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Effects of artificial intelligence-based personalized learning on STEM reading comprehension

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ABSTRACT

Science, technology, engineering, and mathematics (STEM)-based reading comprehension is an important skill in modern education, yet many students still experience difficulties in understanding scientific concepts, technical terminology, and complex STEM texts. Although artificial intelligence (AI)-based personalized learning has been increasingly implemented in education, limited studies have explained how this approach improves STEM reading comprehension (SRC) through cognitive and self-regulation processes. Therefore, this study aims to examine the effects of AI-based personalized learning (AIPL) on SRC by investigating the mediating roles of cognitive engagement (CE) and self-regulated learning (SRL). A quantitative approach using partial least squares structural equation modeling (PLS-SEM) was employed. Data were collected through questionnaires from 250 students from several schools in Ternate City, Indonesia. The findings revealed that AIPL significantly influenced CE, SRL, and SRC. SRL was identified as the strongest factor affecting SRC. Furthermore, CE and SRL significantly mediated the relationship between AIPL and SRC. The study concludes that AIPL can effectively improve SRC by promoting CE and independent learning processes.

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1. INTRODUCTION

The development of artificial intelligence (AI) has brought significant changes to educational practices, especially through adaptive, technology-based, and personalized learning. AI-based personalized learning (AIPL) creates a learning system that adapts the material, difficulty level, feedback, and learning flow to the characteristics and needs of individual learners [1], [2]. This approach is highly relevant to modern education, which requires differentiation in learning and the development of 21st-century skills.

Reading comprehension skills are crucial in science, technology, engineering, and mathematics (STEM) education. In addition to understanding texts literally, students are required to interpret abstract concepts, technical terminology, symbolic representations, graphs, tables, and complex procedural instructions [3]. In the context of learning Indonesian, being able to read scientific and informational texts is essential for building students' academic literacy and critical thinking skills. Even if students have adequate basic reading skills, difficulties understanding STEM texts can hinder the learning process.

As AI becomes more prevalent in education, numerous studies have highlighted its positive potential in enhancing learning outcomes through personalized AI-driven approaches [4]–[6]. AI-based learning systems enable more adaptive delivery of materials, real-time feedback, and adjustment of learning paths based on individual student needs. Several studies show that this approach can increase learning motivation, student engagement, and understanding of learning concepts [7], [8].

However, most of these studies examine the effectiveness of AI by measuring academic performance and levels of learning engagement, usually using experimental or quasi-experimental designs that compare learning outcomes before and after the intervention [9], [10]. In addition, this approach does not fully explain the mechanism of how AI-based learning affects students' learning processes, especially in improving reading comprehension skills in the context of STEM learning. In fact, learning effectiveness is determined not only by the technology used but also by cognitive engagement (CE), self-regulated learning (SRL), and students' perceptions of personalized learning experiences [11]. Several studies have demonstrated that CE and personalized learning experiences can enhance students' understanding of concepts and improve the quality of their learning process [12], [13]. Furthermore, SRL skills also enhance the success of technology-based learning, as students who can organize learning strategies, monitor their progress, and evaluate outcomes tend to have better academic performance [14]. Recent research also shows that students' perceptions of learning experiences can affect the level of learning engagement through self-regulation mechanisms [15], [16]. Hence, the success of AI-based learning depends not only on the sophistication of the technology used but also on how it can encourage students' CE and SRL during the learning process.

In the context of teacher education and teacher professional education (PPG), it is important to understand the mechanisms of influence of AIPL. Teachers are required to be able to utilize technology as a pedagogical tool, not just as an aid, but as a means to support student-centered learning. Therefore, an empirical study is necessary both to measure the impact of AI implementation in reading education and to explain the relationships between factors that enhance students' reading comprehension skills.

To address this need, structural equation modeling (SEM) is an appropriate analytical approach, as it allows researchers to test complex relationships among latent variables simultaneously, including direct and indirect influences [17], [18]. This method enables testing the direct effect of AIPL on STEM reading comprehension (SRC) skills while examining how CE and SRL serve as mediating variables in the research model. This research aims to provide a better understanding of how personalized AI-based learning can improve SRC skills through this analysis.

The novelty of this study lies in its effort to explain the mechanism through which AIPL enhances SRC by incorporating CE and SRL into an integrated partial least squares SEM (PLS-SEM) model. Unlike many previous studies that primarily focused on the direct effects of AI-based learning on academic achievement or general student engagement, this study emphasizes the indirect learning processes that shape students' understanding of STEM-related texts. In addition, this research provides empirical evidence from technology-supported STEM learning environments in Indonesia, particularly by highlighting the important roles of students' cognitive involvement and independent learning behaviors in improving SRC.

2. METHOD

This study used a quantitative approach to examine the relationships among AIPL, CE, SRL, and SRC skills. Data were collected through a structured questionnaire designed to assess participants' perceptions and experiences with AI-based learning technology during the learning process. The population of this study consisted of students involved in digital technology-based learning at various junior and senior high schools in Ternate City, North Maluku Province, Indonesia. The sample was selected through purposive sampling based on the following criteria: i) students who use digital learning technology or AI-based platforms; ii) students who have studied material related to STEM; and iii) students who voluntarily agreed to participate in the study. Based on these criteria, 250 student respondents were obtained. The participants represented technology-supported educational environments implementing STEM-related learning activities. The demographic characteristics of the respondents are presented in Table 1.

