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The pathway from readiness to pedagogy: AI readiness as a catalyst for innovative lesson-designing in preservice teachers

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Abstract
The advancement of artificial intelligence is transforming educational practices, including how teachers design lessons. As artificial intelligence tools increasingly support lesson planning, content development, and assessment preparation, it is important to examine the factors that enable preservice teachers to design artificial intelligence -integrated lessons responsibly and pedagogically. Although the Technology Acceptance Model has been widely used to explain technology adoption, it may not fully capture the cognitive, affective, and pedagogical dimensions of artificial intelligence integration in teacher education. This study employed a quantitative explanatory design and collected survey data from 375 preservice teachers in Indonesia. The findings showed that artificial intelligence readiness was significantly associated with artificial intelligence -integrated lesson design and helped explain how technology self-efficacy and perceived usefulness are linked to pedagogical innovation. Emotional and psychological factors partially mediated the relationships of perceived usefulness and technology self-efficacy with artificial intelligence readiness but did not mediate their relationships with artificial intelligence -integrated lesson design, suggesting that cognitive and competence-related factors are more directly associated with the act of lesson design. The proposed model explained 70.8% of the variance in artificial intelligence -integrated lesson design, indicating strong predictive power. These findings suggest that artificial intelligence readiness plays an important role in connecting preservice teachers' beliefs and capabilities with practical pedagogical innovation.

Keywords: AI readiness; Artificial intelligence in education; Innovative learning design; Preservice teachers; Teacher education; Technology self-efficacy

1. Introduction

Digital transformation is reshaping educational systems and teacher professional practices. From this perspective, current teachers and preservice teachers [PSTs] are expected to develop the competencies needed to respond to rapidly evolving technologies (Akar et al., 2025). One of the most influential developments is the increasing presence of AI in education. As AI tools become part of instructional planning, assessment, and classroom decision-making, teachers need to understand not only how to use these tools but also how to evaluate their pedagogical and ethical implications (Guan et al., 2025).

Preparing PSTs for AI-integrated pedagogical practices is therefore essential for maintaining the relevance and quality of teacher education in a rapidly changing educational landscape (Dayagbil et al., 2025). Developing digital literacy has become an important component of professional competence among future teachers (Rahmawati & Tusyanah, 2025). AI tools are increasingly embedded in classroom environments and instructional design processes, as teachers and students encounter them in learning-related activities (Estaiteyeh & McQuirter, 2024; Mustafa, 2025). Although AI may enrich lesson design, its pedagogical use requires critical judgment to maintain instructional coherence, meaningful student participation, and ethical classroom practice.

Current teachers and PSTs already use generative AI tools, including chatbots, for lesson planning, content summarization, and assessment preparation (Açıkyıldız & Şahin, 2025; Yanar & Ergene, 2025). These practices provide opportunities for PSTs to explore how AI can support fundamental pedagogical tasks. However, AI integration should not be treated merely as a technical activity. PSTs' perceptions of AI may shape their lesson-planning decisions, which highlights the need for teacher education programs that address both technological and pedagogical dimensions of AI use (Celik, 2023; Rui et al., 2024). Teachers also need to reconsider their pedagogical practices and develop innovative mindsets that enable them to respond to diverse learner needs through the ethical and purposeful use of generative AI (Nguyen et al., 2025).

Despite this potential, many PSTs still have limited knowledge of basic AI concepts and limited practical experience with AI tools. This lack of experience may contribute to feelings of incompetence and professional unreadiness to teach with or about AI in authentic educational contexts (Bilbao-Eraña & Arroyo-Sagasta, 2025; Pratiwi et al., 2025). This gap indicates the need for training that moves beyond prompting skills and the evaluation of AI-generated outputs to include ethical implications, pedagogical decision-making, and the limitations of AI systems (Baimukhambetova et al., 2026). Accordingly, the effective and ethical use of AI in pedagogical practice should be examined in relation to multiple factors, including AI readiness.

Lesson planning is central to translating educational theory into effective classroom practice (Blonder et al., 2024). In this study, AI-integrated lesson design [AILD] refers to the purposeful use of AI tools to develop lesson plans, learning activities, instructional materials, assessments, and pedagogical strategies aligned with learning objectives. AILD should not be understood as the simple use of AI-generated outputs; rather, it requires teachers to critically evaluate, adapt, and pedagogically justify AI-supported design decisions. Although AI has the potential to support lesson planning, how it contributes to PSTs' cognitive and pedagogical development remains an important empirical question (An et al., 2025). AILD therefore depends on PSTs' technical proficiency, pedagogical knowledge, and awareness of how to use AI tools appropriately in educational settings (Ertmer & Ottenbreit-Leftwich, 2010; Voogt et al., 2012).

AI readiness should be conceptualized beyond traditional technology acceptance models by incorporating cognitive, affective, pedagogical, and ethical dimensions of AI integration. Although TAM (Davis, 1989) explains technology acceptance through users' beliefs about usefulness and ease of use, AI integration in education requires a broader understanding of teachers' preparedness to evaluate and apply AI in pedagogically meaningful ways. Such readiness includes knowledge of AI's capabilities and limitations, ethical awareness, and the ability to identify appropriate instructional uses of AI in diverse educational settings (Baimukhambetova et al., 2026). Teachers therefore need to understand how AI can personalize learning experiences, support administrative tasks, and provide data-informed insights while also recognizing its pedagogical and ethical boundaries.

