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The Effect of AI-Driven Personalized Learning with a Recommendation System on Students' Conceptual Understanding and Analytical Skills: The Moderating Role of Self-Regulated Learning

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This study investigates the effect of AI-driven personalized learning supported by a recommendation system on students' conceptual understanding (C2) and analytical skills (C4), with self-regulated learning (SRL) as a moderating variable. Although AI-based personalized learning has attracted growing attention in education, empirical evidence regarding its effectiveness in controlled learning environments that consider differences in students' SRL levels remains limited. This study addresses this gap by implementing a structured AI-supported personalized learning approach through a recommendation system. A pretest–posttest control group experimental design was conducted with 60 senior high school students classified into high- and low-SRL groups using z-scores. The experimental group participated in AI-supported personalized learning through a learning management system (LMS) integrated with a recommendation system, whereas the control group received personalized learning without AI support. Data were analyzed using a 2 × 2 factorial MANOVA after meeting the assumptions of normality, homogeneity, and initial equivalence. The results showed that AI-driven personalized learning significantly improves students' C2 and C4. Although SRL does not have a significant direct effect on either

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outcome, it demonstrated a significant interaction effect on C4. These findings suggest that AI-based recommendation systems serve as an effective scaffolding mechanism for learners with different SRL levels. This study provides empirical evidence that integrating AI into controlled personalized learning environments enhances students' C2 and C4 in mathematics learning.

Introduction

Mathematics education plays a crucial role in developing students' cognitive abilities for learning in the era of artificial intelligence (AI), which is increasingly moving toward personalized learning. Among various cognitive abilities, conceptual understanding (C2) and analytical skills (C4) are fundamental because they provide the basis for the development of higher-order cognitive abilities (Anderson & Krathwohl, 2001; Cai, Ding, & Hwang, 2026; Lepore, 2024; M. Wang, Matore, & Rosli, 2025). However, recent studies indicate that many students still struggle to develop C2 and C4 in mathematics, relying more on procedural knowledge than on meaningful understanding (Adeleke, Balogun, & Ayanwale, 2025; Gebremeskel, Ayele, & Wondimuneh, 2025; Ncube & Luneta, 2025; M. Wang, Matore, et al., 2025). Furthermore, the effectiveness of personalized AI-supported learning is influenced by students' levels of SRL, potentially leading to differences in learning outcomes related to C2 and C4 (Eti, Mosia, & Egara, 2026; Lan & Zhou, 2025a). This challenge becomes even more complex as increasingly personalized AI systems can instantly provide answers and learning recommendations, which students may accept without engaging in critical evaluation or regulating their own learning processes. Therefore, mathematics instruction should strengthen students' C2 and C4, enabling them to use AI critically, independently, and responsibly.

C2 is foundation of meaningful mathematics learning. It enables students to connect, explain, and apply mathematical concepts across various learning situations (Anderson & Krathwohl, 2001; Scheiner, Buchholtz, & Kaiser, 2024). Nevertheless, numerous studies have reported that students tend to memorize procedures rather than understand conceptual relationships, which often results in misconceptions (Fitria & Susanto, 2023; Wakhata, Balimuttajjo, & Mutarutinya, 2023). Such limitations reduce students' ability to verify the correctness of mathematical explanations and solutions generated by AI (Turmuzi, Azmi, & Kertiyani, 2026). Strengthening C2 is therefore an essential first step toward developing stronger mathematical thinking skills.

C4 develops from a solid conceptual foundation and enable students to evaluate different approaches to mathematical problem solving. These skills involve distinguishing relevant information, relating mathematical concepts, and providing logical justifications for proposed solutions (Anderson & Krathwohl, 2001; M. Wang, Mohd Matore, & Rosli, 2025). However, mathematics instruction still focuses on procedural fluency and correct answers rather than mathematical reasoning, providing limited opportunities for students to develop analytical thinking (Huincahue, Borromeo-Ferri, Reyes-Santander, & Garrido-Véliz, 2021; Thanheiser & Melhuish, 2023). Consequently, many students struggle to critically validate AI-generated mathematical solutions and compare alternative solution strategies (Zhuang, 2026). Mathematics education should therefore foster C2 and C4 simultaneously.

Developing these thinking skills requires instructional approaches that accommodate individual learning needs. AI enables personalized learning by analyzing students' characteristics, learning progress, and learning behaviors (Firda, 2024; Fortuna et al., 2025; Tan, Hu, Yeo, & Cheong, 2025). However, previous studies have shown that AI does not

always provide learning materials that align with instructional objectives or students' learning needs (Feigerlova, Hani, & Hothersall-Davies, 2025; Funa & Gabay, 2025). Consequently, AI-based personalization has not consistently promoted the development of higher-order thinking skills (Fortuna et al., 2025; Patrick, Yip, & Campbell, 2025). Therefore, more effective mechanisms are needed to improve the accuracy and relevance of AI-supported personalized learning.

An AI-based recommendation system has the potential to enhance the effectiveness of personalized learning. Such systems analyze students' characteristics, learning needs, and learning activities to recommend the most appropriate learning resources (Oubalahcen, Tamym, & Driss El Ouadghiri, 2023; Rahayu, Ferdiana, & Kusumawardani, 2022). However, many existing recommendation systems continue to rely on relatively static learner profiles, making them less responsive to students' evolving learning needs (da Silva, Slodkowski, da Silva, & Cazella, 2023). As a result, their recommendations have not fully supported the development of students' C2 and C4 (Abu-Rasheed et al., 2023). Integrating recommendation systems with AI is therefore expected to produce more adaptive and context-sensitive learning recommendations.

The effectiveness of AI-supported learning depends not only on the quality of the technology but also on students' learning characteristics, particularly their self-regulated learning (SRL) abilities. SRL refers to students' ability to set learning goals, select appropriate learning strategies, monitor their progress, and evaluate their learning outcomes independently (Winne & Perry, 2000; Zimmerman, 2002). Previous studies have shown that students with high SRL tend to use AI to deepen their understanding, whereas students with low SRL are more likely to depend on AI-generated answers without critically evaluating them (Lan & Zhou, 2025; Trinovita, Nurchurifiani, Hastomo, Andewi, & Hasbi, 2025). These findings suggest that SRL influences the effectiveness of AI-driven personalized learning and AI-based recommendation systems in improving students' C2 and C4 (Järvelä, Nguyen, & Molenaar, 2023; Lan & Zhou, 2025). Accordingly, SRL is positioned as a moderating variable because it may strengthen or weaken the impact of AI-supported learning on students' learning outcomes.

