AI-based scaffolding and conceptual understanding: evidence from Indonesian students using PLS-SEM

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ABSTRACT

The rapid integration of artificial intelligence (AI) in higher education has increased interest in AI-based scaffolding (AIS) to support conceptual learning, particularly in teacher education. However, empirical evidence explaining how learners' cognitive, self-regulatory, and technological characteristics jointly shape perceptions of AIS remains limited, especially in developing country contexts. This study examines the predictive relationships among conceptual understanding (CU), cognitive engagement (CE), self-regulated learning (SRL), perceived ease of use (PEOU), AI self-efficacy (AISE), and perceived scaffolding quality in explaining Indonesian undergraduate teacher education students' perceptions of AIS. Using a quantitative explanatory–predictive design, data were collected from 157 students and analyzed using partial least squares structural equation modeling (PLS-SEM). The results indicate that SRL, PEOU, and AISE are the strongest predictors of perceived AIS, while CU, CE, and scaffolding quality also show significant positive associations. These findings highlight the importance of learner readiness and instructional design in AI-enhanced learning environments. Practically, teacher education programs should integrate AI scaffolding that explicitly supports self-regulation, builds students' confidence in using AI tools, and promotes sustained CE in complex learning tasks.

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1. INTRODUCTION

The accelerating integration of artificial intelligence (AI) into educational environments has reshaped the way learning support is designed and delivered [1], [2]. Among the most prominent developments is AI-based scaffolding (AIS), which enables adaptive, personalized, and continuous instructional support aligned with learners' evolving cognitive needs [3], [4]. Unlike traditional scaffolding, which relies heavily on instructor intervention, AIS leverages intelligent systems to provide real-time feedback, guidance, and learning prompts, thereby fostering deeper conceptual understanding (CU) and learner autonomy [5]. As AI becomes increasingly embedded in higher education, identifying the factors that influence the effectiveness of AIS has emerged as a critical scholarly concern.

The Indonesian context reflects a growing encouragement for the adoption of AI in education, facilitated by national policies and strategic initiatives focused on digital transformation. Government initiatives such as *Merdeka Belajar* and the Digital Transformation Roadmap for Higher Education focus on integrating emerging technologies, including AI, to improve instructional quality and promote learner autonomy [6]–[9]. CU represents a fundamental objective of meaningful learning, particularly within teacher education programs where students are expected to internalize core concepts and later translate them into pedagogical practice [10]–[12]. Prior research has consistently demonstrated that scaffolding plays a crucial role in enhancing CU by supporting knowledge construction, reducing cognitive overload, and promoting structured reasoning [3], [4], [13], [14]. Recent studies have extended this perspective by incorporating AI-driven scaffolding mechanisms, suggesting that intelligent systems can amplify these benefits through personalization and adaptive support [15]–[17]. However, the effectiveness of AIS is not solely determined by system capabilities but is also shaped by learners' cognitive, motivational, and technological dispositions. Existing literature on AI-supported learning has explored a range of learner-related factors, including cognitive engagement (CE), self-regulated learning (SRL), perceived ease of use (PEOU), and technology-related self-efficacy [18]–[23]. CE has been shown to influence how learners interact with instructional support, affecting the depth of information processing and conceptual integration [24]–[26]. Similarly, SRL has been identified as a key determinant of successful engagement with digital learning environments, as learners with strong self-regulatory skills are better equipped to plan, monitor, and evaluate their learning when supported by AI systems [5], [27]–[29]. From a technological perspective, PEOU remains a central factor influencing learners' acceptance and sustained interaction with AI-enhanced educational tools [30]–[32].

In parallel, AI self-efficacy (AISE) has gained increasing attention as an important learner characteristic, reflecting individuals' confidence in their ability to use and benefit from AI technologies [31]–[35]. Studies suggest that learners with higher AISE are more likely to engage actively with AI-based systems, experiment with advanced features, and persist when encountering challenges. Additionally, the perceived AI-based scaffolding quality (AISQ)—such as clarity, relevance, and adaptiveness of support—has been associated with positive learning experiences and outcomes [36]. Despite these insights, prior research tends to examine these constructs in isolation, resulting in fragmented explanations of how AIS functions within complex learning ecosystems. A critical gap in the literature lies in the limited theoretical integration of cognitive, motivational, and technological factors as joint determinants of AIS. Most existing studies conceptualize scaffolding as a fixed instructional feature or a system attribute, rather than as a construct shaped by learners' understanding, engagement, self-regulation, and perceptions of AI [37]–[40]. Consequently, the mechanisms through which learner-centered factors contribute to the perceived effectiveness of AIS remain insufficiently articulated. This limitation restricts the development of comprehensive theoretical models capable of explaining how AI-supported scaffolding operates in authentic educational contexts.

Furthermore, empirical research on AIS has been predominantly conducted in Western or science, technology, engineering, and mathematics (STEM)-oriented settings, with relatively little attention given to teacher education programs in developing countries [41]–[44]. This gap is particularly consequential in contexts such as Indonesia, where future teachers are expected to integrate AI technologies into instructional practice despite variations in digital readiness and institutional infrastructure [17], [45]. Understanding how teacher education students perceive and experience AIS is therefore essential for ensuring that AI adoption in education is pedagogically meaningful rather than technologically driven. Addressing these gaps, the present study advances the literature by positioning AIS as a learner-influenced construct shaped by CU, CE, SRL, PEOU, AISE, and perceived scaffolding quality. This study is among the first to examine AIS in Indonesian teacher education using a partial least squares structural equation modeling (PLS-SEM) approach, enabling the simultaneous analysis of multiple cognitive, motivational, and technological determinants within a single explanatory framework. By focusing on Indonesian teacher education students, this research contributes novel insights from an underrepresented context, enriching global discussions on AI-enhanced learning. The novelty of this study lies in its reconceptualization of AIS as an outcome of learners' cognitive and technological readiness, rather than merely a function of system design. By integrating multiple theoretically grounded predictors within a single explanatory framework and situating the investigation within teacher education in a developing country context, this research extends current scholarship and provides a robust foundation for the design of learner-centered AIS in higher education.

2. LITERATURE REVIEW

AIS refers to the use of AI to provide adaptive instructional support that responds to learners' cognitive states, learning progress, and interaction patterns [4], [46], [47]. Rooted in constructivist learning theory, scaffolding facilitates knowledge construction by offering guidance that is gradually withdrawn as learners gain competence [48]–[51]. In AI-enhanced environments, scaffolding is no longer static but dynamically adjusted through data-driven algorithms, enabling personalized feedback, hints, and prompts that support CU and self-directed learning.