AI readiness is therefore shaped by both cognitive and affective domains. In this study, perceived usefulness is grounded in Davis's (1989) definition of users' belief that a technology enhances performance, whereas AI readiness is conceptualized more broadly as PSTs' preparedness to understand, evaluate, and pedagogically integrate AI into lesson design. In addition, emotional and psychological factors [EPF], including AI-related anxiety, attitudes toward AI, and trust in AI, may shape how preservice teachers interpret and respond to AI integration (Wang & Chu, 2023). These factors are examined as affective mechanisms that may mediate the relationships between cognitive beliefs and AI-related readiness or practice.

Building on TAM and self-efficacy theory, this study considers perceived usefulness [PU] and technology self-efficacy [TSE] as foundational predictors of AI readiness among PSTs. PU reflects preservice teachers' beliefs about the instructional value of AI, whereas TSE refers to their confidence in using digital technologies for pedagogical purposes. These cognitive and competence-based beliefs may strengthen PSTs' readiness to integrate AI responsibly and effectively into lesson design. Previous studies have similarly identified AI-related self-efficacy and readiness as important antecedents of technology adoption intentions in educational contexts (Arab et al., 2025; Ramazanoğlu & Akin, 2024).

Accordingly, this study examines how PU, TSE, EPF, and AI readiness [AIR] jointly explain AI-integrated lesson design [AILD] among PSTs. PU and TSE are modeled as exogenous predictors of EPF, AIR, and AILD. EPF is examined as a mediating mechanism in the relationships between

PU/TSE and AIR/AILD. AIR is conceptualized as a proximal antecedent of AILD, indicating the extent to which preservice teachers are prepared to translate AI-related beliefs, competencies, and affective responses into pedagogical design practices. Through this model, the study explains how preservice teachers' beliefs, competencies, emotional-psychological responses, and readiness contribute to their capacity to design AI-integrated learning experiences.

2. Literature Review

This section reviews the theoretical and empirical foundations of the proposed model by clarifying the relationships among PU, TSE, EPF, AIR, and AILD. The review also establishes the conceptual rationale for positioning emotional and psychological factors as a mediating mechanism and AIR as a proximal antecedent of AI-integrated lesson design.

The model developed in this study is grounded primarily in the TAM, which conceptualizes technology adoption as a rational and belief-driven process (Davis, 1989). According to TAM, individuals' intention to use a technology is largely shaped by their perceptions of its usefulness and ease of use (Ajzen & Fishbein, 1974; Venkatesh & Davis, 2000). In educational settings, TAM has been widely used to explain how teachers evaluate and integrate digital technologies into pedagogical practice (Scherer et al., 2019; Teo, 2011). However, the integration of AI into education requires a broader framework because AI adoption involves not only cognitive evaluations of usefulness but also teachers' confidence, emotional responses, ethical concerns, and pedagogical decision-making.

AILD refers to preservice teachers' ability to design lesson plans in which AI tools are purposefully used to support learning objectives, instructional activities, assessment, and ethical decision-making. Lesson planning is one of the four core domains in Danielson's (1996) framework for teaching, together with classroom environment, instruction, and professional responsibilities. The planning domain is particularly relevant to AILD because it is the stage where teachers organize learning objectives, select instructional strategies, design assessment tasks, and anticipate students' learning needs. In this sense, AILD does not simply mean using AI to generate lesson materials; rather, it involves critically refining AI-generated outputs, aligning them with curriculum goals, and adapting them to students' needs. Therefore, AILD can support more coherent, efficient, and personalized lesson planning when AI is used with pedagogical judgment.

Perceived usefulness (PU) is one of the main predictors in this study. It refers to preservice teachers' belief that AI can enhance their future professional practice by improving lesson planning, instructional delivery, assessment design, and learning support. Grounded in Davis's (1989) definition, PU reflects the extent to which preservice teachers believe that AI can make their pedagogical work more efficient, productive, and effective. Previous studies have shown that teachers are more likely to adopt educational technologies when they perceive these tools as useful for achieving pedagogical goals (Gatlin, 2023; Ramazanoğlu & Akin, 2024). In the context of AI, perceived usefulness may encourage preservice teachers to view AI as a practical resource for designing instructional materials, personalizing learning experiences, and improving decision-making in teaching.

Technology self-efficacy [TSE], rooted in Bandura's (1997) social cognitive theory, refers to preservice teachers' belief in their ability to use digital technologies effectively in educational contexts. TSE goes beyond basic technical operation; it also includes confidence in exploring new tools, solving technological problems, adapting to digital environments, and using technology to support teaching and learning. Teachers with higher levels of technology self-efficacy are more likely to experiment with emerging technologies, persist when they face technical challenges, and experience lower levels of anxiety during technology integration (Hatlevik, 2017; Scherer et al., 2020). Thus, TSE functions as an important psychological and competence-based resource that may strengthen preservice teachers' readiness to engage with AI-supported pedagogical practices.

Although TAM provides a useful explanation of technology acceptance, it has been criticized for focusing mainly on cognitive and utilitarian factors while giving limited attention to affective and contextual dimensions (Bagozzi, 2007; Legris et al., 2003). This limitation is particularly important in the context of AI because teachers' engagement with AI may be shaped not only by perceived usefulness and self-efficacy but also by anxiety, attitudes, trust, and ethical concerns. Therefore, this study extends the TAM framework by incorporating emotional and psychological factors and AI readiness. In this extended model, PU and TSE are expected to influence not only AI readiness and AI-integrated lesson design directly but also EPF, which may serve as a mediating mechanism in the relationship between cognitive-competence beliefs and readiness or pedagogical action.