Research on the application of AI in mathematics education has expanded rapidly in recent years. Most existing studies focus on developing AI technologies or evaluating their advantages and limitations, while relatively few have examined their effects on students' C2 and C4 (Feigerlova et al., 2025; Funa & Gabay, 2025). Likewise, research on recommendation systems has primarily concentrated on algorithm development and recommendation accuracy, with limited attention to AI-driven adaptive learning recommendations (da Silva et al., 2023; Oubalahcen et al., 2023). In addition, most studies on SRL have treated SRL as an outcome of instructional interventions rather than as a moderating variable in AI-supported learning environments (Panadero et al., 2017; Xia et al., 2026). These gaps indicate the need for research that integrates personalized learning, AI-based recommendation systems, and the moderating role of SRL in improving students' C2 and C4 in mathematics.

This study aims to examine the effect of AI-driven personalized learning supported by an AI-based recommendation system on students' C2 and C4 in mathematics. The recommendation system is integrated into an LMS to provide adaptive learning recommendations based on students' characteristics, learning needs, and learning progress while allowing teachers to maintain pedagogical control over learning objectives, instructional resources, and recommended materials (Oubalahcen et al., 2023; da Silva et al., 2023; Abu-Rasheed et al.,

2023; Tan et al., 2025; Wu, 2024). Furthermore, this study positions SRL as a moderating variable to examine the effectiveness of AI-driven personalized learning among students with different levels of SRL. This study aims to provide empirical evidence on the effectiveness of pedagogically guided AI-supported personalized learning in improving students' C2 and C4 in mathematics across different levels of SRL.

Methodology

Research Design

An experimental approach was used in this study, using a pretest–posttest control group design. The design involved two groups: an experimental group that received the treatment and a control group that received personalized learning without AI-based recommendation system support. Both groups were administered a pretest to assess their initial abilities prior to the intervention. Following the implementation of the treatment, both groups completed a posttest to measure changes in learning outcomes, as presented in Table 1.

Table 1. Pretest–Posttest Control Group Design

Group	Pretest	Treatment	Posttest
Experimental	O_1	X_1	O_2
Control	O_1	X_2	O_2

Figure 1 illustrates the relationships among the study variables. The independent variable was personalized learning with two conditions: AI-based recommendation system support and no AI-based recommendation system support SRL, classified as high or low, served as the moderating variable. The dependent variables were C2 and C4. The model examined the direct effects of the learning strategy and the moderating effect of SRL on learning outcomes.

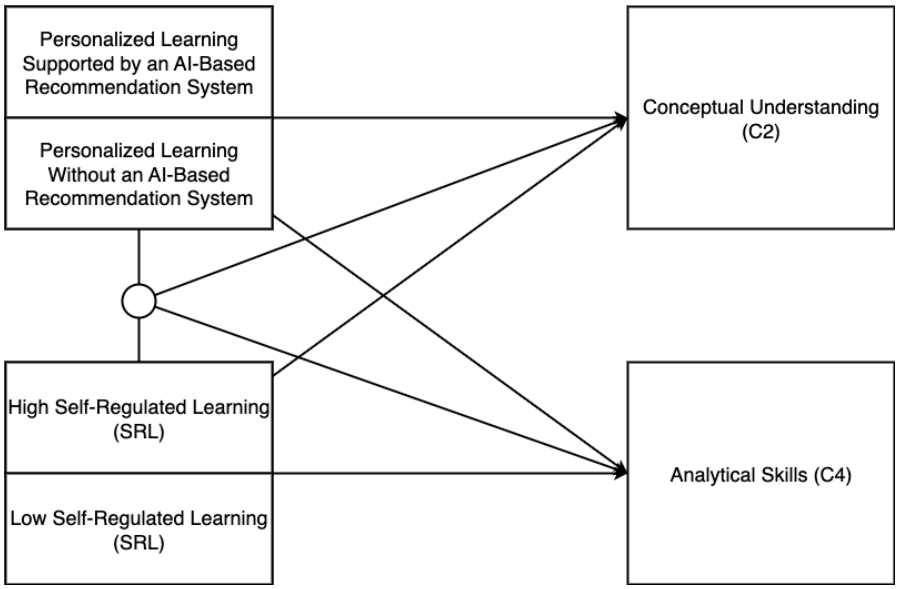


Figure 1. The Relationship Among the Research Variables

Participants

The population of this study consisted of senior high school students who served as the research subjects. Participants were classified into high- and low-SRL groups according to their SRL scores, applying the z-score method. The grouping and sample selection were conducted in several stages, as illustrated in the Figure 2, resulting in 15 students in each category within both the experimental and control groups. Thus, the total sample comprised 60 students who met the criteria based on the procedure presented in Figure 2

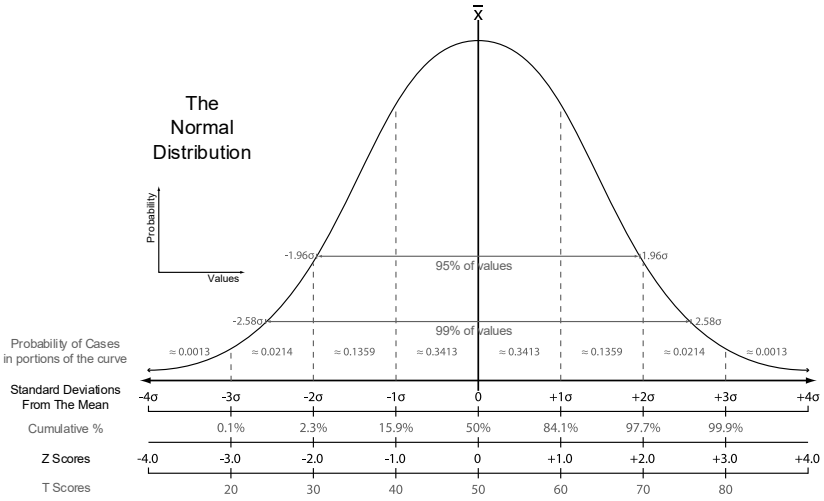


Figure 2. Normal Distribution Curve

This study employed purposive sampling involving all Grade 10 students from three existing classes. All students completed the SRL questionnaire, and their scores were classified into high and low SRL groups using z-score analysis. Two classes with the most balanced distribution of high- and low-SRL students were selected as the experimental and control groups. If no classes met this criterion, participants were reorganized into new classes to achieve balanced SRL representation. This procedure resulted in a total sample of 60 students and enabled an objective examination of the moderating role of SRL in the effect of AI-driven personalized learning on students' C2 and C4.