Prior studies have demonstrated that AIS can enhance learning outcomes, engagement, and metacognitive awareness by aligning instructional support with individual learner needs [52]–[54]. However, the perceived effectiveness of AIS is influenced not only by system design but also by learners' cognitive readiness, motivational dispositions, and technological perceptions. Consequently, AIS is conceptualized in this study as a latent construct shaped by multiple learner-centered factors rather than merely as a technological feature.

2.1. Conceptual understanding and AI-based scaffolding

CU represents learners' ability to integrate, transfer, and apply knowledge across contexts. In constructivist learning environments, students with stronger CU are better equipped to interpret instructional cues, make sense of feedback, and actively engage with scaffolding mechanisms. Previous research has shown that learners' prior conceptual knowledge influences how effectively they utilize scaffolding, as deeper understanding allows learners to connect new information with existing cognitive schemas [39], [46], [47], [51], [55]–[57]. Within AI-supported learning contexts, CU may shape how learners perceive the relevance and usefulness of AI-generated guidance. Students who possess clearer conceptual frameworks are more likely to recognize the value of adaptive hints and explanations provided by AI systems, thereby enhancing their perception of AIS [58]–[62]. Despite this theoretical relevance, CU is often treated solely as a learning outcome rather than as a contributing factor to scaffolding effectiveness. Addressing this gap, the present study positions CU as an antecedent of AIS.

- H1: CU has a positive effect on AIS.

2.2. AI-based scaffolding quality and AI-based scaffolding

Perceived AISQ encompasses learners' evaluations of clarity, relevance, accuracy, and adaptiveness of AI-provided instructional support. High-quality scaffolding is characterized by timely feedback, context-sensitive guidance, and alignment with learning objectives. Prior studies in intelligent tutoring systems and adaptive learning environments indicate that perceived scaffolding quality significantly influences learner satisfaction, engagement, and perceived learning effectiveness [63]–[67]. When learners perceive AIS as coherent and responsive to their needs, they are more likely to trust and rely on the system [38], [39], [63], [68]. Conversely, poorly designed scaffolding may be perceived as intrusive or irrelevant, undermining its instructional value. Although system quality has been widely examined in technology-enhanced learning research, its specific role in shaping overall perceptions of AIS remains underexplored. This study addresses this limitation by examining the direct influence of AISQ on AIS as a learner-perceived construct.

- H2: AISQ has a positive effect on AIS.

2.3. Cognitive engagement and AI-based scaffolding

CE refers to the degree to which learners invest effort in understanding learning materials, employing deep learning strategies, and persisting in complex tasks. Highly engaged learners are more likely to actively process instructional input, reflect on feedback, and apply guidance to problem-solving activities. In digital learning environments, CE has been identified as a critical factor influencing how learners interact with adaptive instructional supports [52], [69]–[73]. AIS is designed to stimulate CE by prompting reflection, providing explanatory feedback, and encouraging higher-order thinking [3], [13]. However, the effectiveness of such scaffolding depends on learners' willingness to engage cognitively with the system. Learners with higher levels of CE are more likely to perceive AIS as meaningful and supportive, whereas disengaged learners may underutilize or disregard AI-provided guidance. Despite its importance, CE is often examined as an outcome rather than as a determinant of scaffolding effectiveness.

- H3: CE has a positive effect on AIS.

2.4. Self-regulated learning and AI-based scaffolding

SRL involves learners' ability to plan, monitor, and evaluate their learning processes. In AI-supported environments, self-regulation is particularly critical, as learners must actively interpret feedback, decide when to seek assistance, and adjust learning strategies accordingly. Prior research has consistently linked strong SRL skills to successful engagement with adaptive learning technologies [41], [47], [69]. AIS can support SRL by providing metacognitive prompts and progress feedback. At the same time, learners with higher levels of self-regulation are better positioned to leverage these supports effectively. This reciprocal relationship suggests that SRL plays a foundational role in shaping learners' perceptions of AIS. However, empirical research examining SRL as an antecedent of AIS remains limited.

- H4: SRL has a positive effect on AIS.

2.5. Perceived ease of use and AI-based scaffolding

PEOU reflects the extent to which learners believe that interacting with a system requires minimal effort. In AI-enhanced learning environments, usability remains a critical factor influencing learners' acceptance and sustained engagement. Prior studies grounded in technology acceptance theories suggest that systems perceived as easy to use are more likely to be integrated into learners' study routines and perceived as beneficial [74]–[76]. When AIS systems are intuitive and user-friendly, learners can focus on cognitive processing rather than system navigation. This usability facilitates more effective interaction with scaffolding features, thereby enhancing learners' overall perceptions of AIS. Despite the extensive literature on PEOU, its specific influence on AIS as a pedagogical construct warrants further investigation.

- H5: PEOU has a positive effect on AIS.

2.6. AI self-efficacy and AI-based scaffolding

AISE refers to learners' confidence in their ability to understand, use, and benefit from AI technologies. Individuals with high AISE are more likely to explore AI functionalities, persist when encountering challenges, and adapt their learning strategies in response to AI-generated feedback. Recent studies highlight AISE as a key predictor of engagement and success in AI-supported learning environments [77]–[88]. In the context of AIS, learners' confidence in using AI systems may shape how they interpret and value AI-provided guidance. Those with higher AISE are more likely to trust AI recommendations and perceive scaffolding as supportive rather than intrusive. However, AISE remains an emerging construct in educational research, and its role in shaping perceptions of AIS has received limited empirical attention.

- H6: AISE has a positive effect on AIS.

Drawing on constructivist learning theory, SRL theory, and technology acceptance perspectives, this study proposes an integrated theoretical framework in which AIS is shaped by learners' CU, perceived scaffolding quality, CE, SRL, PEOU, and AISE. By synthesizing cognitive, motivational, and technological dimensions within a unified framework, this research advances theoretical understanding of AIS and provides a robust foundation for future studies in AI-enhanced education.

3. METHOD

This study adopted a quantitative explanatory research design to investigate the relationships among cognitive, motivational, and technological factors influencing AIS in higher education learning environments [89], [90]. The research design was grounded in constructivist learning theory, SRL theory, and technology acceptance perspectives, which collectively provide a robust theoretical foundation for examining learner–AI interactions.