Emotional and psychological factors refer to preservice teachers' affective and psychological responses to AI, including AI anxiety, attitudes toward AI, and trust in AI. AI anxiety may arise from concerns about technical reliability, errors, privacy, data security, ethical risks, or the possibility that AI may threaten teachers' professional roles. Attitude toward AI reflects preservice teachers' general positive or negative evaluation of AI's role in society and education, while trust in AI refers to their confidence that AI systems are reliable, transparent, and appropriate for educational use (Yuan et al., 2022). These emotional and psychological factors may either strengthen or weaken the influence of perceived usefulness and technology self-efficacy on readiness. For example, high trust and positive attitudes may help preservice teachers translate their confidence and perceived benefits into AI readiness, whereas high anxiety may inhibit this process even when AI is perceived as useful.

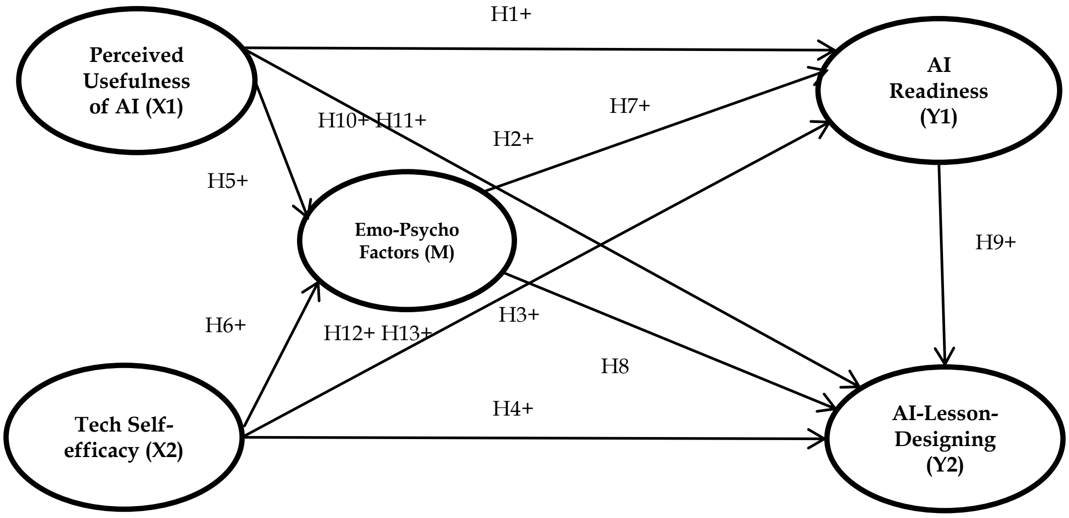
AI readiness is conceptualized as a multidimensional state of preparedness for the ethical, critical, and pedagogically meaningful integration of AI into educational practice. It goes beyond general digital literacy by combining technical understanding, critical evaluation, and pedagogical integration capacity. This conceptualization includes three interrelated domains. The technical-knowledge domain refers to preservice teachers' basic understanding of AI concepts, capabilities, applications, and limitations, including areas such as machine learning and natural language processing. The critical-evaluation domain involves their ability to assess AI tools and outputs in terms of bias, accuracy, privacy, ethical risks, transparency, and appropriateness for specific educational contexts (Ng et al., 2023). Finally, the pedagogical-integration domain reflects their confidence and competence in deciding when, where, and how AI can be meaningfully embedded into instructional activities to create added pedagogical value rather than superficial novelty (Celik, 2023).

In the proposed model, AI readiness represents a key link between preservice teachers' beliefs, affective responses, and pedagogical design practices. Preservice teachers who perceive AI as useful and believe in their ability to use technology are expected to demonstrate stronger readiness for AI integration. At the same time, their emotional and psychological responses may influence how these beliefs are transformed into readiness. AIR is therefore positioned as a proximal antecedent of AILD, indicating that readiness helps preservice teachers move from general beliefs and confidence toward the practical ability to design AI-integrated lessons. In this sense, readiness is not merely an intention to use AI but a preparatory condition that enables responsible and pedagogically meaningful lesson design.

AILD, as the final outcome of the model, involves the purposeful use of AI to support lesson planning in ways that are pedagogically valid, ethically appropriate, and aligned with instructional goals. Effective AILD requires teachers to identify genuine instructional needs, select suitable AI tools, evaluate AI-generated outputs, and adapt these outputs to students' learning characteristics and curricular expectations. It also requires attention to data privacy, fairness, accessibility, and the teacher's continuing role as the central pedagogical decision-maker (An et al., 2025; Daher, 2025). Therefore, AILD should not be understood as the automatic generation of lesson plans through AI, but as a reflective design process in which teachers combine content knowledge, pedagogical reasoning, technological competence, and ethical awareness.

Taken together, the proposed framework suggests that PU and TSE function as foundational predictors of AIR and AILD, while EPF serves as a mediating mechanism that may explain how cognitive and competence-based beliefs are translated into readiness and pedagogical design. AIR, in turn, is expected to serve as a direct antecedent of AILD because preservice teachers need readiness before they can meaningfully integrate AI into lesson planning. Thus, the model explains AI-integrated lesson design as the outcome of an interaction among perceived usefulness, technology self-efficacy, emotional-psychological responses, and AI readiness.