As shown in Table 1, the study involved 250 student respondents from junior and senior high schools in Ternate City, Indonesia. Female students accounted for 54.8% of the sample, while male students represented 45.2%. Most respondents were aged between 15 and 16 years (48.0%), followed by students aged 13–14 years (38.0%) and 17 years (14.0%), reflecting the representation of secondary-level students participating in technology-supported STEM learning activities. In this study, AIPL refers to the use of adaptive digital learning systems that provide personalized learning pathways, adaptive feedback, and customized learning materials according to students' learning needs and learning progress. These systems were implemented within technology-supported learning activities experienced by the participants during STEM-related learning processes.

Table 1. Demographic characteristics of respondents

Characteristics	Frequency (n)	Percentage (%)
Gender		
Male	113	45.2
Female	137	54.8
Age group		
13–14 years	95	38.0
15–16 years	120	48.0
17 years	35	14.0
Total	250	100

The PLS-SEM was used to analyze the relationships among constructs in the research model. This method was selected because it can analyze complex relationships between latent variables simultaneously and assess both direct and indirect effects through mediation mechanisms [19], [20]. Furthermore, PLS-SEM is also suitable for predictive research involving latent constructs measured by multiple observable indicators.

The proposed relationships in this study are grounded in engagement theory and SRL theory. According to Fredricks *et al.* [21], CE reflects the extent to which students invest mental effort and employ learning strategies to understand academic content. AIPL can enhance CE by providing adaptive learning pathways, personalized feedback, and learning materials tailored to individual needs. Furthermore, Zimmerman's SRL theory [22] suggests that cognitively engaged students are more likely to develop self-regulatory behaviors, including planning, monitoring, and evaluating their learning activities. These SRL processes enable students to manage complex learning tasks more effectively and improve academic performance. In the context of STEM education, self-regulated learners are better able to comprehend scientific concepts, technical terminology, and complex informational texts, thereby enhancing SRC.

Based on these theoretical perspectives, AIPL is expected to increase CE by providing personalized and adaptive learning experiences. Higher levels of CE are expected to promote SRL because engaged students are more likely to actively monitor and manage their learning processes. Furthermore, SRL is expected to improve SRC by enabling students to employ effective reading strategies, monitor their understanding, and overcome difficulties when interpreting complex STEM-related texts.

The following hypotheses were formulated to examine the relationships between research variables:

- H1: AIPL has a positive effect on CE.
- H2: CE has a positive effect on SRL.
- H3: SRL has a positive effect on SRC.
- H4: AIPL has a positive effect on SRC.
- H5: CE mediates the relationship between AIPL and SRL.
- H6: SRL mediates the relationship between CE and SRC.
- H7: CE and SRL sequentially mediate the relationship between AIPL and SRC.

The conceptual research model describing the relationship among these variables is presented in Figure 1. The model illustrates the hypothesized relationships among AIPL, CE, SRL, and SRC. It also provides the theoretical basis for the subsequent PLS-SEM analysis.

After presenting the conceptual research model in Figure 1, the next step is to explain the constructs used in the study and their measurement indicators. Each variable in the research model is operationalized into multiple indicators to measure the latent construct with a questionnaire. Operationalizing these variables is essential to allow systematic measurement aligned with the research objectives. The variables in this study included AIPL, CE, SRL, and SRC. Each variable is assessed through various indicators that reflect key aspects of the construct being examined. These indicators were determined based on a literature review related to AI-based learning, student CE, SRL, and reading literacy in the STEM context.

Specifically, the AI-driven personalized learning variable is assessed using indicators that reflect the system's capacity to offer adaptive feedback, adjust learning paths, and deliver personalized educational content. The CE variable describes the level of mental involvement of students in understanding learning materials, while SRL reflects students' ability to regulate and monitor their learning process independently. Meanwhile, SRC is associated with students' ability to understand scientific concepts, technical terms, and the relationships between ideas in STEM-based texts. Details of the research variables and their measurement indicators are shown in Table 2. Each construct was operationalized through several indicators to capture the main dimensions of the concept being measured. These indicators served as the basis for developing the questionnaire items used in this study.