Variables

This study involved three interrelated types of variables in examining students' learning outcomes. The independent variable was personalized learning assisted by an AI-based recommendation system, which was applied to the experimental group. The moderator variable was SRL, which was used to classify students based on their level of learning autonomy. The dependent variables were C2 and C4, as summarized in Table 2.

Table 2. Variables Under Investigation

Variables	Description
Independent Variable	Personalized learning assisted by an AI-based recommendation system
Control Group	Personalized learning without an AI-based recommendation system
Moderator Variable	SRL
Dependent Variable	C2 and C4

Instruments

The SRL instrument was used to measure students' level of learning autonomy through a structured questionnaire. The instrument assessed multiple dimensions, including goal setting, self-monitoring, self-discipline, persistence, self-guided instruction, outcome focus, emotional control, self-efficacy, remedial assistance, and environmental adaptation (Farkhunda Rasheed Choudhary, Azhar Mahmood, & Sidra Khushnood, 2020; Shi & Yang, 2025; Winne & Perry, 2000). The SRL measurement was used to classify students based on their level of SRL. The detailed SRL aspects are presented in Table 3.

Table 3. SRL Indicators

No	SRL Aspect
1	Goal reference
2	Self-observation
3	Self-discipline
4	Persistence
5	Self-instruction
6	Outcome orientation
7	Emotional regulation
8	Self-efficacy
9	Remedial support
10	Environmental adaptation

The instrument for measuring C2 was designed to assess students' ability to comprehend mathematical concepts, particularly in the topic of exponents. The indicators included the ability to interpret, explain, and classify concepts (Anderson & Krathwohl, 2001). The instrument consisted of questions emphasizing deep C2. The detailed indicators of C2 are presented in Table 4.

Table 4. Indicators of the C2 Instrument

Indicators C2	Operational Verb
Interpreting the conceptual relationship between exponents and multiplication operations with the same base to explain underlying principles	Interpret
Exemplifying the application of division of exponents with the same base as part of conceptual relationships	Exemplify
Classifying exponent operations based on conceptual structures and exponent rules	Classify
Summarizing conceptual principles explaining zero and negative exponents	Summarize
Inferring the relationship between fractional exponents and radical forms	Infer
Comparing similarities and differences among properties of exponents	Compare
Explaining conceptual relationships among exponent properties forming a system of principles	Explain

The instrument for measuring C4 was developed to assess students' ability to decompose and relate mathematical concepts. The indicators included the ability to differentiate, organize, and connect information in problem-solving (Anderson & Krathwohl, 2001). This instrument was also based on exponent material at the analysis cognitive level. The detailed indicators of C4 are presented in Table 5.

Table 5. C4 Indicators and Instrument

Indicator of Analyzing Skills (C4)	Operational Verb
Differentiate the relationships among concepts in multiplication of exponents to determine the appropriate exponent rule.	Differentiate
Organize conceptual relationships in division of exponents to explain the mathematical structure of the solution.	Organize
Attribute the application of the power of powers rule by identifying the underlying mathematical principles and assumptions.	Attribute

Instrument Validation

All research instruments underwent content validation through expert judgment before data collection. Three experts evaluated the instruments for their relevance, clarity, and alignment with the research objectives, and their feedback was used to revise and improve the instruments before empirical testing.

Following the expert validation process, the revised instruments were administered in a pilot study involving 60 students to evaluate their empirical validity and reliability. Item validity was assessed using the Pearson product–moment correlation coefficient by comparing the correlation coefficient of each item with the critical value of the correlation table (r-table = 0.254, $\alpha = 0.05$, $n = 60$). An item was considered valid if its correlation coefficient exceeded the critical r-table value and the significance level was less than 0.05.

Instrument reliability was evaluated using Cronbach's Alpha coefficient to measure internal consistency. A Cronbach's Alpha value of 0.60 or higher was considered acceptable for exploratory educational research, following the recommendations of Taber (2018). The pilot testing produced Cronbach's Alpha coefficients of 0.668 for the C2 instrument and 0.658 for the C4 instrument, indicating acceptable internal consistency. Only instruments that satisfied the established validity and reliability criteria were used in the main study.

Procedure

The research procedure began with the distribution of the SRL questionnaire to all research subjects, namely tenth-grade high school students. The results were used to classify students and determine the sample based on SRL categories. Subsequently, both groups were administered a pretest to assess their initial abilities.

The experimental group received personalized learning supported by an AI-based LMS with a recommendation system, while the control group received personalized learning without AI support. The treatment design is presented in Table 6.

Table 6. Research Design

SRL (Moderator B)	AI-Based Personalized Learning (A1 - Experimental)	Non-AI Personalized Learning (A2 - Control)
High (B1)	Group 1 (A1B1)	Group 3 (A2B1)
Low (B2)	Group 2 (A1B2)	Group 4 (A2B2)

The AI integration framework within the LMS consists of developers, instructional design, learning data, and learning processes. Developers build the AI engine to support instructional design. Teachers define learning rules and strategies. Student data are analyzed to generate personalized content. The learning process includes content delivery, practice, and evaluation. Feedback is continuously used to improve the system.

Treatment

Both groups in this study learned through the same personalized learning approach. However, the experimental group used AI-supported personalized learning with a recommendation system, whereas the control group received personalized learning without the AI-based recommendation system as shown in Table 7.