Figure 1
Research Model



H1: PU has a positive and significant effect on AIR.
H2: PU has a positive and significant effect on AILD.
H3: TSE has a positive and significant effect on AIR.
H4: TSE has a positive and significant effect on AILD.
H5: PU has a positive and significant effect on EPF.
H6: TSE has a positive and significant effect on EPF.
H7: EPF has a positive and significant effect on AIR.
H8: EPF has a positive and significant effect on AILD.
H9: AIR has a positive and significant effect on AILD.
H10: EPF significantly mediates the relationship between PU and AIR.
H11: EPF significantly mediates the relationship between PU and AILD.
H12: EPF significantly mediates the relationship between TSE and AIR.
H13: EPF significantly mediates the relationship between TSE and AILD.

3. Method

3.1. Research Design

A quantitative explanatory design using a survey method, testing a hypothesized model of relationships among PU, TSE, EFP, AIR, and AILD of preservice teachers. SEM is a suitable statistical method for testing complex relationships among the variables (Hair et al., 2017).

3.2. Participants

The total population was 6,300 eighth-semester PSTs from the 2022 intake at Universitas Negeri Semarang. Thus, using Slovin's formula with a 5% margin of error, the sample size was 375 respondents. The respondent characteristics are shown in Table 1.

3.3. Data Collection

An online questionnaire was organized using Google Forms for data collection. The instrument was organized with the following validated scales or indicators, as seen in Table 2: TSE (Bandura, 1997), PU (Himel et al., 2021), EPF (Ryff, 1989), AIR (World Economic Forum, 2023), and AILD (Shulman, 1987). Due to the potential for neutrality bias, a 4-point Likert scale (1 = Strongly Disagree to 4 = Strongly Agree) was employed. The statements for each indicator were adapted from previous studies grounded in these theories and then translated into Bahasa Indonesia.

Table 1
The Respondent Characteristics

Characteristics	*Number (n)*	*Percentage (%)*
Gender		
Male	120	32.0
Female	255	68.0
Study Programs		
STEM education	156	41.6
Social education	109	29.1
Humanities education	110	29.3
AI usage for designing the learning (Can be selected more than one)		
Lesson planning	293	78.1
Content summarization	244	65.1
Assessment preparation	263	70.1

A content validator and a language validator validated the translated statements. Subsequently, the final questionnaire was distributed to PSTs at *Universitas Negeri Semarang*. The validity and reliability of the instrument were measured using an outer-model analysis; the detailed results are presented in the Findings section.

3.4. Data Analysis

SmartPLS 4.0 was used to analyze the data validity. Convergent validity of the measurement model was assessed using outer loadings and Average Variance Extracted [AVE]. In contrast, the Fornell-Larcker criterion and the heterotrait-monotrait [HTMT] ratio were applied to check discriminant validity. Path coefficients, bootstrapped significance tests (5,000 resamples), and R^2 values were used to evaluate the structural model. Next, bootstrapped confidence intervals were used to examine the mediating role of AI readiness.

Table 2
Operational Definitions and Indicators of Research Variables

No	*Variables*	*Operational Definition*	*Indicator*	*Indicator Source*
1	Technology Self-Efficacy (X1)	An individual's belief in his or her ability to use a variety of digital technologies (hardware and software) effectively for common tasks in an educational context.	Level (magnitude) Strength Broad field of behavior (generality)	(Bandura, 1997)
2	Perceived Usefulness (X2)	Individual cognitive beliefs regarding the value and utility of AI technology to improve learning processes and outcomes.	Increase productivity Useful Efficiency Work more quickly Facilitate	(Himel et al., 2021)
3	Emotional & Psychological Factors (M1)	An individual's affective (emotional) state and psychological evaluation of AI, including anxiety, attitudes, and beliefs.	Self acceptance Positive relation with others Autonomy Environmental mastery Purpose of life	(Ryff, 1989)

Table 2 continued

No	*Variables*	*Operational Definition*	*Indicator*	*Indicator Source*
4	AI Readiness (Y1)	An individual's multidimensional readiness includes technical knowledge, critical evaluation skills, and confidence to integrate AI into professional practice.	Individual Readiness Organizational Readiness Readiness of the supporting ecosystem	(World Economic Forum, 2023)
5	AI-Integrated lesson-designing (Y2)	The ability to design and produce a structured lesson plan in which AI tools are employed for achieving specific learning objectives, while ensuring pedagogical and ethical appropriateness.	Knowledge of material representation Knowledge about students' difficulties and misconceptions Knowledge of content-appropriate pedagogical strategies	(Shulman, 1987)

Source: Processed secondary data (2026)

4. Results

4.1. Outer Model Test (Measurement Model)

According to Hair et al. (2017), Structural Equation Modeling [SEM] analysis with Smart PLS has three criteria for assessing the outer model: convergent validity, discriminant validity, and reliability, as shown in Figure 2.

Figure 2

Outer model (measurement model)