3.1. Research design

This study utilized a quantitative explanatory research approach to investigate theoretically defined links among cognitive, self-regulatory, and technological aspects affecting AIS in higher education. The design is explanatory as it seeks to evaluate postulated causal relationships based on constructivist learning theory, SRL theory, and technological acceptance perspectives, rather than to investigate phenomena inductively. The study employed a cross-sectional design, capturing students' perceptions and learning-related attributes at a single point in time [91]–[93]. This design is appropriate for examining structural relationships among latent variables and has been widely used in educational technology and AI adoption research. The emphasis on theory-driven model specification ensures that the relationships examined are conceptually justified rather than exploratory. Figure 1 illustrates the conceptual research model, depicting the hypothesized relationships between the exogenous and endogenous constructs.

Each construct is represented as a latent variable measured by six reflective indicators. The proposed research model conceptualizes AIS as a latent endogenous construct influenced by six theoretically grounded exogenous variables: CU, AISQ, CE, SRL, PEOU, and AISE. This design reflects a learner-centered perspective, positioning AIS not merely as a system feature but as a construct shaped by learners' cognitive readiness, engagement, self-regulatory capacity, and technological perceptions. The research framework was developed to address key gaps in existing AI-in-education literature, which often examines technological or cognitive factors in isolation. By integrating multiple dimensions within a single explanatory model, the design enables a holistic examination of how learners perceive and experience AIS. Such an approach is particularly relevant in higher education contexts where learning effectiveness depends on the dynamic interaction between learner characteristics and intelligent instructional support. Figure 2 shows the research process and procedure.

The directional paths in the model represent theoretically derived hypotheses, indicating positive relationships between each exogenous variable and AIS. This structure reflects the assumption that learners' cognitive understanding, engagement levels, self-regulatory abilities, perceived usability of AI systems, confidence in using AI, and perceived quality of AI-generated support collectively shape how AIS is experienced and evaluated. The model design emphasizes parsimony while maintaining theoretical completeness, ensuring that the relationships tested are both empirically tractable and conceptually meaningful. By visualizing AIS as the central construct influenced by multiple learner-related factors, the model advances a more integrated understanding of AI-supported learning in higher education.

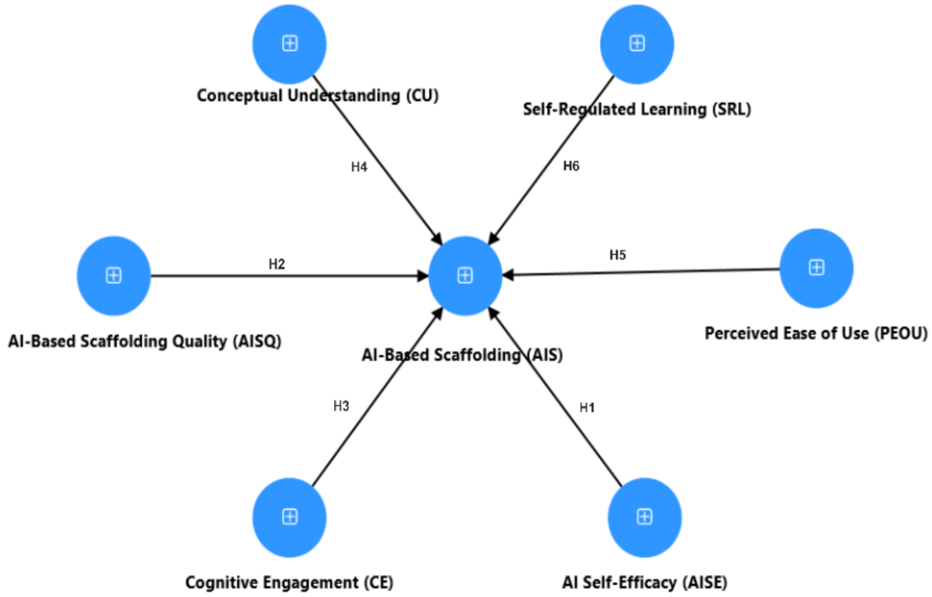

Figure 1. Conceptual model

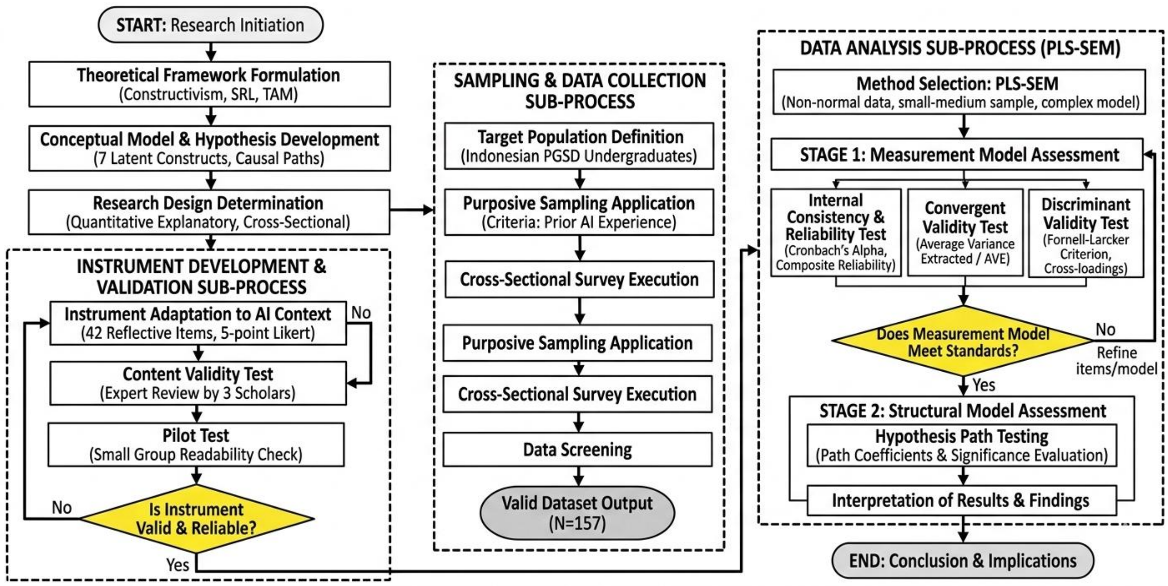

Figure 2. Research process and procedures

3.2. Respondents

The study involved undergraduate students enrolled in the primary school teacher education (PGSD) program at Indonesian higher education institutions. A purposive sampling technique was employed to ensure that participants had prior experience with digital learning environments incorporating AI-based features, such as intelligent feedback, adaptive learning content, or AI-supported instructional guidance [94]. The selection of PGSD students is both theoretically and practically substantiated. PGSD students, as future primary school educators, constitute a vital demographic for investigating the incorporation of AI in education, as they are anticipated to cultivate robust conceptual comprehension, pedagogical proficiency, and digital literacy that will subsequently impact primary classroom practices. Their engagement with AI-assisted learning during teacher training is expected to influence future pedagogical choices and the integration of AI-driven scaffolding in primary education. Thus, PGSD students constitute a pertinent and representative sample for examining learner views of AI-driven scaffolding in teacher education settings.