Table 7. AI Recommendation Integration in Personalized E-Learning

Personalized Learning Syntax	**How the AI-Based Recommendation System Works in LMS**	**AI-Based LMS Features**	**Teacher's Role**	**Student's Role**
Encouraging independent learning	The LMS collects initial student data through diagnostic tests. Student responses are analyzed by AI to identify C2, strengths, and learning weaknesses. The AI then generates learning profiles and text-based learning recommendations.	AI diagnostic test	The teacher explains how to complete the diagnostic test and its purpose in the AI-based learning system.	Students complete the diagnostic test as a basis for initial ability analysis.
Connecting learning with students' interests, passions, and aspirations	AI constructs adaptive text-based learning paths based on diagnostic results and student learning activities. The system provides sequences of materials and exercises according to students' understanding levels.	Adaptive learning path, learning step recommendations, AI concept explanations	The teacher explains how to use adaptive learning path features in the LMS.	Students follow AI-recommended learning paths according to their needs.
Developing skills in selecting and using technology and learning resources	AI generates various text-based concept explanations such as summaries, case examples, and conceptual illustrations to support understanding.	AI-generated explanations, automatic summaries, text-based case examples	The teacher explains how to use content generation features in the AI-based LMS.	Students study materials based on AI-generated content recommendations.
Demonstrating content mastery in competency-based models	AI generates guiding questions and text-based analysis. Students can also interact with AI chatbots to gain further explanations.	AI learning chatbot, automatic guiding questions, text-based exercises	The teacher explains how to use the AI chatbot as a discussion and exploration tool.	Students explore learning materials by asking and discussing with the AI chatbot.
Using assessment as part of the learning process	AI recommends text-based learning strategies based on student difficulties, such as steps to understand concepts, problem-solving strategies, and appropriate learning approaches.	AI-based practice and recommendations	The teacher explains how to use AI-based evaluation features in the LMS.	Students complete exercises recommended by the AI system.
Becoming independent learners who monitor and reflect on progress	AI analyzes evaluation results and provides text-based feedback on conceptual errors along with improvement recommendations.	AI adaptive evaluation based on learning history	The teacher explains how to use self-evaluation features in the AI-based LMS.	Students generate learning progress reports analyzed by the AI system.

The learning process is supported by an e-learning system equipped with a recommendation system through the integration of the Gemini AI API (Figure 3). In this process, students receive personalized materials and interact with AI features available within the e-learning platform. These interactions include content exploration, practice exercises, and automated feedback, all of which are stored in a database. The collected data are analyzed to identify learning patterns and generate more accurate recommendations continuously.

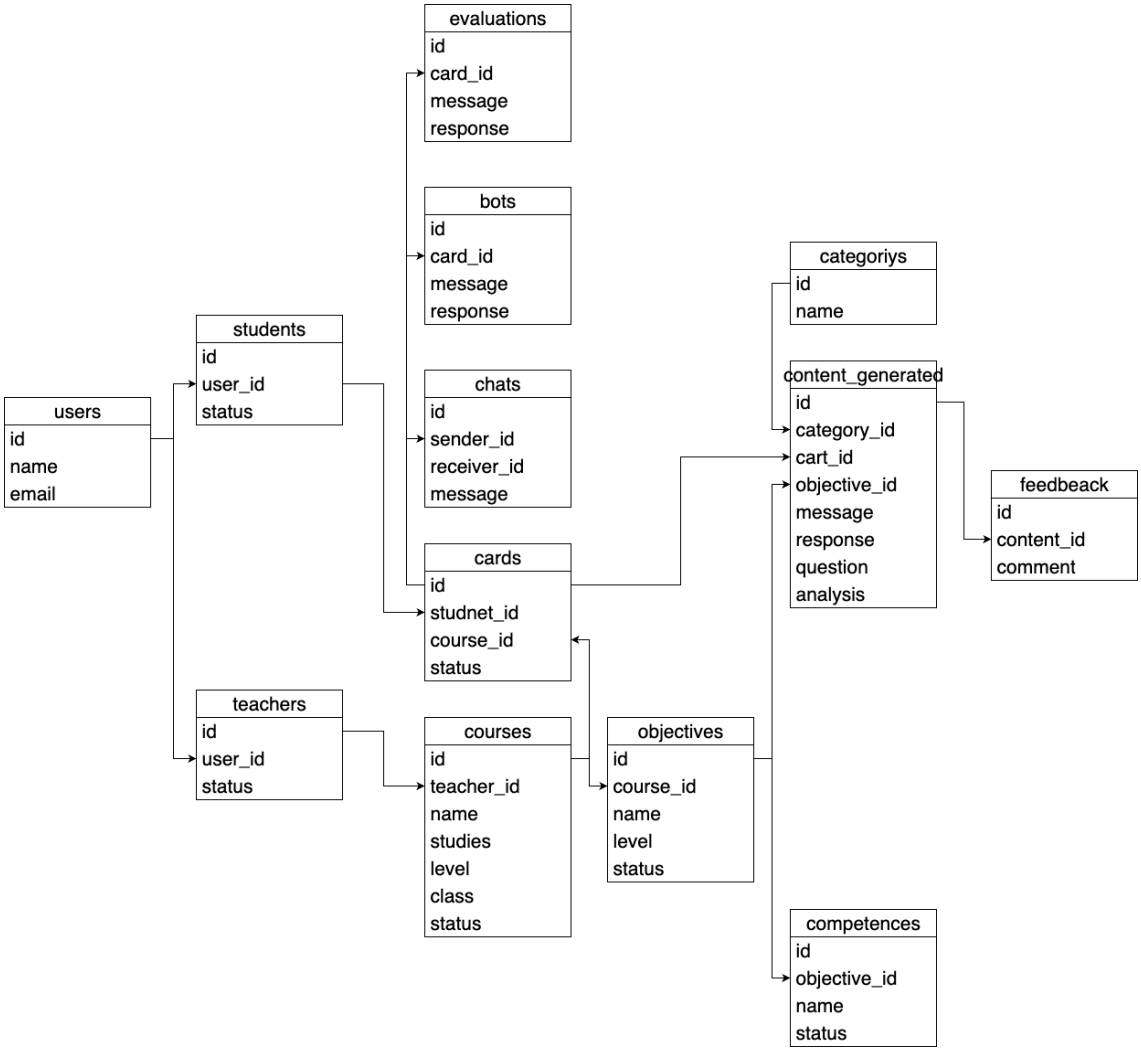


Figure 3. AI-Based Personalized E-Learning Database Schema

All student learning activities are automatically stored in the LMS database and used as learning analytics for teachers and educational institutions to monitor progress and evaluate learning outcomes. Therefore, the proposed learning design integrates teachers, developers, and students to support data-driven personalized learning.