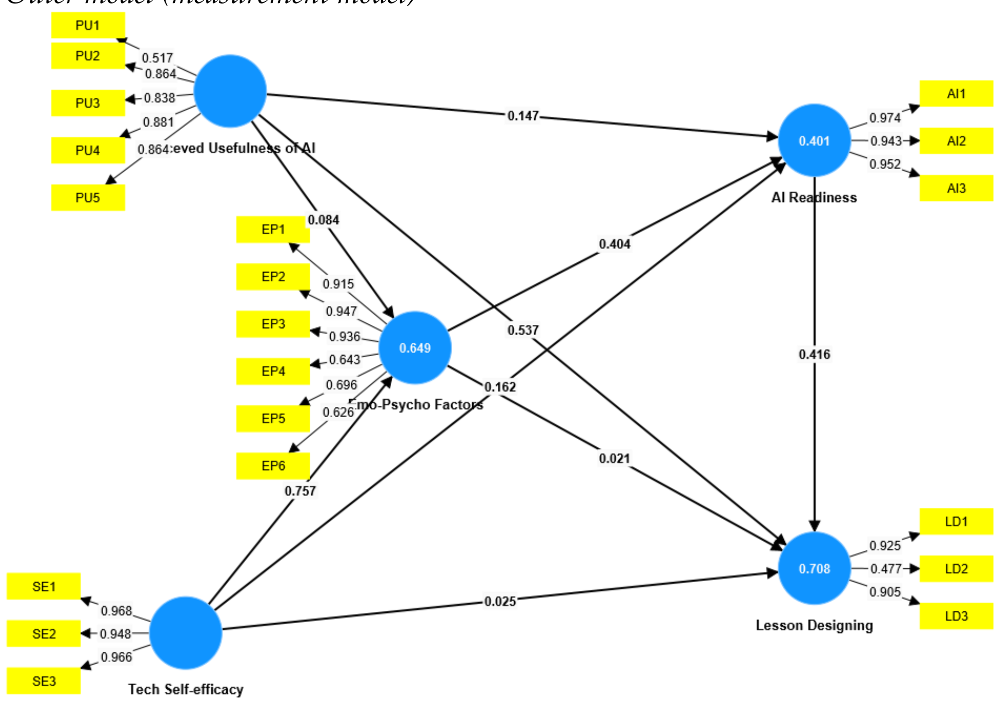


Figure 2 shows the measurement model to measure the latent constructs.

4.1.1. Convergent validity

The convergent validity test assesses outer loadings and AVEs. An indicator is considered of good quality if the outer loading is > 0.7 (Hair et al., 2017). The higher the outer loading value, the more important the factor loading is in interpreting the factor matrix. The following is a convergent validity test, as shown by the outer loadings in Table 3.

Table 3
Outer loading of each indicator of the variables

	Outer loadings	*AVE*	*Notes*
AI1 → AI Readiness	0.974	0.915	Valid
AI2 → AI Readiness	0.943		Valid
AI3 → AI Readiness	0.952		Valid
EP1 → Emo-Psycho Factors	0.915	0.650	Valid
EP2 → Emo-Psycho Factors	0.947		Valid
EP3 → Emo-Psycho Factors	0.936		Valid
EP4 → Emo-Psycho Factors	0.643		Valid
EP5 → Emo-Psycho Factors	0.696		Valid
EP6 → Emo-Psycho Factors	0.626		Valid
LD1 → lesson-designing	0.925	0.636	Valid
LD2 → lesson-designing	0.477		Valid
LD3 → lesson-designing	0.905		Valid
PU1 → Perceived Usefulness	0.517	0.630	Valid
PU2 → Perceived Usefulness	0.864		Notes
PU3 → Perceived Usefulness	0.838		Valid
PU4 → Perceived Usefulness	0.881		Valid
PU5 → Perceived Usefulness	0.864		Valid
SE1 → Tech Self-efficacy	0.968	0.923	Valid
SE2 → Tech Self-efficacy	0.948		Valid
SE3 → Tech Self-efficacy	0.966		Valid

Source. Processed data, 2026.

The outer loadings and AVE values for each construct in Table 2. Although some indicators (EP4 = 0.643; EP5 = 0.696; EP6 = 0.626; LD2 = 0.477; P1 = 0.517) are lower than the generally acceptable threshold of 0.70, all constructs yield AVE values greater than the accepted threshold of 0.50 (0.630 to 0.923). Following Fornell and Larcker (1981), information convergent validity is established when the AVE is greater than 0.50, showing that the construct explains more than half of the variance of its indicators. Furthermore, Hair et al. (2017) also suggested that indicators with loadings between 0.40 and 0.70 can be retained if they contribute to acceptable composite reliability and AVE. Therefore, despite lower individual loadings, the indicators met the AVE criterion for convergent validity.

4.1.2. Discriminant validity

Discriminant validity is used to determine whether an indicator is a good measure of its construct; each indicator is not highly correlated with indicators of other constructs. The discriminant validity test should meet the following thresholds: (1) the HTMT (Heterotrait-Monotrait Ratio) value is less than 0.90, and (2) the Fornell-Larcker Criterion indicates that the square root of the AVE (Average Variance Extracted) value should be greater than its highest correlation with other constructs (Hair et al., 2017). Table 4 presents the HTMT and the Fornell-Larcker criterion. All values in the HTMT matrix are below the 0.85 threshold, confirming that the constructs are valid and statistically different.

4.1.3. Reliability test

Reliability is the consistency, dependability, and accuracy of indicators of the variable over time. It is carried out by examining Cronbach’s alpha and composite reliability. It is shown in Table 5.

Table 4

Discriminant validity of the HTMT and the Fornell-Larcker criterion test result

	Heterotrait-monotrait ratio (HTMT) - Matrix					
	AI Readiness	*Emo-Psycho Factors*	*Lesson-designinging*	*Perceived Usefulness*	*Tech Self-efficacy*	*Notes*
AI Readiness						
Emo-Psycho Factors	0.656					Valid
Lesson-designinging	0.839	0.737				Valid
Perceived Usefulness	0.447	0.553	0.940			Valid
Tech Self-efficacy	0.590	0.856	0.732	0.591		Valid
	Fornell-Larcker criterion					
	AI Readiness	*Emo-Psycho Factors*	*Lesson-designing*	*Perceived Usefulness*	*Tech Self-efficacy*	*Notes*
AI Readiness	0.956					Valid
Emo-Psycho Factors	0.607	0.806				Valid
Lesson-designinging	0.678	0.562	0.796			Valid
Perceived Usefulness	0.438	0.500	0.744	0.805		Valid
Tech Self-efficacy	0.567	0.803	0.573	0.550	0.961	Valid