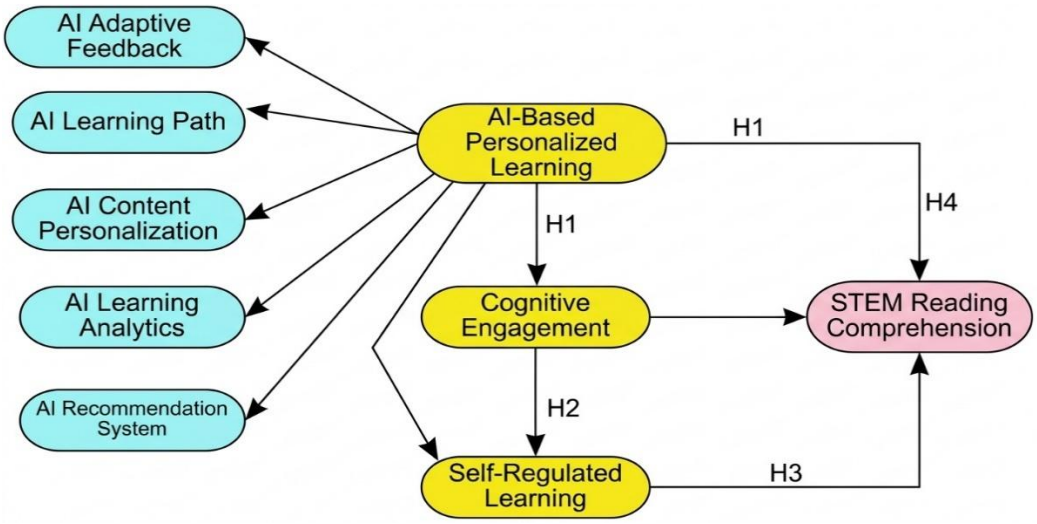


Figure 1. Proposed conceptual research model

Table 2. Variables and measurement indicators

Variables	Indicators	Code	Theoretical basis
AIPL	AI adaptive feedback	AIPL1	Developed based on the concepts of AI-supported personalized learning and adaptive learning systems reported in previous studies [4], [7], [23]
	Personalized learning path	AIPL2	
	AI-based content personalization	AIPL3	
	Learning analytics support	AIPL4	
	AI recommendation system	AIPL5	
CE	Effort to understand learning materials deeply	CE1	Developed based on engagement theory proposed [21]
	Use of cognitive strategies in learning	CE2	
	Reflecting on learning content	CE3	
	Connecting new knowledge with prior knowledge	CE4	
SRL	Planning learning strategies	SRL1	Developed based on SRL theory [22]
	Monitoring learning progress	SRL2	
	Evaluating learning outcomes	SRL3	
	Managing learning time and effort	SRL4	
SRC	Understanding scientific concepts	SRC1	Developed based on STEM literacy and reading comprehension concepts reported in previous studies [8], [14]
	Interpreting technical terminology	SRC2	
	Identifying relationships between ideas in text	SRC3	
	Drawing conclusions from STEM texts	SRC4	

Based on the indicators presented in Table 2, each research construct is operationalized in the form of statement items on a questionnaire measured using a five-level Likert scale. The data obtained from respondents were then analyzed using the PLS-SEM, assisted by SmartPLS software. This approach enables researchers to analyze the relationships between latent constructs simultaneously and test both direct and indirect effects in the research model. The analysis process consisted of two main stages: evaluating the measurement model (outer model) and assessing the structural model (inner model). At the measurement model stage, testing was conducted to confirm that the indicators were valid and reliable enough to represent the research constructs. This assessment included convergent validity testing, measured by outer loadings and average variance extracted (AVE) values, as well as internal consistency reliability, evaluated with Cronbach's alpha and composite reliability (CR). Furthermore, discriminant validity was tested to ensure that each construct in the research model was distinct from the others. The next step was to evaluate the structural (inner) model to examine the relationships between the constructs in the research model. This stage involved examining path coefficient values, t-statistics, and p-values to determine the significance of the relationships among variables. Significance testing was performed through a bootstrapping procedure with multiple resamples to obtain more stable parameter estimates. Moreover, the strength of the structural model was also evaluated through the coefficient of determination (R^2) value to see the ability of the independent variables to explain the dependent variables in the research model.

3. RESULTS

3.1. Descriptive analysis of research data

A descriptive analysis was performed to provide an initial overview of the condition of the research data and the tendency of respondents' answers to each variable studied. This analysis explains how respondents perceive their learning experiences related to AIPL, CE, SRL, and SRC. Descriptive statistics for the study variables are shown in Table 3. The descriptive analysis provides an overview of respondents' perceptions regarding AIPL, CE, SRL, and SRC. These results help identify the general tendencies and distribution of responses before proceeding to the measurement and structural model evaluations.

Table 3. Descriptive statistics of research variables

Variables	Minimum	Maximum	Average	Std. Deviation
AIPL	1.00	5.00	2.84	0.64
CE	1.25	4.50	2.90	0.60
SRL	1.00	5.00	2.91	0.76
SRC	1.00	5.00	2.95	0.79

Based on the results in the Table 3, the average values for all variables range from 2.84 to 2.95 on a 1-5 Likert scale. This indicates that respondents generally rated their learning experience as moderate. The SRC variable achieves the highest average score, suggesting that most respondents felt capable of understanding scientific concepts, technical terminology, and the connections between ideas in STEM texts.

Meanwhile, SRL and CE also show relatively balanced average values. These findings indicate that students not only put their effort into actively understanding the learning material but also start to develop the ability to manage their learning process independently, such as planning learning strategies, monitoring understanding, and evaluating learning outcomes. On the other hand, the AIPL variable has a slightly lower average score compared to the other variables. This indicates that AI-based learning technology is still not fully optimized or equally experienced by all respondents during their learning process.

Based on the standard deviation values, the variation in respondents' answers is moderate. The SRC variable shows slightly more variation than the other variables, indicating that students' ability to understand STEM texts still varies. In contrast, CE shows smaller variations, suggesting that most respondents demonstrated a relatively consistent level of CE in the learning process.