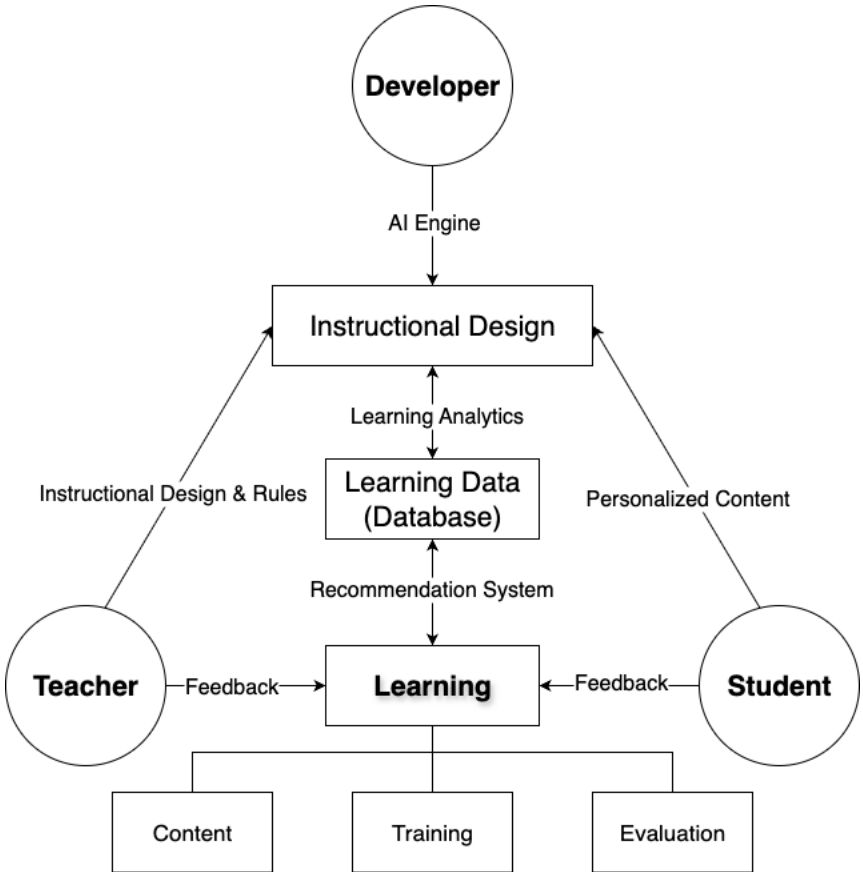


Figure 4. Smart Learning System Framework

Figure 4 presents the Smart Learning System Framework employed in this study. The framework integrates teachers, students, instructional design, learning analytics, a recommendation system, and an AI engine into a unified learning environment. Teachers establish instructional rules and learning objectives, while the AI engine analyzes students' learning data to generate personalized content and recommendations. Throughout the learning process, continuous feedback from students and teachers is utilized to refine instructional strategies and improve the effectiveness of personalized learning.

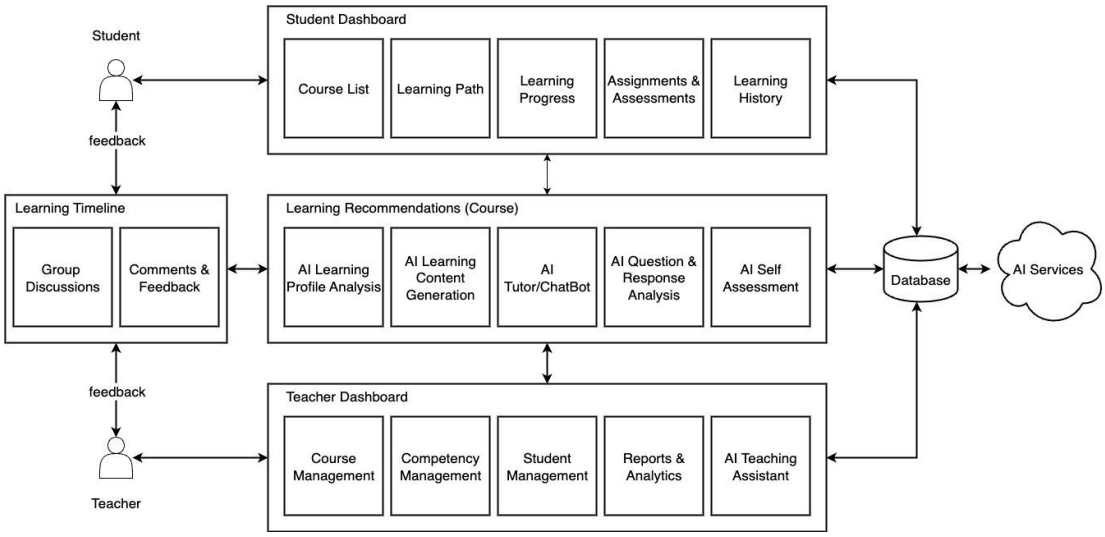


Figure 5. Architecture of an AI-Based LMS

Figure 5 illustrates the architecture of the proposed AI-Based LMS. Students interact with the AI Recommendation Engine, which analyzes learning profiles, generates personalized learning content, provides AI tutoring, evaluates responses, and supports self-assessment using data stored in the database and external APIs. The learning outcomes and user interactions are processed into feedback and learning analytics, enabling continuous monitoring of student performance and learning progress. Teachers access these analytics through the Teacher Dashboard to manage courses, competencies, students, and learning progress while making data-driven instructional decisions.

Data Analysis

Data analysis was conducted in several stages to ensure the validity and reliability of the findings. The preliminary analysis included tests of normality and homogeneity to verify that the data satisfied the assumptions for multivariate analysis. An initial equivalence test was then performed to confirm that the experimental and control groups had comparable baseline conditions before the intervention. These preliminary analyses ensured that any differences observed in the posttest could be attributed to the learning treatments rather than pre-existing group differences.

The primary analysis used a 2 × 2 factorial multivariate analysis of variance (MANOVA). MANOVA was selected because the pretest equivalence test confirmed that the experimental and control groups had comparable baseline conditions. The analysis examined the effects of learning strategy and SRL on C2 and C4 simultaneously. This approach also tested the interaction effect while accounting for the correlation between the dependent variables. Significant multivariate effects were interpreted using the multivariate test results.

Findings

The analysis began by identifying the distribution of students' SRL to ensure the balance of initial characteristics across research groups. The grouping was conducted based on high and low SRL categories to determine the proportion of students in each group. This distribution served as the basis for establishing initial equivalence prior to the treatment. The detailed SRL distribution is presented in Table 8.