Source: Processed data, 2026

Table 5
Cronbach's Alpha research variable

	Cronbach's alpha	*Composite reliability (rho_a)*	*Composite reliability (rho_c)*	*Cronbach's Alpha Level*	*Notes*
AI Readiness	.953	.957	.970	.70	Reliable
Emo-Psycho Factors	.884	.917	.915	.70	Reliable
Lesson-designinging	.657	.695	.829	.70	Reliable
Perceived Usefulness	.857	.847	.899	.70	Reliable
Tech Self-efficacy	.958	.958	.973	.70	Reliable

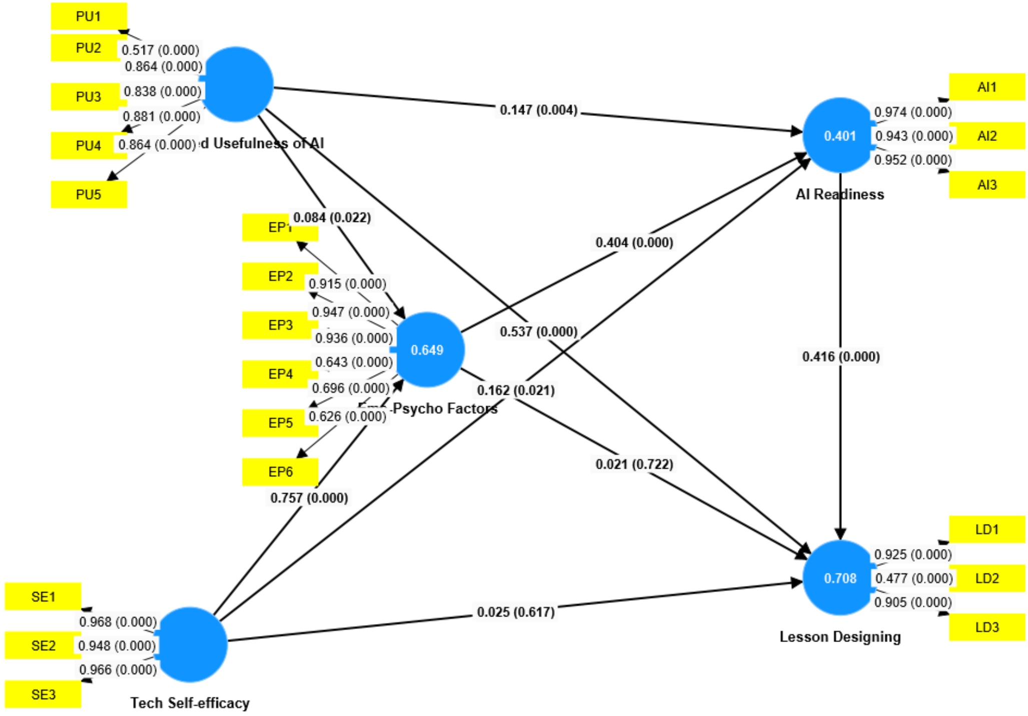
Source: Processed data, 2026.

Table 4 shows that all constructs meet the reliability criteria, with Cronbach's Alpha values > .7. The highest Cronbach's Alpha values are held by TSE (.958) and AIR (.953), indicating excellent internal consistency. Meanwhile, AILD has the lowest Cronbach's Alpha value (.657), which is below 0.7; however, because the AVE is above .5, the variable can be relied upon (Hair et al., 2017). These results show that all constructs are reliable and convergent, and thus suitable for further analysis in a structural model.

4.2. Inner Model (Structural Model)

Hair et al. (2017) state that a structural model illustrates the relationships among latent variables (constructs) based on the proposed hypotheses. The results of this inner model testing are shown in Figure 3.

Figure 3
Inner model (structural model)



4.2.1. Direct effects

The structural model, or inner model, aims to predict the relationships among hypothesized latent variables. The structural model shows the direct effect using the original sample, with *t*-statistics or P-values as shown in Table 6.

Table 6
Direct Effects Hypothesis Testing Results

	Original sample (O)	*Sample mean (M)*	*Standard deviation (STDEV)*	*T statistics (|O/STDEV|)*	*P values*	*Hi*	*Noted*
PU → AIR	0.181	0.184	0.054	3.380	.001	H1	Accepted
PU→AILD	0.614	0.616	0.026	24.064	<.001	H2	Accepted
TSE →AIR	0.467	0.467	0.049	9.548	<.001	H3	Accepted
TSE →AILD	0.235	0.233	0.035	6.662	<.001	H4	Accepted
PU → EPF	0.084	0.085	0.037	2.286	.022	H5	Accepted
TSE → EPF	0.757	0.757	0.032	23.288	<.001	H6	Accepted
EPF → AIR	0.404	0.403	0.061	6.587	<.001	H7	Accepted
EPF →AILD	0.189	0.190	0.057	3.292	.001	H8	Accepted
AIR →AILD	0.416	0.418	0.050	8.291	<.001	H9	Accepted

Note. Source: Processed data, 2026; PU: Perceived Usefulness; TSE: Technology Self-Efficacy; EPF: Emotional-Psychological Factors; AI readiness: AI Readiness; AILD: AI-Integrated lesson-designing.