3.2. Evaluation of the measurement model

Measurement model (outer model) evaluation was conducted to assess the extent to which the indicators in this study represent the latent constructs being measured. This analysis used the confirmatory factor analysis (CFA) approach within the PLS framework to ensure that each indicator had an adequate contribution in explaining the latent variable. Construct validity is evaluated by considering the factor loading value of each indicator. An indicator is declared to have good validity if the t-statistic value is ≥ 1.96 and the standardized loading value is ≥ 0.50 [23], [24]. This value indicates that the indicator has a significant relationship with the construct being measured. Moreover, construct reliability was evaluated using CR and AVE values. A construct is considered reliable if the CR value is ≥ 0.70 and AVE is ≥ 0.50, which shows that the indicators within the construct have good internal consistency in measuring the latent variables. A summary of the results of the measurement model evaluation (outer model) is shown in Table 4. The evaluation includes the assessment of indicator validity, convergent validity, and construct reliability using outer loading, AVE, and CR values. These measures are essential to ensure that the indicators accurately represent the latent variables examined in this study.

The results of the measurement model (outer model) evaluation in Table 4 show that all indicators used to measure latent variables have outer loading values above 0.5, which means that all indicators are declared partially valid. Furthermore, the AVE value for each construct is also above 0.5, namely AIPL=0.572; CE=0.529; SRL=0.684; and SRC=0.699. Those values show that each construct has good convergent validity, which means that the indicators used are able to explain the latent variables adequately. In terms of reliability, the CR values for all variables are above 0.7, namely AIPL=0.870; CE=0.816; SRL=0.896; and SRC=0.903. This indicates that the research instrument has good internal consistency in measuring the constructs of AIPL, CE, SRL, and SRC.

Based on the strength of each indicator's contribution, the indicator with the highest outer loading value is considered the most dominant indicator in shaping its construct. For the AIPL variable, the strongest indicator is AIPL2 (personalized learning path), with a value of 0.784. This indicates that the personalized learning path is the most significant aspect of AI-based learning. For the CE variable, the most dominant indicator is CE1 (effort to understand learning materials deeply), with a value of 0.791. This shows that

students' efforts to understand the material deeply are the strongest form of CE. For the SRL variable, the most influential indicator is SRL4 (managing learning time and effort), with a value of 0.847. This suggests that the ability to manage learning time and effort plays a core role in self-regulation in the learning process. Meanwhile, for the SRC variable, the strongest indicator is SRC3 (identifying relationships between ideas in text), with a value of 0.861. This reveals that the ability to recognize relationships between ideas in text is a crucial part of understanding STEM-based reading. These results suggest that each construct is not only statistically valid but also has key indicators that reflect the main aspects of each concept studied.

Table 4. Summary of measurement model evaluation (outer model)

Latent variables	Observed variables	Partial validity (per indicator) (Loading factor>0.5=valid)		Ranking	Overall validity (per construct) (AVE>0.5=valid)		CR>0.7	
		Outer loading	Description		AVE	Conclusion	CR	Description
AIPL	AIPL1	0.746	Valid	5	0.572	Valid	0.870	Reliable
	AIPL2	0.784	Valid	1				
	AIPL3	0.749	Valid	3				
	AIPL4	0.754	Valid	2				
	AIPL5	0.748	Valid	4				
CE	CE1	0.791	Valid	1	0.529	Valid	0.816	Reliable
	CE2	0.780	Valid	2				
	CE3	0.731	Valid	3				
	CE4	0.591	Valid	4				
SRL	SRL1	0.817	Valid	4	0.684	Valid	0.896	Reliable
	SRL2	0.846	Valid	2				
	SRL3	0.834	Valid	3				
	SRL4	0.847	Valid	1				
SRC	SRC1	0.826	Valid	2	0.699	Valid	0.903	Reliable
	SRC2	0.812	Valid	3				
	SRC3	0.861	Valid	1				
	SRC4	0.808	Valid	4				

3.3. Evaluation of discriminant validity

Discriminant validity was assessed to confirm that each construct in the research model is clearly distinct from the others. This test aims to verify that each latent variable genuinely represents a separate concept and does not overlap excessively. In this study, discriminant validity was evaluated using the Heterotrait–Monotrait ratio (HTMT) method, which is among the recommended approaches in PLS-SEM analysis. Generally, a construct is considered to have good discriminant validity if the HTMT value is below 0.90. The results of the discriminant validity test using the HTMT method are shown in Table 5. The HTMT approach was employed to assess whether the latent constructs measure different conceptual domains and do not excessively overlap with one another. Establishing discriminant validity is important to ensure the accuracy and credibility of the relationships examined in the structural model.

Table 5. HTMT (discriminant validity) test results

Constructs	AIPL	CE	SRC	SRL
AIPL				
CE	0.882			
SRC	0.866	0.889		
SRL	0.840	0.893	0.871	

Based on the results of discriminant validity testing using the HTMT method, all ratio values between constructs range from 0.840 to 0.893. Generally, a construct is considered to have good discriminant validity if the HTMT value is below 0.90 [25]. These results show that all pairs of variables in this study remain below the recommended threshold.