Table 8. Distribution of SRL

Class	High	Low	Total
X-1/A	19	17	36
X-2/B	18	17	35
X-3/C	18	13	31
Total	**52**	**50**	**102**

Table 8 presents the distribution of students according to their self-regulated learning (SRL) levels across the three classes. The distribution shows the number of students classified as having high and low SRL in each class. These data were used as a basis for selecting participants for the experimental and control groups. The final research sample is presented in Table 9.

Table 9. Research Sample Based on SRL Characteristics

Group	Class	High SRL	Low SRL	Total
Experimental	X-1/A	15	15	30
Control	X-2/B	15	15	30
Total		**30**	**30**	**60**

Following the classification of participants based on their SRL characteristics, the validity and reliability of the research instruments were evaluated before conducting the main data analysis. The Pearson correlation test showed that all 35 C2 items were valid, with correlation coefficients ranging from 0.257 to 0.324, exceeding the critical r-table value of 0.254, and significance values below 0.05. These findings indicate that all items were able to measure the construct of C2 appropriately. Furthermore, the instrument demonstrated acceptable reliability with a Cronbach's alpha coefficient of 0.668, indicating that it was suitable for subsequent data analysis.

Similarly, the C4 instrument also demonstrated satisfactory measurement quality. All 30 items were declared valid, with correlation coefficients ranging from 0.263 to 0.415, exceeding the critical r-table value of 0.254, and significance values below 0.05. These results confirm that each item adequately measured the construct of C4. In addition, the instrument achieved a Cronbach's alpha coefficient of 0.658, indicating acceptable internal consistency and confirming its suitability for the subsequent statistical analyses.

The next step involved conducting normality tests on pretest and posttest data for both groups. This test aimed to ensure that the data were normally distributed as a requirement for parametric analysis.

Table 10. Normality Test

Variable	Group	Sig. Kolmogorov-Smirnov	Sig. Shapiro-Wilk
Pretest C2	Control	0.157	0.360
	Experiment	0.184	0.265
Pretest C4	Control	0.200	0.533
	Experiment	0.200	0.340
Posttest C2	Control	0.084	0.608
	Experiment	0.200	0.125
Posttest C4	Control	0.159	0.620
	Experiment	0.200	0.307

Based on Table 10, all significance values obtained from the Kolmogorov–Smirnov and Shapiro–Wilk tests are greater than 0.05. These results indicate that the pretest and posttest scores for students' C2 and C4 are normally distributed. Therefore, no violations of the

normality assumption were identified, indicating that the data satisfy the assumptions required for subsequent parametric analyses.

The next step involved conducting a homogeneity of variance test between groups to ensure that the data variances were homogeneous.

Table 11. Homogeneity Test

Variable	Levene Statistic	df1	df2	Sig.
Pretest C2	0.045	1	58	0.833
Pretest C4	0.008	1	58	0.930
Posttest C2	0.086	1	58	0.770
Posttest C4	0.014	1	58	0.905

Based on Table 11, all significance values are greater than 0.05, indicating that the data variances are homogeneous. There are no significant differences in variance between the control and experimental groups. Thus, the homogeneity assumption is satisfied.

The next stage involved testing the equivalence of initial abilities using the Independent Samples t-test on pretest data. This analysis aimed to ensure that there were no significant differences between groups before the treatment.

Table 12. Independent Samples t-Test (Pretest Data)

Variable	t	df	Sig. (2-tailed)	Mean Difference	Std. Error	95% CI Lower	95% CI Upper
Pretest C4	0.242	58	0.810	0.55567	2.29559	-4.03946	5.15079
Pretest C2	-1.888	58	0.064	-4.85667	2.57305	-10.00718	0.29385

Based on Table 12, the significance values for both variables are greater than 0.05. This finding shows that no significant differences were observed between the control and experimental groups during the pretest phase. Thus, the initial abilities of students in both groups can be considered equivalent, allowing for a fair comparison of posttest results.

The main analysis was conducted using MANOVA to examine the effects of the treatment and SRL on learning outcomes, considering both dependent variables simultaneously.

Table 13. Tests of Between-Subjects Effects

Source	Dependent Variable	F	Sig.
Corrected Model	Posttest C2	16.521	0.000
	Posttest C4	17.150	0.000
Group	Posttest C2	48.263	0.000
	Posttest C4	44.274	0.000
SRL	Posttest C2	0.164	0.687
	Posttest C4	1.356	0.249
Group * SRL	Posttest C2	1.137	0.291
	Posttest C4	5.821	0.019

Table 13 presents the results of the 2 × 2 factorial MANOVA examining the effects of learning strategy, SRL, and their interaction on students' C2 and C4. The corrected model was statistically significant for both C2 ($F = 16.521$, $p < .001$) and C4 ($F = 17.150$, $p < .001$), indicating that the model accounted for significant variation in both dependent variables. The learning strategy (group) exhibited a significant main effect on C2 ($F = 48.263$, $p < .001$) and C4 ($F = 44.274$, $p < .001$). These findings demonstrate that students who received personalized learning supported by an AI-based recommendation system achieved

significantly better learning outcomes than those who received personalized learning without the AI-based recommendation system.

In contrast, SRL did not produce a significant main effect on either C2 (F = 0.164, p = .687) or C4 (F = 1.356, p = .249), suggesting that differences in SRL levels alone were insufficient to explain variations in students' performance. However, the interaction between learning strategy and SRL was significant for C4 (F = 5.821, p = .019) but not for C2 (F = 1.137, p = .291). This result indicates that the effectiveness of the AI-based personalized learning strategy in improving C4 depended on students' SRL levels, whereas its positive effect on C2 was consistent across both high- and low-SRL students. Overall, the findings suggest that the learning strategy was the primary determinant of improvements in both learning outcomes, while SRL functioned as a moderator only for C4. In the final stage, post hoc analyses were performed using pairwise comparisons to explore differences among SRL categories.