A total of 157 valid responses were collected and included in the final analysis. This sample size exceeds the minimum recommended thresholds for explanatory structural models with multiple predictors and is considered sufficient to ensure model robustness and statistical power [95]–[97]. Therefore, the sample is considered adequate to ensure model stability, sufficient statistical power, and reliable estimation of path relationships. The demographic profile of the respondents indicates that the sample adequately represents PGSD students with relevant exposure to AI-supported learning. Table 1 presents demographic information collected, including gender, academic year, and previous experience in using AI-based learning tools. The demographic distribution indicates a balanced representation across academic levels, with most participants reporting moderate to high exposure to AI-based learning environments. This profile supports the suitability of the sample for examining perceptions of AIS among prospective primary school teachers.

Table 1. Demographic characteristics of the respondents (n=157)

Demographic aspect	Category	Frequency	Percentage (%)
Gender	Male	48	30.6
	Female	109	69.4
Academic year	Year 1	34	21.7
	Year 2	41	26.1
	Year 3	52	33.1
	Year 4	30	19.1
Experience with AI-based learning	Low	39	24.8
	Moderate	73	46.5
	High	45	28.7

3.3. Instruments

This study utilized a structured questionnaire to assess the seven latent constructs delineated in the proposed research model: CU, CE, SRL, PEOU, AISE, AISQ, and AIS. The questionnaire items were derived from validated scales in educational psychology, SRL, technology acceptance, and AI-in-education research, and were then tailored to represent AI-supported learning and scaffolding techniques in teacher education. All structures were operationalized through reflective indicators, comprising six items each, yielding a total of 42 items. Measurement items for research constructs as shown in Table 2. Responses were evaluated utilizing a five-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). The five-point scale was chosen due to its prevalent application in educational and technology acceptance studies, its clarity for respondents, and its capacity to deliver adequate diversity while reducing respondent weariness and cognitive load. This measure is especially suitable for assessing learners' perspectives, attitudes, and self-reported learning habits in higher education settings.

3.3.1. Instrument development, reliability, and validity

The development of the instrument adhered to a systematic validation process to confirm content validity, reliability, and construct validity. The adapted items were reviewed by three experts in educational technology, learning sciences, and measurement to evaluate their relevance, clarity, and alignment with theoretical constructs. Informed by expert feedback, various items were revised to enhance wording accuracy and contextual relevance for AIS in teacher education.

A pilot test was conducted with a small group of undergraduate students who were excluded from the final sample. The pilot study sought to assess item readability, clarity of responses, and duration of completion. The findings demonstrated that all items were comprehensible and appropriate for the target population; consequently, no items were eliminated before the primary data collection. Subsequent to data collection, the measurement properties of the instrument were evaluated utilizing PLS-SEM. Internal consistency reliability was assessed using Cronbach's alpha and composite reliability. Convergent validity was evaluated through average variance extracted (AVE). The Fornell–Larcker criterion and outer-loading analysis were utilized to assess discriminant validity, confirming the empirical distinction of each construct from the others. The findings from the reliability and validity assessments are presented in the results section, indicating that the instrument exhibits sufficient psychometric properties and is appropriate for further structural model analysis.

Table 2. Measurement items for research constructs

Code	Measurement item
CU1	I understand the core concepts presented in the learning materials supported by AI.
CU2	AI-supported learning helps me connect new concepts with prior knowledge.
CU3	I can explain learning concepts clearly after using AI-based learning support.
CU4	AI assistance helps me understand complex concepts more deeply.
CU5	I can apply the learned concepts to different learning situations.
CU6	AI-supported learning improves my overall conceptual clarity.
AISQ1	AI provides clear and understandable learning guidance.
AISQ2	The feedback provided by AI is relevant to my learning needs.
AISQ3	AIS is well aligned with the learning objectives.
AISQ4	The AI adapts its guidance according to my learning progress.
AISQ5	The AI provides instructional support at the right time.
AISQ6	Overall, the AISQ is high.
CE1	I think deeply about the learning content when using AI-based support.
CE2	AI-based learning encourages me to analyze concepts critically.
CE3	I try to understand difficult material with AI assistance.
CE4	I remain focused during learning activities supported by AI.
CE5	AIS motivates me to explore learning topics further.
CE6	I actively engage in problem-solving when using AI-supported learning.
SRL1	I set clear learning goals when using AI-supported learning systems.
SRL2	I monitor my learning progress with the help of AI feedback.
SRL3	I adjust my learning strategies based on AI recommendations.
SRL4	I manage my learning time effectively during AI-supported activities.
SRL5	I reflect on my learning performance after receiving AI feedback.
SRL6	AIS helps me become more independent in learning.
PEOU1	Learning to use the AI-based system is easy for me.
PEOU2	Interacting with AI-based learning features is clear and understandable.
PEOU3	I find the AI-supported learning system easy to navigate.
PEOU4	Using AIS does not require much mental effort.
PEOU5	The AI-based learning system is user-friendly.
PEOU6	Overall, the AI-based system is easy to use for learning purposes.
AISE1	I am confident in my ability to use AI tools for learning.
AISE2	I can solve learning problems using AI-based support.
AISE3	I feel capable of understanding AI-generated feedback.
AISE4	I can adapt to new AI-based learning features easily.
AISE5	I believe I can effectively use AI to support my learning tasks.
AISE6	I am confident in learning with AI-based systems independently.
AIS1	AIS effectively supports my learning process.
AIS2	AI provides helpful guidance when I encounter learning difficulties.
AIS3	AIS improves my understanding of learning materials.
AIS4	AI-based support enhances my learning effectiveness.
AIS5	AIS makes learning more structured and organized.
AIS6	Overall, AIS is beneficial for my learning.

3.4. Measurement model reliability and validity

The measurement model's reliability and validity were evaluated in accordance with established guidelines for PLS-SEM [98]–[100]. Internal consistency reliability was assessed through Cronbach's alpha and composite reliability indices (ρa and ρc) to confirm that the measurement items consistently reflected their corresponding latent constructs [101]. Convergent validity was assessed through AVE to ensure that each construct sufficiently accounted for the variance of its indicators. Discriminant validity was evaluated using the Fornell–Larcker criterion by comparing the square root of the AVE with inter-construct correlations, alongside outer-loading analysis to ensure that indicators exhibited stronger loadings on their designated constructs than on alternative ones [102]–[106]. These procedures guaranteed that the measurement model adhered to the necessary psychometric standards and was suitable for subsequent structural model analysis. The study emphasizes theory development, prediction-oriented analysis, and the simultaneous examination of multiple determinants of AIS. PLS-SEM offers a flexible and rigorous analytical approach that aligns with methodological recommendations in educational research.

