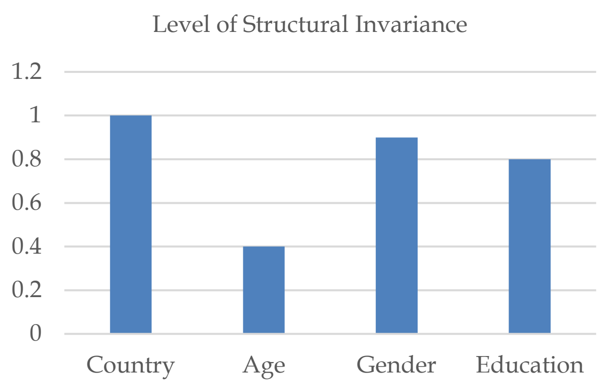

Figure 5. Multi Group Analysis (MGA) Result Overview

Figure 5 shows that the model's structural relationships are most consistent across Country, followed by Gender and Education, with the highest invariance observed in these groups. Age shows the lowest invariance, suggesting that age may influence how the model's relationships are perceived or applied.

The descriptive analysis reveals that the key constructs in this study such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Teacher Readiness, and Deep Learning Orientation (DLO) are generally rated quite highly by the teachers surveyed. This suggests that teachers hold favorable views toward integrating augmented reality (AR) into their teaching practices. High mean scores for PEOU and PU reflect that educators view AR as both user friendly and beneficial for enhancing STEM education, which aligns with the results of previous studies showing that these perceptions are pivotal in shaping technology adoption behaviors (Jamrus & Razali, 2021; Mundy et al., 2022). Furthermore, the findings highlight that teacher readiness both pedagogical and psychological is an essential factor influencing these perceptions.

In addition to the descriptive analysis, the Structural Equation Modeling (SEM) results indicate a strong, statistically significant relationship between Teacher Readiness and both PEOU and PU, which in turn influence Attitude Toward Use (ATU) and Behavioral Intention (BI). This model's robust explanatory power (R^2 values ranging from 0.23 to 0.56) underscores the importance of preparing teachers for technology integration, as their readiness directly impacts their perceptions and willingness to adopt AR for deep learning purposes. These findings are in line with the Technology Acceptance Model (TAM), which posits that perceived ease of use and usefulness shape attitudes and intentions toward technology use (Alfeo B. Tulang, 2025).

Importantly, the Multi Group Analysis (MGA) results indicate that the proposed model operates consistently across teachers from different countries, genders, and education levels, suggesting that the mechanisms through which teacher readiness and perceptions of augmented reality (AR) influence deep learning orientation are largely universal (Amores-Valencia et al., 2023; Stojšić et al., 2022). This stability implies that AR-based sustainable STEM integration aligned with the SDGs can be promoted using a common conceptual framework across diverse educational contexts (Badilla-Quintana et al., 2020; Chen, 2025; Hidayat et al., 2026; Ruiz-Muñoz et al., 2024; Sırakaya & Alsancak Sırakaya, 2022). However, the partial differences observed across age groups highlight that younger and older teachers may engage with AR differently, particularly in how readiness and perceived ease of use shape their attitudes toward adoption. This suggests that while the overall model is broadly generalizable, age-sensitive professional development and training programs are necessary to ensure effective AR integration that supports deep learning and sustainability oriented STEM education outcomes (Alfeo B. Tulang, 2025; Badilla-Quintana et al., 2020; Carrillo-ros, 2023; Chen, 2025; Hidayat et al., 2026; Ruiz-Muñoz et al., 2024; Sırakaya & Alsancak Sırakaya, 2022).

Thus, while the model demonstrates strong applicability across varied contexts, educators' specific needs especially regarding age-related factors must be addressed to ensure that AR can be effectively integrated into teaching strategies aimed at achieving sustainable development goals (SDGs). The findings suggest that teacher readiness is a key determinant for successful technology adoption, and targeted professional development could enhance teachers' capacity to foster deep learning in STEM education through AR (Cahyana et al., 2023; Listiana et al., 2025).

Conclusion

This study demonstrates that Teacher Readiness is a key determinant in teachers' acceptance of Augmented Reality (AR) and their adoption of deep learning-based STEM instruction. A survey of 250 teachers from Indonesia and Malaysia revealed that Teacher Readiness significantly influences both Perceived Ease of Use ($\beta = 0.48$) and Perceived Usefulness ($\beta = 0.42$) of AR, which in turn shape teachers' attitudes ($\beta = 0.31$ and $\beta = 0.46$) and intentions to use AR ($\beta = 0.52$). These attitudes have a strong influence on Deep Learning Orientation ($\beta = 0.57$), indicating the impact on fostering critical thinking and problem-solving in students. The model explains 56% of the variance in Behavioral Intention ($R^2 = 0.56$), showing strong explanatory power. Practical implications include focusing on teacher readiness through professional development and infrastructure support. However, the study's limitations, such as its focus on elementary school teachers from two countries, suggest the need for further research on the broader impact of AR across different educational contexts.

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Author Contributions
Conceptualization was carried out by W.S. and K.A.K.; methodology was developed by W.S.; software was managed by F.C.A.B.; validation was conducted by W.S., K.A.K., and N.B.J.; formal analysis was performed by S.M.; investigation was undertaken by F.C.A.B.; resources were provided by H.S.; data curation was handled by H.A.A.; writing—original draft preparation was completed by W.S.; writing—review and editing were carried out by S.M.; visualization was prepared by F.C.A.B.; supervision was provided by K.A.K.; project administration was managed by N.B.J.; and funding acquisition was secured by H.S. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest
The authors declare no conflict of interest

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