A closer look shows a high HTMT value, with relationships between CE and SRL at 0.893, and between CE and SRC at 0.889. This suggests that CE is closely connected to both SRL and SRC. It makes sense conceptually, as students who are more cognitively engaged tend to manage their learning more effectively and understand academic readings better.

Meanwhile, a relatively low correlation was observed between SRL and AIPL at 0.840. This suggests that although AI-based learning supports students' self-regulation, the two constructs still represent different aspects of learning. Overall, these results indicate that all constructs in the study meet the criteria for discriminant validity, enabling the measurement model to proceed to the next stage of analysis.

3.4. Evaluation of structural model (inner model)

After confirming that the measurement model meets the criteria for validity and reliability, the next step is to assess the structural (inner) model. This evaluation aims to test the relationships between constructs and determine the model's effectiveness in explaining the dependent variable. In the PLS-SEM approach, assessing the structural model typically involves analyzing key indicators, such as the coefficient of determination (R^2), the path coefficient, and the significance of the relationships between variables through a bootstrapping process [26].

In evaluating a structural equation model using PLS, the R^2 value is first examined for each endogenous latent variable, which measures the predictive power of the structural model, similar to regression interpretation. Changes in the R^2 value are then used to explain how a specific exogenous latent variable influences the endogenous latent variable and to determine whether that influence is significant. In PLS, the R^2 value indicates the proportion of variance in the construct that the model explains. The higher the R^2 value, the greater the percentage of variance accounted for by the model [27]. Table 6 presents the results of the PLS R^2 evaluation. The coefficient of determination (R^2) was used to assess the predictive accuracy of the structural model and to determine the proportion of variance explained by the independent variables. These values provide important information regarding the model's ability to explain variations in CE, SRL, and SRC.

Table 6. PLS R^2 evaluation results

Endogenous constructs	Structural paths	R^2
CE	AIPL→CE	0.453
SRL	AIPL→SRL	0.582
SRC	AIPL→SRC; CE→SRC; SRL→SRC	0.660

The R^2 value presented in Table 6 indicates the proportion of variance explained by the predictor variables in the research model. The results show that AIPL explains 45.3% of the variance in CE. In addition, the R^2 values for the other endogenous constructs indicate the explanatory power of the model for the respective dependent variables. Furthermore, AIPL can explain 58.2% of the variation in SRL, indicating that AI-based learning systems help students organize learning strategies, manage study time, and monitor their progress more independently. Moreover, the R^2 value of 0.660 for the SRC variable means that the combination of variables in the research model—namely AIPL, CE, and SRL—can explain approximately 66% of the variation in students' SRC skills. These findings show that AIPL, along with increased CE and SRL, significantly enhances students' comprehension of STEM texts.

To evaluate the overall strength of the model, additional analysis was conducted by examining the global strength of the structural model. This assessment aims to determine how well the research model as a whole explains the relationships among the analyzed variables. In this study, the strength of the structural model is measured by the total R^2 value, which shows the model's ability to explain the variables in the research model. The results of the overall structural model strength assessment are shown in Table 7. This evaluation was conducted to determine the overall explanatory power of the proposed research model. The assessment provides an indication of how well the relationships among AIPL, CE, SRL, and SRC are represented within the structural model.

Based on Table 7, the total R^2 value of 0.922 shows that the structural model created in this study is at a strong level of strength. This value reveals that about 92.2% of the variation in the relationship between variables in the research model can be explained by the constructs used, specifically AIPL, CE, SRL, and SRC. This value is well above the category of 0.000–0.299 (very weak) used as a benchmark for assessing model strength, which means the model has an excellent capacity to explain the relationships between the analyzed variables.

Table 7. Structural model strength level (global optimization)

No	R^2 criteria standard		Total R^2	Description
	Interval	Category		
1	0.000–0.299	Very weak	0.922	Strong
2	0.300–0.499	Weak		
3	0.500–0.699	Moderate		
4	0.700–1.000	Strong		

3.5. Hypothesis testing (path analysis)

After confirming the structural model's robustness, the next step was to perform hypothesis testing to examine the relationships among variables in the research model. Hypothesis testing was carried out using the bootstrapping method in PLS-SEM to obtain path coefficients, t-statistics, and p-values. The path coefficient showed the direction and strength of the relationship among variables, while the t-statistics and p-values were used to assess the significance of these relationships.

Generally, a relationship among variables is deemed significant if the t-statistic is above 1.96 and the p-value is below 0.05 at the 5% significance level. Conversely, a relationship is considered insignificant if the t-statistic falls between -1.96 and 1.96, or if the p-value is greater than 0.05. These criteria are used to determine whether the hypothesis proposed in this study is accepted or rejected. The results of hypothesis testing based on path coefficient analysis in the structural model are shown in Table 8. This analysis evaluates the direct effects among the latent constructs by examining the magnitude and significance of the path coefficients. The findings are used to determine the acceptance or rejection of the proposed hypotheses and to assess the relationships among the variables in the research model.