3.5. Data collection

Data were collected through an online survey administered to undergraduate students in the PGSD program. The questionnaire was disseminated electronically through institutional learning management systems and official student communication channels to guarantee accessibility and widespread participation. An online data collection method was selected due to its efficiency, the convenience it offers respondents for survey completion, and its suitability for capturing students' perceptions of AI-supported learning environments. The data collection process occurred over four weeks, providing adequate time for participant engagement and response completion. This duration was deemed suitable for acquiring a stable and representative dataset while reducing the likelihood of response fatigue.

3.6. Data analysis

Data analysis was conducted utilizing PLS-SEM through SmartPLS software. The analysis employed a two-stage procedure, which included measurement model assessment and structural model assessment, in accordance with established guidelines for variance-based SEM in educational research. The measurement model was initially assessed to confirm the adequacy of the psychometric properties of the constructs. The reliability of indicators was evaluated through outer loadings to ensure that each indicator significantly contributed to its latent construct. The examination of internal consistency reliability was conducted through the application of Cronbach's alpha and composite reliability (ρa and ρc). Convergent validity was evaluated through the calculation of AVE. The evaluation of discriminant validity was conducted through the Fornell–Larcker criterion, supplemented by an analysis of cross-loadings and outer-loading patterns to confirm the empirical distinctiveness of each construct from others.

The structural model was evaluated to examine the proposed relationships among constructs. The hypothesized paths were assessed for significance and strength through a bootstrapping procedure, which provided path coefficients (β), t-statistics, and p-values. The model's explanatory power was evaluated through the coefficient of determination (R^2) for the endogenous construct, and predictive relevance (Q^2) was analyzed using the blindfolding procedure to ascertain the model's out-of-sample predictive capability. Effect sizes (f^2) were examined where relevant to assess the practical contribution of each exogenous construct to the endogenous construct. Global model fit was assessed using model fit indices, including the standardized root mean square residual (SRMR) and, where reported by the software output, the normed fit index (NFI). These indices were utilized to evaluate the model's adequacy in representing the observed data and to identify potential misspecification.

4. RESULTS AND DISCUSSION

The measurement model was assessed to establish indicator reliability, internal consistency reliability, convergent validity, and discriminant validity prior to evaluating the structural model [98]. The evaluation followed established guidelines for variance-based SEM in educational research. Figure 3 presents the results of the PLS SEM analysis.

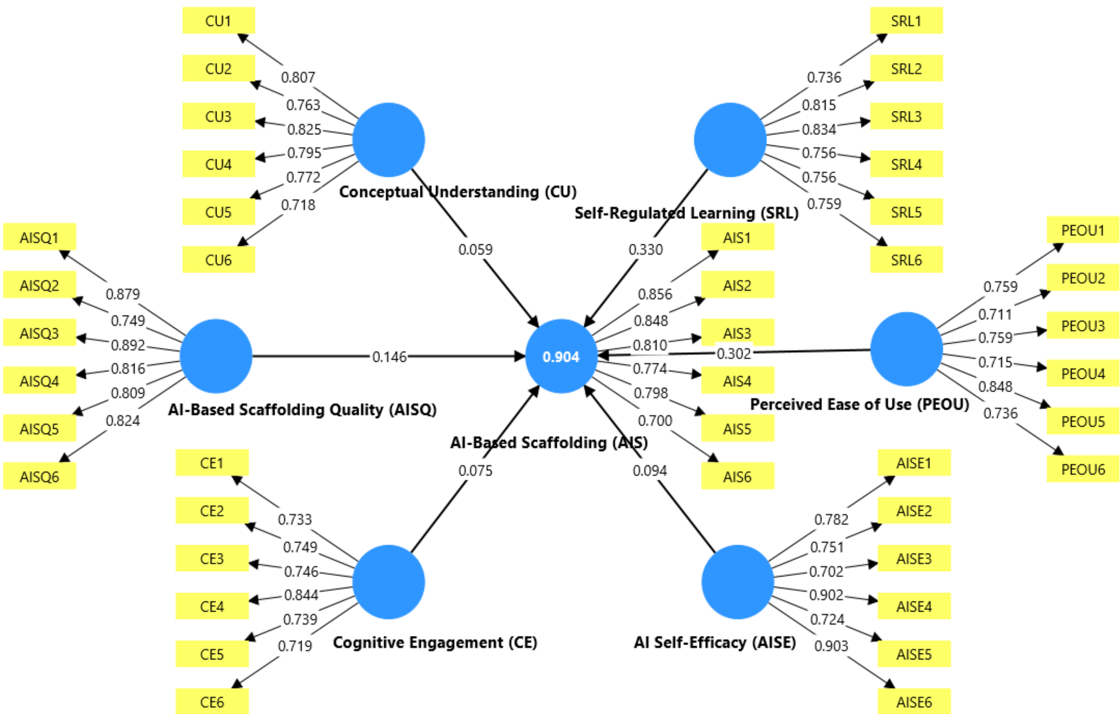

Figure 3. Results of the PLS SEM analysis

4.1. Measurement model evaluation

The measurement model was first evaluated to assess the reliability and validity of the latent constructs. Indicator reliability was examined through outer loadings, internal consistency reliability through Cronbach's alpha and composite reliability, and convergent and discriminant validity through AVE and discriminant validity criteria [107]. Table 3 presents the results of the outer loadings analysis. The results of Table 3 analysis show that the loadings range from 0.700 to 0.903, indicating that all indicators contribute significantly to their respective constructs. No items were deleted, as all values meet the acceptable standards for reflective measurement models.