As shown in Table 5, all direct effect hypotheses were supported. PU demonstrated a significant positive effect on AIR ($\beta = 0.181$, $p = .001$) and a strong effect on AILD ($\beta = 0.614$, $p < .001$). TSE significantly influenced AIR ($\beta = 0.467$, $p < .001$) on AILD ($\beta = 0.235$, $p < .001$), and EPF ($\beta = 0.757$, $p < .001$) significantly predicted AIR ($\beta = 0.404$, $p < 0.001$) and AILD ($\beta = 0.189$, $p = .001$). Finally, AIR demonstrated a significant positive effect on AILD with $\beta = 0.416$ and $p < .001$.

4.2.2. Mediation effects

Table 7 presents the results of mediation hypothesis testing, examining the indirect effects through EPF.

Table 7
Mediation Effects Hypothesis Testing Results

	Original sample (O)	*Sample mean (M)*	*Standard deviation (STDEV)*	*T statistics (|O/STDEV|)*	*P values*	*Hi*	*Noted*
PU→EPF→AIR	0.034	0.035	0.017	2.012	.044	H10	Accepted
PU→EPF→AILD	0.002	0.002	0.005	0.326	.745	H11	Rejected
TSE→EPF→AIR	0.305	0.304	0.045	6.751	<.001	H12	Accepted
TSE→EPF→AILD	0.016	0.0017	0.045	0.353	.724	H13	Rejected

Source: Processed data, 2026.

The analysis revealed that EPF partially mediated the relationships between PU and AIR for H10 ($\beta = 0.034$, $p = .044$) and between TSE and AIR for H12 ($\beta = 0.305$, $p < .001$). In both cases, the direct effects remained significant, indicating partial mediation. However, EPF did not significantly mediate the relationships between PU and AILD for H11 ($\beta = 0.002$, $p = .745$) or between TSE and AILD for H13 ($\beta = 0.016$, $p = .724$), thereby rejecting H11 and H13.

4.2.3. Model predictive power

The model's predictive power was assessed using R^2 values for each endogenous construct. Table 8 presents the R^2 results.

Table 8
R-Square test result

	R-square	*R-squa e adjusted*	*Notes*
AI Readiness	0.401	0.397	Moderate
Emo-Psycho Factors	0.649	0.647	Moderate
AI lesson-designing	0.708	0.705	Strong

Source: Processed data, 2026.

As shown in Table 7, the model shows a strong predictive power for AILD, explaining 70.8% of the variance. The model explained 64.9 percent of the variance in EPF and 40.1 percent of the variance in AIR. They had moderate predictive power according to Chin's (1998) criteria.

5. Discussion

5.1. The Differential Roles of Perceived Usefulness and Technology Self-Efficacy

There is a differential pattern of effects for PU and TSE across the model. PU emerged as the dominant predictor of AILD, while TSE more strongly influenced AIR and EPF. This result suggests a division of labor between these two foundational beliefs.

PU serves as a motivational driver. When PSTs clearly see AI's practical value for their teaching, they may be motivated to attempt integration even before they feel fully prepared. This interpretation aligns with Davis's (1989) original formulation of TAM, which posited PU as the primary determinant of usage intentions. The strong effect on lesson design suggests that PU directly translates into pedagogical action.

TSE functions more as an enabling resource that operates through multiple pathways. Confident teachers develop greater AI readiness and experience more positive emotional states. Through these mechanisms, they become better positioned to practice lesson planning. The strong effect of self-efficacy on EPF is noteworthy. It suggests that confidence in one's technological capabilities is a powerful antidote to AI-related anxiety and a foundation for positive attitudes and trust. It aligns with Bandura's (1997) social cognitive theory, which posits that self-efficacy is a primary determinant of affective responses to novel challenges. The critical role of self-efficacy is further underscored by Brozmanová et al. (2022), who found that teacher self-efficacy is fundamental to adapting practice in a complex educational atmosphere.

The relatively modest effect of PU on EPF is informative. Simply believing that AI is useful does not automatically reduce anxiety or increase attitudes. Teachers may recognize AI's potential benefits while still feeling uneasy about its implications for their professional autonomy or concerned about ethical issues. This finding highlights the limitations of cognitive approaches to technology acceptance and supports calls for greater attention to affective dimensions (Bagozzi, 2007; Legris et al., 2003).

5.2. AI Readiness as a Mediating Mechanism

AIR significantly predicts AILD, thereby validating the role of the bridge between foundational beliefs and pedagogical practice. PSTs who have technical knowledge, critical evaluation skills, and pedagogical confidence are better equipped to design lessons that meaningfully integrate AI. It aligns with a study by Sekarwangi et al. (2021), which found that well-designed technology in enhanced learning environments, grounded in sound pedagogical models, can significantly improve educational outcomes. Similarly, the principles of adaptive learning discussed by Kalmakov (2026) suggest that effective technology integration requires a deep understanding of both technological capabilities and pedagogical goals.

The fact that direct effects of PU and TSE on AILD remained significant even with AIR in the model suggests that AIR does not fully account for the translation of beliefs into practice. Teachers may sometimes design AILD solely based on strong utility perceptions or confidence, even without full multidimensional readiness. This finding has practical implications, suggesting that teacher education programs should not delay AI integration until perfect readiness is achieved; rather, they should provide opportunities for simultaneous development of readiness and implementation experience.

5.3. The Nuanced Role of Emotional-Psychological Factors

The mediation findings reveal important nuances regarding how EPF operates along the pathways to AIR and AILD. EPF partially mediated the relationships between foundational beliefs and AIR for H10 and H12, but did not mediate the relationships with AILD for H11 and H13.