Table 8. Hypothesis testing (path analysis)

Effect among latent variables			Path coefficient	t-value	p-value	Conclusion
Exogenous variables	-->	Endogenous variables				
AIPL	-->	CE	0.673	23.488	0.000	Significant
AIPL	-->	SRL	0.430	8.428	0.000	Significant
CE	-->	SRL	0.404	7.796	0.000	Significant
AIPL	-->	SRC	0.312	5.023	0.000	Significant
CE	-->	SRC	0.238	4.179	0.000	Significant
SRL	-->	SRC	0.361	5.241	0.000	Significant

The PLS-SEM path analysis results in Table 8 show that all relationships among variables in the research model are statistically significant, as indicated by a p-value of 0.000 (<0.05) and a t-value greater than 1.96. These results revealed that AIPL significantly affected CE, SRL, and SRC. The strongest effect was observed in the relationship between AIPL and CE, with a path coefficient of 0.673, suggesting that implementing AI-based learning can enhance students' CE in the learning process. Additionally, AIPL directly affected SRL (0.430), while CE also affected SRL (0.404). These findings show that students' ability to regulate their learning is affected not only by the AI-based learning system but also by their level of CE during the learning process.

Furthermore, these variables were also shown to significantly influence SRC. The strongest effect came from SRL at 0.361, followed by AIPL (0.312) and CE (0.238). This suggests that self-regulation of learning is the most powerful factor in enhancing students' comprehension of STEM-based texts. Therefore, AI-based learning not only directly affects SRC but also boosts it by increasing students' CE and SRL.

3.6. Analysis of mediating variables (indirect effect)

Besides examining the direct effects between variables, this study also explored the indirect effects to understand the role of mediating variables in the research model. The purpose of this analysis is to determine whether CE and SRL serve as mediators in the relationship between AIPL and SRC. The findings of the indirect effect analysis are shown in Table 9. The mediation analysis was performed to determine whether CE and SRL serve as significant intermediary variables linking AIPL and SRC. These results help explain the underlying mechanisms through which AIPL contributes to improvements in students' SRC.

The results of the indirect effect analysis in Table 9 show that all mediation paths in the research model are statistically significant, with a p-value of 0.000 (less than 0.05) and a t-value above 1.96. The strongest mediation path for SRC is between AIPL and SRC through CE, with a coefficient of 0.160. This indicates that AI-based learning can enhance SRC by increasing students' CE. The next significant path is AIPL→SRL→SRC, with a coefficient of 0.155, suggesting that the AI-based learning system also boosts reading comprehension by improving students' ability to self-regulate their learning process.

Table 9. Mediation test results (indirect effect)

Indirect effect	Coefficient	t value	p values
AIPL → CE → SRC	0.160	3.887	0.000
AIPL → SRL → SRC	0.155	4.818	0.000
CE → SRL → SRC	0.146	4.012	0.000
AIPL → CE → SRL	0.272	6.982	0.000
AIPL → CE → SRL → SRC	0.098	3.972	0.000

Furthermore, the CE→SRL→SRC path, with a coefficient of 0.146, shows that students' CE can boost SRC by enhancing self-regulation in learning. There is also a chain mediation path AIPL→CE→SRL→SRC with a coefficient of 0.098, indicating that AI-based learning can gradually improve reading comprehension by increasing CE, which then promotes the development of learning self-regulation. Meanwhile, the largest indirect effect occurs in the path AIPL→CE→SRL with a coefficient of 0.272, demonstrating that CE plays a key role in linking AI-based learning to students' ability to self-regulate their learning process. These findings suggest that the success of AI-based learning depends not only on the technology used but also on its capacity to enhance students' CE and SRL. To give a clearer understanding of the relationships among variables in the research model, the results of the PLS-SEM analysis are also presented visually as a path model shown in Figure 2. This visualization illustrates the direct and indirect relationships between AIPL, CE, SRL, and SRC, along with the path coefficient values and indicator loading values for each construct.

Based on Figure 2, the SRC variable is affected by AIPL, CE, and SRL. The strongest effect on SRC comes from SRL (with a path coefficient of 0.361), followed by AIPL (0.312) and CE (0.238). This suggests that students' ability to self-regulate their learning process is the most significant factor in enhancing SRC.

From a mediation perspective, the effects of AIPL on SRC primarily occur through CE, as the relationship between AIPL→CE (0.673) is stronger than between AIPL→SRL (0.430). This is followed by the path CE→SRL (0.404), which finally impacts SRC. Additionally, within the AIPL variable, the most prominent indicator is AIPL2 (personalized learning path), with an outer loading value of 0.784. This indicates that providing a personalized learning path is a key component in enhancing CE, SRL, and students' SRC.