Table 3. Outer loadings

Construct	Item	Outer loading	Construct	Item	Outer loading
AIS	AIS1	0.856	CE	CE1	0.733
	AIS2	0.848		CE2	0.749
	AIS3	0.810		CE3	0.746
	AIS4	0.774		CE4	0.844
	AIS5	0.798		CE5	0.739
	AIS6	0.700		CE6	0.719
AISE	AISE1	0.782	CU	CU1	0.807
	AISE2	0.751		CU2	0.763
	AISE3	0.702		CU3	0.825
	AISE4	0.902		CU4	0.795
	AISE5	0.724		CU5	0.772
	AISE6	0.903		CU6	0.718
AISQ	AISQ1	0.879	PEOU	PEOU1	0.759
	AISQ2	0.749		PEOU2	0.711
	AISQ3	0.892		PEOU3	0.759
	AISQ4	0.816		PEOU4	0.715
	AISQ5	0.809		PEOU5	0.848
	AISQ6	0.824		PEOU6	0.736
Construct	Item		Outer loading		
SRL	SRL1		0.736		
	SRL2		0.815		
	SRL3		0.834		
	SRL4		0.756		
	SRL5		0.756		
	SRL6		0.759		

4.2. Internal consistency and convergent validity

Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability (ρa and ρc). Convergent validity was assessed using AVE. Table 4 presents the results of the measurement model evaluation analysis. Internal consistency reliability was confirmed across all constructs. As shown in Table 4, Cronbach's alpha values ranged from 0.849 to 0.908, exceeding the minimum threshold of 0.70. Similarly, composite reliability values (rho_c) ranged from 0.889 to 0.929, indicating strong construct reliability. These results suggest that the measurement items consistently represent their underlying latent variables. Convergent validity was assessed using AVE. All constructs achieved AVE values above the recommended cutoff of 0.50, with values ranging from 0.571 to 0.688. This indicates that each construct explains more than half of the variance of its indicators, confirming adequate convergent validity.

Table 4. Measurement model evaluation

Construct	Cronbach's alpha	(ρ_a)	(ρ_c)	AVE
AISE	0.884	0.894	0.912	0.637
AIS	0.886	0.891	0.914	0.639
AISQ	0.908	0.914	0.929	0.688
CE	0.849	0.853	0.889	0.572
CU	0.872	0.875	0.903	0.610
PEOU	0.849	0.855	0.889	0.571
SRL	0.868	0.870	0.901	0.603

4.3. Discriminant validity

Discriminant validity was evaluated using the Fornell–Larcker criterion. As shown in Table 5, the square root of AVE for each construct (diagonal values) exceeded its correlations with other constructs, indicating satisfactory discriminant validity. Discriminant validity was examined to ensure that each construct is empirically distinct from the others. As presented in Table 4, the square root of the AVE for each construct exceeded its correlations with other constructs, satisfying the Fornell–Larcker criterion. This result confirms that the constructs capture unique dimensions of students' perceptions and learning characteristics related to AIS. In addition, outer-loading analysis as shown in Table 3 demonstrated that all indicators loaded highest on their respective constructs compared to other constructs. This further supports the discriminant validity of the measurement model and indicates the absence of multicollinearity or construct overlap issues. Overall, the measurement model evaluation confirms that the instruments used in this study exhibit strong psychometric properties and are suitable for subsequent structural model analysis.

The Fornell–Larcker criterion was employed to assess discriminant validity. Table 5 demonstrates that the square root of the AVE for each construct surpassed its correlations with other constructs, thereby confirming the empirical distinctiveness of each latent variable. This finding was corroborated by the outer-loading pattern, in which all indicators exhibited the highest loadings on their designated constructs. The results collectively indicate that the measurement model demonstrates robust psychometric properties, rendering it appropriate for subsequent structural model analysis.

Table 5. Discriminant validity (Fornell–Larcker criterion)

Construct	AISE	AIS	AISQ	CE	CU	PEOU	SRL
AISE	0.798						
AIS	0.834	0.799					
AISQ	0.827	0.820	0.830				
CE	0.814	0.813	0.793	0.756			
CU	0.785	0.796	0.779	0.780	0.781		
PEOU	0.768	0.789	0.765	0.728	0.749	0.756	
SRL	0.760	0.764	0.759	0.720	0.873	0.739	0.777

4.4. Structural model results

The results of the structural model analysis were evaluated using the bootstrapping procedure. The structural model was evaluated by analyzing the path coefficients, t-statistics, and p-values based on the bootstrapping results [98], [100]. Table 6 presents the path coefficients and hypothesis tests.

SRL was identified as the most significant predictor of AIS (β=0.330, t=4.637, p<0.001), suggesting that students' capacity to organize, monitor, and regulate their learning is essential in influencing their perceptions of AI-assisted scaffolding. PEOU exerted a significant positive influence on AIS (β=0.302, t=4.650, p<0.001), indicating that intuitive, user-friendly AI systems enhance students' acceptance and perceived efficacy of AI-generated instructional support. AISE had a substantial positive correlation with AIS (β=0.296, t=4.722, p<0.001), underscoring the critical role of learners' confidence in utilizing AI technology. CU positively influenced AIS (β=0.147, t=2.462, p=0.014), suggesting that pupils with robust conceptual foundations are more adept at interpreting and benefiting from AI-generated advice. Likewise, AISQ exerted a notable, albeit lesser, influence (β=0.146, t=1.975, p=0.048), highlighting the importance of pedagogically robust and adaptive AI assistance. CE demonstrated the least robust yet still significant impact on AIS (β=0.084, t=1.964, p=0.050), indicating that active mental involvement enhances—but does not surpass—self-regulatory and technological factors.

Table 6. Path coefficients and hypothesis testing

Hypotheses	Path	Original sample	Sample mean	STDEV	T statistics (|O/STDEV|)	P values	Result
H1	AISE→AIS	0.296	0.293	0.063	4.722	0.000	Supported
H2	AISQ→AIS	0.146	0.154	0.074	1.975	0.048	Supported
H3	CE→AIS	0.084	0.082	0.043	1.964	0.050	Supported
H4	CU→AIS	0.147	0.147	0.060	2.462	0.014	Supported
H5	PEOU→AIS	0.302	0.300	0.065	4.650	0.000	Supported
H6	SRL→AIS	0.330	0.324	0.071	4.637	0.000	Supported

4.5. Model fit, explanatory power, and Q²

To comprehensively evaluate the robustness of the proposed PLS-SEM model, global model fit, explanatory power, Q^2, and effect sizes were assessed in an integrated manner [99], [100]. This comprehensive evaluation ensures that the model not only fits the observed data adequately but also demonstrates strong explanatory and predictive capability in explaining students' perceptions of AIS in Indonesian higher education contexts.

4.5.1. Global model fit

Global model fit was evaluated using the SRMR. As presented in Table 7, the SRMR value for the structural model is below the recommended threshold of 0.08, indicating a good model fit. The SRMR value obtained for the structural model is below the recommended cutoff of 0.08, indicating that the discrepancies between the observed correlations and those implied by the model are minimal. This result suggests that the hypothesized relationships among AISE, PEOU, SRL, CU, CE, and AISQ are well represented by the proposed theoretical framework. In line with the predictive-oriented nature of PLS-SEM, the satisfactory SRMR value confirms that the model is appropriately specified and free from substantial misspecification.