This hypothesis suggests that affective factors are more influential in shaping the readiness than in directly driving implementation. When PSTs perceive AI as useful and feel confident in their technological capabilities, these beliefs contribute to more positive emotional states, which in turn enhance their multidimensional readiness. However, once teachers reach the stage of active lesson-designing, affective factors recede in importance, and implementation is driven more directly by cognitive beliefs and readiness.

Interestingly, the indirect effect through EPF was substantial for the TSE-to-AIR pathway but negligible for pathways to AILD. Emotional states matter for getting ready; they matter less for actually doing. Aligned with the work of Arhin et al. (2026), who demonstrated that self-efficacy beliefs mediate the impact of affective states, such as anxiety, on performance outcomes. The situation suggests a similar layered pathway in which foundational affects shape competencies, which then directly influence action or behavior.

The significant role of EPF in shaping readiness also connects to broader research on teacher well-being and engagement. Efridita (2026) highlighted how emotional exhaustion can negatively influence professional engagement, underscoring the importance of addressing affective dimensions in teacher preparation. Similarly, Werang et al. (2025) also found that several factors, including psychological states, influence academic engagement.

5.4. Theoretical Contributions

This study contributes to the literature on technology acceptance and on teacher preparation in several ways. It first combines the TAM by treating AIR as a mediating mechanism between the classical TAM constructs and the pedagogical outcome (in particular, perceived usefulness). Although previous studies have applied TAM-derived concepts to predict behavioral intention, this study suggests that for complex technologies such as AI, a unidimensional measure of readiness may not be sufficient for a meaningful implementation experience.

Second, results incorporate affective components of technology acceptance models. This study shows that EPF is vital and partially mediates the effects, implying that a purely cognitive approach cannot fully explain AI adoption. In doing so, it responds to longstanding criticisms around neglect of affective factors in TAM (Bagozzi, 2007) and extends recent efforts to explore the role of emotions in AI adoption (Wang & Chu, 2023; Yuan et al., 2022). The complex nature of these factors parallels achievement motivation research by Evsen and Canses (2025), which restates the complex interactions among psychological variables in determining educational outcomes.

Third, this study adds to the limited literature on AIR by acknowledging the multidimensional nature and the empirical link to pedagogical practice of the foundational beliefs that constitute AIR. R^2 indicates strong predictive power of the model for lesson design, supporting the articulation of AIR as an important pathway for preparing teachers for AI-mediated classroom delivery (Martínez-Martínez & Fernández-Larragueta, 2026). This conceptualization and its potential relevance to broader debates on professional identity development argue that innovative practices become embedded in teachers' conceptions of their professional role.

5.5. Practical Implications

The practical implications for teacher education programs based on the study are:

First, the strong influence of PU on AILD suggests that teachers should clearly demonstrate the practical value of AI for solving real pedagogical problems. Rather than treating AI as a standalone topic, programs should embed it in authentic design tasks to ground its relevance. It aligns with the principle that meaningful learning, including the development of digital resources such as e-modules (Armiati et al., 2026), should be authentic.

Second, the significant effect of TSE on both readiness and lesson-designing highlights the need to build PSTs' confidence with AI tools before expecting them to teach with them. It can be reached through scaffolded, hands-on experiences that allow problem-solving in low-stakes environments. Developing digital competencies: Asrizal et al. (2026) noted that training experiences foster positive attitudes and confidence in the use of innovative tools.

Third, the EPF relates to the need for attention to the affective domain. PSTs should understand

and normalize anxiety around AI, model positive attitudes through successful integration examples, and create trusting spaces where concerns can be openly discussed. Addressing these emotional responses is critical, as unresolved psychological pressure can lead to disengagement (Werang et al., 2025). Supporting PSTs' emotional well-being can, in turn, foster the resilience needed for sustained academic engagement (Efridita, 2026).

Finally, given AIR as the mediating role, programs should improve all three of its dimensions: technical knowledge, critical evaluation skills, and pedagogical confidence. Curriculum design should combine all dimensions through structured learning experiences, as AI can provide basic knowledge (Armiati et al., 2026). Then, critical evaluation skills can be developed by analyzing AI-generated content and its biases. Pedagogical confidence, meanwhile, can be developed through supervised, hands-on practice in designing and delivering AI-integrated lessons grounded in the frameworks. These experiences help form PSTs' identities as innovative and confident practitioners prepared to teach in an AI-driven era (Martínez-Martínez & Fernández-Larragueta, 2026).

6. Conclusion

The results reveal that AIR is an important pathway linking preservice teachers' foundational beliefs and affective states to their ability to design innovative AI-integrated lessons. PU and TSE both significantly influence AIR, but in different ways. PU has a direct but moderate effect on AIR, while TSE affects it both directly and indirectly through EPF. It implies that internalizing familiarity with technology is critical for training PSTs to improve their multidimensional readiness needed for AI use.

EPF is also important, but in a more subtle way. It partially mediates the relationship between foundational beliefs and AI readiness, suggesting that affective states help interpret cognitive beliefs and confidence into actual readiness. However, they do not mediate relationships with AILD, suggesting that, at the implementation stage, cognitive and competence factors might have a more direct effect.

AI readiness is an important mechanism between future teachers' beliefs, skills, and psychological states and their actual skills in designing innovative AI-based learning. The results of this study have theoretical and practical implications for enhancing digital-era teacher education in Indonesia.

However, this study does have limitations. The study can only provide evidence of correlation, not of cause-and-effect relationships. Since the sample is from a single Indonesian university, the information may not apply to other settings. Also, the model does not account for all external influences that might affect an educationist's personality map; instead, it identifies potential avenues for cross-cultural and longitudinal research for future work.

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