Table 14. Multivariate Test Results of the Effects of SRL and Learning Group on the Dependent Variables

Effect	Multivariate Test	Value	F	Hypothesis df	Error df	Sig.
Intercept	Pillai's Trace	0.988	2330.093	2	55	0.000
	Wilks' Lambda	0.012	2330.093	2	55	0.000
	Hotelling's Trace	84.731	2330.093	2	55	0.000
	Roy's Largest Root	84.731	2330.093	2	55	0.000
SRL	Pillai's Trace	0.025	0.713	2	55	0.495
	Wilks' Lambda	0.975	0.713	2	55	0.495
	Hotelling's Trace	0.026	0.713	2	55	0.495
	Roy's Largest Root	0.026	0.713	2	55	0.495
Group	Pillai's Trace	0.604	41.975	2	55	0.000
	Wilks' Lambda	0.396	41.975	2	55	0.000
	Hotelling's Trace	1.526	41.975	2	55	0.000
	Roy's Largest Root	1.526	41.975	2	55	0.000
SRL × Group	Pillai's Trace	0.105	3.230	2	55	0.047
	Wilks' Lambda	0.895	3.230	2	55	0.047
	Hotelling's Trace	0.117	3.230	2	55	0.047
	Roy's Largest Root	0.117	3.230	2	55	0.047

Table 14 presents the results of the MANOVA analysis, indicating that SRL did not have a statistically significant effect on the combined dependent variables. The Pillai's Trace value of 0.025, with F(2,55) = 0.713 and p = 0.495, indicates that the significance level exceeded the threshold of 0.05. This finding suggests that differences in students' levels of SRL did not produce significant simultaneous differences in the dependent variables examined. Therefore, the study found no evidence that SRL independently influenced the combined learning outcomes.

The multivariate analysis further demonstrated that the learning group (Group) had a statistically significant effect on the combined dependent variables. The Pillai's Trace value of 0.604, with F(2,55) = 41.975 and p < 0.001, indicates that the probability value was below the significance level of 0.05. This result demonstrates a significant multivariate difference between the experimental group and the control group with respect to the dependent variables. Accordingly, the implementation of the instructional model in the experimental group produced significantly different learning outcomes compared with those of the control group.

The interaction analysis also demonstrated a statistically significant interaction effect between SRL and the learning group (Group) on the combined dependent variables. The Pillai's Trace value of 0.105, with F(2,55) = 3.230 and p = 0.047, indicates that the interaction effect was

statistically significant at the 0.05 level. This finding suggests that the effect of the instructional model on the dependent variables varied according to students' levels of SRL. Therefore, the effectiveness of the instructional model was influenced not only by the learning group but also by its interaction with students' SRL, jointly contributing to differences in learning outcomes.

DISCUSSION

The Effect of AI-Based Learning

This study demonstrates that AI-driven personalized learning supported by a recommendation system significantly improves students' C2 and C4. These findings align with previous empirical studies showing that adaptive learning systems enhance learning outcomes by tailoring instructional content to students' needs and proficiency levels (Sibley et al., 2024). Recommendation-based adaptive learning has significantly improved students' learning performance compared to traditional instruction, while AI-supported personalized learning environments have increased students' engagement and C2 (Mohamed et al., 2024; S. Wang et al., 2023). Furthermore, AI-based recommendation systems improve C4 by providing targeted learning materials (Song, 2024a; Zhou & Abisado, 2025a). These findings support the argument that adaptive systems make learning more relevant and effective by aligning instructional content with individual learner characteristics.

Previous studies also reveal several important limitations despite these positive findings. Most prior research has focused primarily on system performance indicators, such as recommendation accuracy, usability, and learner satisfaction, rather than directly examining C2 and C4 (Mohamed et al., 2024; Song, 2024; Zhou & Abisado, 2025). Many studies have also relied on open digital learning environments in which students freely access external learning resources, making it difficult to isolate the contribution of AI-based recommendation systems to learning outcomes (Li et al., 2025; Rasheed, Ghwanmeh, & Abualkishik, 2023). These methodological limitations have reduced the strength of causal claims regarding the effectiveness of AI-supported personalized learning.

The improvement in students' C2 and C4 may be attributed to the adaptive mechanism of the AI-based recommendation system. The system continuously recommends learning materials that match students' current knowledge and learning needs, allowing them to learn more effectively (S. Wang et al., 2023; Mohamed et al., 2024). Personalized learning pathways also help students connect concepts progressively and analyze problems more systematically (Song, 2024a; Zhou & Abisado, 2025). Consequently, the observed learning gains appear to be associated with adaptive instructional support rather than the use of AI technology alone.

Effect on C2

The experimental group showed greater improvement in C2 than the control group. The adaptive system helped students interpret and explain concepts more systematically (Soelistianto, Andrasmoro, Yusriati, Mardiati, & Fawait, 2024; Xia et al., 2026). The structured presentation of learning materials enabled students to connect multiple representations of mathematical concepts (Bicer, 2021; Post & Prediger, 2024). Guided learning activities also supported students in constructing conceptual knowledge progressively (Al Mamun, Lawrie, & Wright, 2022). Therefore, AI-based learning appears to strengthen students’ C2.

The improvement in C2 can be explained by the adaptive recommendation mechanism embedded within the learning system. The system continuously adjusts learning materials to students' current levels of understanding, allowing them to master prerequisite concepts before progressing to more complex topics (S. Wang et al., 2023; Mohamed et al., 2024). Unlike many previous studies that primarily evaluated recommendation accuracy, usability, or learner satisfaction, this study provides evidence that AI-supported personalization contributes to measurable improvements in C2. These findings suggest that the educational value of AI may lie not only in delivering personalized recommendations but also in providing structured learning pathways that facilitate meaningful conceptual development.

Effect on C4

AI-based learning also significantly enhances students' C4. The recommendation system helps students identify patterns and relationships among concepts (Urdaneta-Ponte, Mendez-Zorrilla, & Oleagordia-Ruiz, 2021). Students use this information to solve problems more critically (Hou et al., 2026). This process involves higher-order thinking activities. Thus, the adaptive system appears to promote the development of students' C4.

The improvement in students' C4 may be explained by the adaptive learning process provided by the AI-based recommendation system (Hou et al., 2026; Song, 2024a). The system presents learning materials in a sequence that matches students' current levels of understanding, allowing them to identify patterns and relationships more effectively (Urdaneta-Ponte, Mendez-Zorrilla, & Oleagordia-Ruiz, 2021). Personalized feedback encourages students to evaluate their reasoning and improve their problem-solving strategies throughout the learning process (Zhou & Abisado, 2025a). Therefore, the improvement in C4 appears to result from structured adaptive support rather than from the use of AI technology alone.