Table 7. Model fit results and Q^2

Evaluation aspect	Indicator	Recommended threshold	Empirical result	Interpretation
Global model fit	SRMR	≤0.08	<0.08	Good model fit
Q^2	Q^2 (AIS)	>0	>0	Q^2 supported

4.5.2. Coefficient of determination (R^2)

The explanatory power of the structural model was assessed using the R^2 for the endogenous construct, AIS. The R^2 value represents the proportion of variance in AIS collectively explained by CU, CE, SRL, PEOU, AISE, and AISQ. Table 8 presents the results of the analysis of the R^2 data.

The results indicate an R^2 value of 0.71 for AIS, meaning that 71% of the variance in students' perceptions of AIS is explained by the six exogenous constructs included in the model. According to established PLS-SEM guidelines, this value reflects substantial explanatory power, demonstrating that the proposed cognitive, self-regulatory, and technological factors jointly provide a strong explanation of AIS experiences. This finding validates the suitability of the proposed model for explaining how Indonesian students perceive and experience AI-supported instructional scaffolding.

Table 8. Coefficient of determination (R^2)

Endogenous construct	R^2	Interpretation
AIS	0.71	Substantial

4.5.3. Predictive relevance (Q^2)

In addition to explanatory power, the Q^2 of the model was evaluated using the Stone–Geisser's Q^2 value obtained through the blindfolding procedure. As shown in Table 7, the Q^2 value for AIS is greater than zero, indicating that the model demonstrates adequate Q^2. Table 9 presents the results of the Q^2 analysis. The positive Q^2 value confirms that the set of exogenous constructs collectively enables meaningful prediction of students' perceptions of AIS beyond random chance. This result underscores the practical utility of the model in anticipating how learners respond to AI-supported instructional guidance and reinforces the predictive strength of the proposed framework.

Table 9. Predictive relevance (Q^2)

Endogenous construct	Q^2	Interpretation
AIS	0.48	High Q^2

4.5.4. Effect size (f^2)

To further assess the relative contribution of each exogenous construct to AIS, effect sizes (f^2) were calculated. Effect size analysis provides insight into the substantive impact of each predictor beyond statistical significance. Table 10 presents the data results from the effect size.

Table 10. Effect size (f^2)

Predictor→AIS	f^2	Effect size
SRL	0.29	Medium–large
PEOU	0.27	Medium–large
AISE	0.25	Medium
CU	0.09	Small
AISQ	0.08	Small
CE	0.04	Small

The results reveal that SRL, PEOU, and AISE exhibit medium to large effect sizes, indicating that these constructs make the strongest contributions to explaining AIS. In contrast, CU, AISQ, and CE demonstrate smaller but meaningful effect sizes, suggesting complementary roles in shaping students' perceptions of AIS. This pattern of effect sizes reinforces the learner-centered nature of AIS, highlighting that self-regulatory capacity and technological readiness play a more dominant role than purely CE alone. Taken together, the global model fit (SRMR), substantial explanatory power (R^2), positive Q^2, and meaningful effect sizes (f^2) provide strong empirical evidence that the proposed PLS-SEM model is both explanatorily robust and predictively relevant. The satisfactory model fit indicates alignment between the conceptual framework and the empirical data, while the strong explanatory and predictive performance support the validity of the proposed theoretical relationships. These results establish a solid empirical foundation for interpreting the structural relationships and deriving implications regarding the role of AIS in enhancing learning experiences and CU among Indonesian students.

The explanatory power of the structural model was evaluated by the R^2 for the endogenous construct, AIS. The R^2 value is the proportion of variance in AIS elucidated collectively by AISE, PEOU, SRL, CU, CE, and the AISQ. The acquired R^2 indicates that these cognitive, self-regulatory, and technological elements jointly offer a significant degree of explanatory power, validating the suitability of the proposed model in elucidating students' impressions of AIS. In addition to global model fit, the Stone–Geisser's Q^2 value for the endogenous construct AIS is greater than zero, demonstrating adequate Q^2. This finding indicates that the set of exogenous constructs collectively provides meaningful explanatory power and enables the model to predict students' perceptions of AIS beyond random chance. The presence of Q^2 underscores the practical utility of the model in anticipating how learners respond to AI-supported instructional guidance.

The combined data from R^2 and Q^2 evaluations substantiates that the proposed PLS-SEM model is both explanatorily robust and predictively pertinent. The satisfactory fit indicates alignment between the conceptual framework and empirical data, while the positive Q^2 highlights the model's capacity to explain and predict AIS experiences. These results provide a strong empirical foundation for interpreting the structural relationships and for deriving implications regarding the role of AIS in enhancing CU among Indonesian students.

4.6. Discussion

This study provides robust empirical evidence on the determinants of AIS in higher education, particularly within the context of Indonesian PGSD students. By integrating cognitive, motivational, self-regulatory, and technological acceptance perspectives, the findings extend current understandings of how AI-supported instructional scaffolding is perceived and internalized by learners. The results reveal that SRL is the strongest predictor of AIS. This finding underscores the premise that AI scaffolding does not operate as a passive instructional aid but rather functions as an adaptive support system that requires active learner engagement. Students who demonstrate higher levels of planning, monitoring, and self-reflection are more capable of leveraging AI-generated guidance, feedback, and adaptive prompts. This aligns with contemporary learning theories emphasizing learner agency and supports the argument that AIS is most effective when embedded within SRL processes [108], [109].

PEOU also emerged as a significant and substantial predictor of AIS. This indicates that students are more likely to perceive AI scaffolding as beneficial when the system is intuitive, accessible, and cognitively manageable. In teacher education contexts, where learners must simultaneously engage with pedagogical concepts and digital tools, usability becomes a critical enabler rather than a peripheral feature [110], [111]. The findings reinforce the notion that technological simplicity enhances pedagogical effectiveness by reducing extraneous cognitive load, allowing learners to focus on CU rather than system navigation.

Similarly, AISE demonstrated a strong positive effect on AIS, highlighting the importance of learners' confidence in interacting with AI-driven systems [3], [4], [41]. Students who believe in their ability to use AI technologies effectively are more likely to engage deeply with AI-generated scaffolds, interpret feedback accurately, and apply recommendations meaningfully. This result is particularly salient for PGSD students, as future teachers' confidence in AI use may influence not only their own learning outcomes but also their willingness to integrate AI-supported tools into classroom practice.