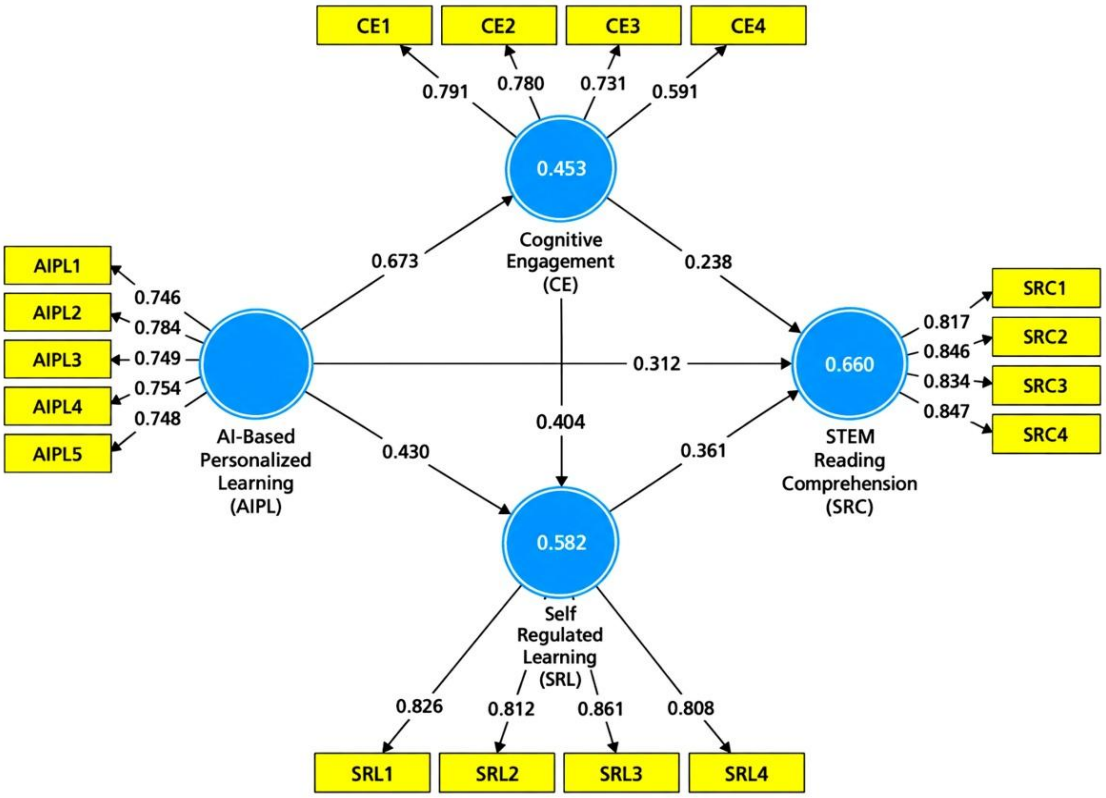


Figure 2. Path diagram of measurement and structural models (overall)

4. DISCUSSION

This study examined the effects of AIPL on SRC by exploring the mediating roles of CE and SRL. The findings demonstrate that AIPL contributes positively to students' CE, SRL, and understanding of STEM texts. These results provide evidence that adaptive learning systems capable of personalizing learning

materials, feedback, and learning pathways can create more interactive and student-centered learning experiences. One possible explanation is that AI-supported learning environments provide adaptive feedback and individualized learning pathways that align with students' learning needs and progress. Such personalization may reduce cognitive overload by presenting learning materials at an appropriate level of difficulty while simultaneously increasing the relevance of learning activities. As a result, students are more likely to invest cognitive effort in understanding STEM concepts and actively engage with learning materials. This interpretation aligns with engagement theory, which emphasizes that meaningful and relevant learning experiences encourage deeper cognitive involvement in academic activities. Furthermore, the present findings corroborate previous studies reporting that adaptive learning technologies can enhance student engagement, improve learning experiences, and support personalized learning pathways [28]–[30].

The study also revealed that CE significantly influences SRL. Students who are cognitively engaged tend to demonstrate stronger abilities in planning learning strategies, monitoring their understanding, and evaluating their learning progress independently. One possible explanation is that cognitively engaged students are more motivated to actively manage their learning process and become more aware of their academic goals. From the perspective of SRL theory, CE encourages learners to become more reflective and strategic in their learning activities. Students who actively process information are more likely to plan learning strategies, monitor their comprehension, and evaluate their learning outcomes. These behaviors represent essential components of SRL and contribute to greater learning autonomy. Furthermore, continuous engagement in learning activities promotes metacognitive awareness, enabling students to recognize their strengths and weaknesses and make appropriate adjustments to their learning strategies. Consequently, cognitively engaged learners are better equipped to regulate their learning processes and adapt to academic challenges. This finding supports previous research identifying CE as an important factor in developing SRL skills [31], [32].

Furthermore, SRL emerged as the strongest factor influencing SRC. This finding highlights the importance of students' abilities to independently organize learning strategies, manage learning efforts, and reflect on their understanding when dealing with complex STEM texts containing scientific concepts and technical terminology. Students with stronger SRL skills tend to employ effective reading strategies, monitor their understanding while reading, and revisit difficult concepts when necessary. These behaviors are particularly important in STEM learning because STEM texts often contain abstract concepts, scientific terminology, symbolic representations, and complex informational structures that require active cognitive processing. Students who effectively plan, monitor, and evaluate their learning are better able to identify important information, regulate comprehension difficulties, interpret technical information, and integrate concepts across different STEM domains. Consequently, self-regulated learners are better positioned to comprehend and interpret STEM-related content successfully. This finding provides evidence that self-regulation functions as a critical learning mechanism that enables students to transform learning opportunities into meaningful academic outcomes. These results are also consistent with previous studies reporting that SRL serves as a key predictor of academic achievement and reading comprehension because SRL are more likely to employ effective learning strategies and actively monitor their understanding throughout the learning process [21], [22]. From a theoretical perspective, these findings indicate that the impact of AIPL on learning outcomes occurs not only directly but also indirectly through CE and SRL. This result supports the proposition that effective learning technologies enhance learning outcomes when they simultaneously foster engagement and learner autonomy.