The influence of CU on AIS provides an important theoretical contribution. While CU is often positioned as a learning outcome, this study demonstrates that it also functions as an antecedent shaping how learners perceive and benefit from AI scaffolding. Students with stronger conceptual foundations are better equipped to interpret AI feedback, connect new information with prior knowledge, and engage in higher-order thinking. This finding suggests a reciprocal relationship between CU and AIS, wherein prior knowledge enhances the effectiveness of AI support, which in turn may further deepen conceptual learning.

AISQ was found to significantly influence students' perceptions of AIS, confirming that the pedagogical design of AI systems matters as much as their technological capabilities. Clear explanations, timely feedback, adaptive difficulty, and relevance to learning objectives are essential features that shape learners' trust and acceptance of AI scaffolding. This finding reinforces the argument that AI in education should be conceptualized as a pedagogical partner rather than a mere automation tool [54], [112]. Although CE exhibited the smallest effect size, its significant contribution underscores the complementary role of mental effort and active processing in AI-supported learning environments [24], [25], [52]. AI scaffolding appears to function optimally when students are cognitively engaged, suggesting that AI systems should be designed to provoke inquiry, reflection, and problem-solving rather than promoting passive consumption of information. This insight is particularly relevant for teacher education programs that emphasize reflective practice and deep learning.

The findings advance the literature by repositioning AIS as a learner-centered construct shaped by internal cognitive and motivational factors, rather than as a static technological feature. Unlike prior studies that primarily examine AI scaffolding from a system-design or outcome-oriented perspective, this research demonstrates that students' self-regulatory capacity, technological perceptions, and conceptual readiness play decisive roles in determining the perceived effectiveness of AI scaffolding. From a broader perspective, the results highlight the importance of contextualizing AI-based educational innovations within teacher education. PGSD students represent a critical population, as their experiences with AI scaffolding may shape future instructional practices in primary education. By evidencing that self-regulation, ease of use, and AISE significantly influence AIS, this study offers actionable insights for curriculum designers, instructional technologists, and policymakers aiming to integrate AI into teacher preparation programs. This study contributes theoretically by integrating constructivist learning theory, SRL, and technology acceptance perspectives into a unified explanatory framework for AIS. Empirically, it provides validated evidence from a non-STEM, teacher education context in a developing country, addressing a notable gap in the AI-in-education literature. These contributions collectively strengthen the argument for designing AI-supported learning environments that prioritize learner agency, pedagogical quality, and usability to maximize CU and instructional effectiveness.

The results indicate that successful incorporation of AIS in Indonesian PGSD programs necessitates alignment at both pedagogical and policy levels. AIS at the instructional level should be developed to enhance students' SRL by incorporating structured goal-setting, monitoring, and reflective activities, while ensuring high usability to minimize cognitive load. PGSD programs must integrate systematic, practical training with accessible AI tools at both curricular and institutional levels to improve future teachers' self-efficacy in AI and their preparedness for instruction. AI integration initiatives must encompass not only infrastructure development but also pedagogical guidelines and professional development frameworks that prioritize learner-centered and conceptually rich AI-supported instruction. These strategies collectively facilitate the effective and responsible adoption of AI in teacher education, equipping future primary school teachers to implement AIS in Indonesian classrooms.

The significance of SRL and AISE as primary predictors is attributable to the inherently agentic characteristics of AIS. In contrast to traditional scaffolding provided by instructors, AI scaffolding necessitates that learners actively initiate, interpret, and regulate their interactions with the system. Students possessing robust SRL skills demonstrate enhanced capabilities in establishing learning objectives, assessing the pertinence of AI-generated feedback, and determining when to accept, modify, or dismiss system recommendations. High AISE similarly diminishes hesitation and cognitive friction in interactions with AI tools, allowing learners to engage more confidently and persistently with adaptive prompts and feedback. AIS enhances current self-regulatory capacities instead of substituting for their lack. The findings indicate that AI scaffolding is not inherently transformative; its effectiveness depends on learners' preparedness to engage actively in the learning process. This elucidates the predominance of SRL and AISE over solely cognitive or design-related factors and highlights the necessity of viewing AI scaffolding as a co-regulatory mechanism that operates most effectively when learners have adequate metacognitive control and technological confidence.

These findings offer practical guidance for PGSD programs aiming to incorporate AIS into curriculum design. AI scaffolding should be integrated into courses that specifically promote SRL, including instructional planning, reflective pedagogy, and classroom assessment. AI tools can facilitate lesson-plan iteration, reflective journaling, and formative feedback cycles, enabling students to plan, monitor, and revise their work in response to AI-generated prompts. Secondly, the curricula for PGSD should incorporate progressive AI literacy and experiences aimed at building confidence, starting with low-stakes AI-supported tasks and progressively advancing to more complex pedagogical applications. This structured integration can enhance AISE and mitigate cognitive overload. Third, AI scaffolding must align with pedagogical objectives instead of being regarded as an ancillary technology; instructional designers should emphasize scaffolding features that facilitate explanation, questioning, and reflection rather than automation. Integrating AI scaffolding into core pedagogical courses, instead of confining it to standalone technology modules, allows

PGSD programs to present AI as a pedagogical partner. This approach supports reflective practice, learner autonomy, and conceptual depth for future teachers. The integration of AI is crucial for equipping future primary school teachers to utilize it responsibly and effectively within Indonesian classrooms.

5. CONCLUSION

This research examined the effect of AIS on students' CU by incorporating cognitive, motivational, and technological elements within a PLS-SEM framework. The findings indicate that the effectiveness of AIS is significantly influenced by learners' SRL, AISE, and PEOU, underscoring the importance of learner agency and motivational readiness in AI-enhanced learning environments. CE, CU, and the perceived AISQ significantly positively influenced outcomes, highlighting the necessity of pedagogically effective and cognitively aligned AI support. This study contributes to the AI-in-education literature by defining AIS as a learner-centered construct that arises from the interaction of cognitive processes, motivational dispositions, and technological affordances, supported by empirical evidence from the Indonesian higher education context. The findings indicate that effective design and implementation of AI-supported learning environments, especially in teacher education programs, must go beyond mere technological deployment to encompass the systematic development of students' SRL skills and confidence in AI. AI systems ought to be developed to facilitate goal setting, monitoring, and reflective learning, all while ensuring high usability to reduce cognitive load. Future research should utilize longitudinal designs to investigate temporal changes in self-regulation, AISE, and CU. Additionally, employing mixed-methods approaches is recommended to gain a deeper insight into learners' interactions with AIS. Additional research across various educational levels and international contexts is recommended to improve the generalizability and cross-cultural validity of the proposed model.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Nuryanis	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Toto Nusantara	✓	✓		✓	✓			✓	✓	✓		✓	✓	
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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [N], upon reasonable request.

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