The mediation findings further indicate that CE and SRL function as important psychological mechanisms through which AIPL influences SRC. More specifically, the results support a sequential pathway in which AI-supported personalized learning first enhances students' CE, which subsequently promotes SRL behaviors, ultimately leading to improved SRC. The significant indirect effects suggest that students benefit from AI-supported learning environments not only because they receive personalized content but also because such environments encourage deeper cognitive involvement and stronger self-management skills. This sequential mediation mechanism represents one of the most important contributions of the present study because it demonstrates that the effectiveness of AI-supported learning extends beyond content personalization and operates through interconnected cognitive and self-regulatory processes. These findings provide empirical support for the integration of Engagement Theory and SRL theory in explaining how technology-enhanced learning environments contribute to improved academic outcomes. Moreover, the results highlight the importance of considering both cognitive and behavioral learning processes when evaluating the effectiveness of AI-supported educational technologies. Similar findings have been reported in recent studies emphasizing engagement and self-regulation as key mediating mechanisms linking technology-enhanced learning environments to improved educational outcomes.

In classroom practice, these findings suggest that teachers can utilize AIPL systems to provide adaptive feedback, personalized learning pathways, and learning support tailored to students' individual needs. Such approaches can help students become more actively engaged in STEM-related reading activities, improve independent learning skills, and facilitate better understanding of complex scientific concepts and

technical terminology. The findings further support the integration of adaptive AI-supported learning technologies into STEM learning environments to promote more effective and student-centered learning processes. In addition, educational institutions should prioritize AI-supported learning systems that foster learner autonomy, metacognitive monitoring, and active CE rather than focusing solely on content personalization. Educational policymakers may also consider promoting the adoption of AI-supported learning systems as part of broader digital transformation initiatives aimed at improving students' STEM literacy and learning outcomes.

Overall, this study demonstrates that AIPL can effectively support SRC when combined with strong CE and SRL processes. The findings provide evidence that adaptive learning systems can encourage students to become more actively involved in understanding STEM-related materials while simultaneously strengthening their capacity to regulate their own learning. Therefore, the educational value of AI-supported learning extends beyond content personalization by fostering the cognitive and self-regulatory competencies required for successful STEM learning in contemporary educational environments. More importantly, the study extends the literature on AI-supported learning by demonstrating that the effectiveness of personalized learning operates through engagement and self-regulation mechanisms, thereby providing a more comprehensive explanation of how AI technologies contribute to STEM learning outcomes.

5. CONCLUSION

The findings of this study demonstrate that AIPL plays an important role in improving SRC through the sequential mechanisms of CE and SRL. The results indicate that AI-powered personalized learning systems not only provide adaptive learning support but also encourage students to become more cognitively engaged and actively regulate their own learning processes. Among the examined variables, SRL emerged as the strongest factor influencing SRC, highlighting the importance of students' abilities to plan, monitor, and evaluate their learning when engaging with complex STEM texts containing scientific concepts and technical terminology.

A key contribution of this study lies in identifying the sequential pathway through which AIPL influences SRC. The findings provide evidence that the effectiveness of AI-supported learning operates through CE and SRL mechanisms rather than through direct instructional support alone. This contribution extends the literature on AI-supported learning by offering a more comprehensive explanation of how AI technologies facilitate STEM learning outcomes through interconnected cognitive and self-regulatory processes. Furthermore, the findings support the integration of engagement theory and SRL theory in explaining learning outcomes within technology-enhanced educational environments. From a practical perspective, the findings suggest that AI-based educational platforms should be designed not only to provide adaptive learning content but also to foster learner autonomy, metacognitive monitoring, and active CE. Educational institutions and policymakers should therefore prioritize AI-supported learning systems that strengthen students' self-regulatory competencies in addition to delivering personalized learning experiences.

This study has several limitations. The data were collected from a limited educational context in Ternate City, Indonesia, and relied on self-reported questionnaire responses, which may not fully represent actual classroom behavior and long-term learning outcomes. In addition, SRC was assessed through students' self-perceptions rather than objective reading comprehension tests or STEM literacy assessments. Therefore, the findings should be interpreted as reflecting perceived SRC rather than actual measured comprehension performance. Furthermore, the cross-sectional design of the study limits the ability to observe long-term changes in students' learning processes and STEM literacy development.

For future research, it is recommended to involve larger and more diverse educational settings to improve the generalizability of the findings. Future studies may also employ longitudinal or experimental approaches, including pilot testing of AIPL systems in real classroom environments, to further examine their long-term effects on students' CE, SRL, and STEM literacy development. In addition, future research may incorporate objective measures such as SRC tests, STEM literacy assessments, or performance-based evaluations to provide a more comprehensive understanding of students' actual comprehension abilities.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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CONFLICT OF INTEREST STATEMENT

The authors state no conflict of interest.

DATA AVAILABILITY

The data used in this study are not publicly available due to privacy and ethical considerations involving participant responses but are available from the corresponding author upon reasonable request.

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