The Role of SRL

SRL did not have a significant effect on students' C2 and C4. The adaptive learning system provides equitable learning support to all students (Carceles-Poveda & Giannitsarou, 2007; Chen et al., 2018; Tan et al., 2025; Taylor et al., 2021). It supports the learning process by providing direction, organization, and ongoing feedback (Kevin, Bakker, van Loon, Kral, & Camp, 2025; Makhno, Kireeva, & Shurygin, 2022; Pachón-Basallo et al., 2022). This finding indicates that the technology functions as a form of scaffolding during learning.

Technology-supported learning may also reduce differences in Self-Regulated Learning levels among students (C. M. Chen, 2009; Fuchs et al., 2022; Ingkavara, Panjaburee, Srisawasdi, & Sajjapanroj, 2022; Wu, Lee, Li, Huang, & Huang, 2023). The system helps students with low SRL engage in learning more optimally. Meanwhile, students with high SRL continue to utilize the system to deepen their understanding. This finding shows that adaptive systems accommodate differences in student characteristics (Boussakssou, Hssina, & Erittali, 2020; Su, 2020). Thus, the findings suggest that technology can function as a balancing mechanism in learning.

Interaction Between Learning and SRL

The interaction between learning and SRL does not have a significant effect on students' C2. This finding suggests that the controlled use of AI within an adaptive learning system may help mitigate differences associated with students' SRL levels. The systematic

and gradual presentation of materials becomes the key factor in achieving uniform understanding (Martin & Evans, 2018; Schwamborn, Thillmann, Opfermann, & Leutner, 2011). Consequently, learning outcomes related to C2 were more similar between students with high and low SRL.

Several studies have reported that students' use of AI in learning is often insufficiently regulated due to differences in SRL levels (Molenaar, 2022; C.-Y. Wang & Lin, 2023). Students with high SRL tend to benefit more, while those with low SRL are less directed. This situation may contribute to disparities in learning outcomes.

Interpretation of the AI-Based Learning Ecosystem

The findings of this study can be interpreted through an AI-based adaptive learning ecosystem that integrates the roles of developers, teachers, and students. Developers design systems that generate adaptive learning recommendations (Kabassi, 2010; Nation, Habichler, Tadepalli, Ng, & ..., 2007). Teachers guide the learning process to ensure alignment with pedagogical objectives (Biggs, 1996; C. M. Reigeluth & Moore, 2009). Students use the system to develop C2 and C4 (C. Reigeluth, 1999; C. M. Reigeluth & Moore, 2009). This integration connects learning facilitation, learning experience, and learning performance, thereby supporting improvements in students' learning outcomes (Figure 6).

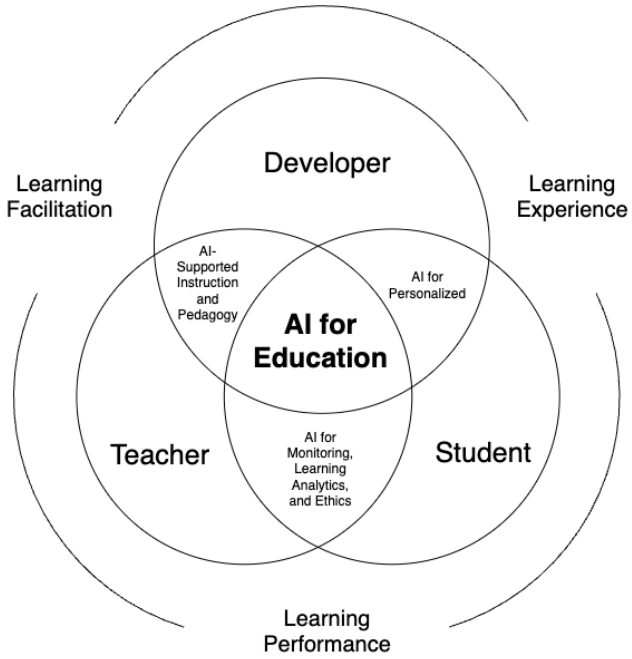


Figure 6. AI for Education Ecosystems

Control of Learning in AI

AI-driven learning encourages a transition from teacher-centered instruction to learner-centered approaches. The system enables students to take a more active role in regulating their learning process. Teachers still function as facilitators who support and direct the learning process. Students begin to determine learning strategies that align with their individual needs. This finding suggests that learning becomes more autonomous and flexible.

Personalization as Adaptive Learning

The findings of this study suggest that personalized learning should be supported through adaptive systems. At the initial stage, the system guides students' learning processes in a structured manner. Students then gradually take a more active role in directing their learning activities. At advanced stages, students develop their own learning strategies independently. Personalization theory explains that this process evolves from adaptive to dynamic personalization (Figure 7).

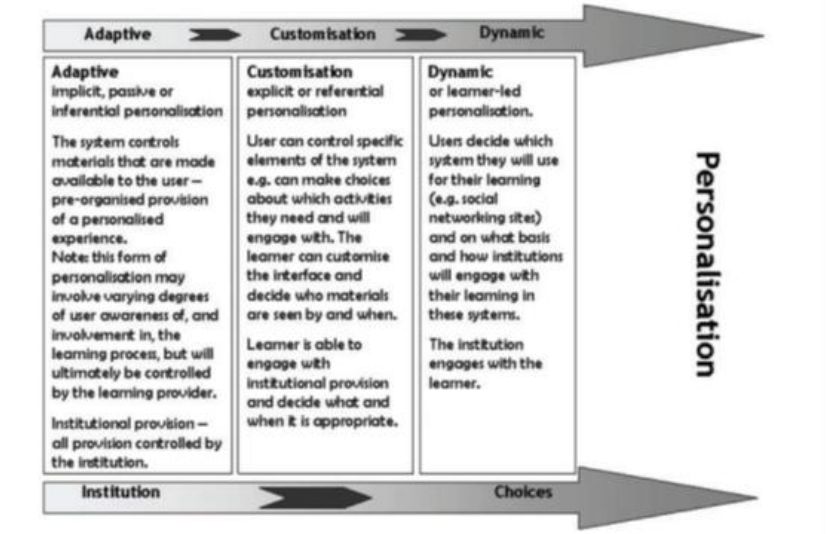


Figure 7. Levels of personalisation provided through technology (O'Donoghue, 2009)

Implications for Learning

AI-based learning should be designed in an adaptive and structured manner to maximize its effectiveness. The system should adjust learning materials according to students' needs. Both teachers and the system should support students' active thinking processes. Learning should not merely focus on information delivery. Therefore, the integration of AI may represent a valuable strategy for improving the quality of learning.

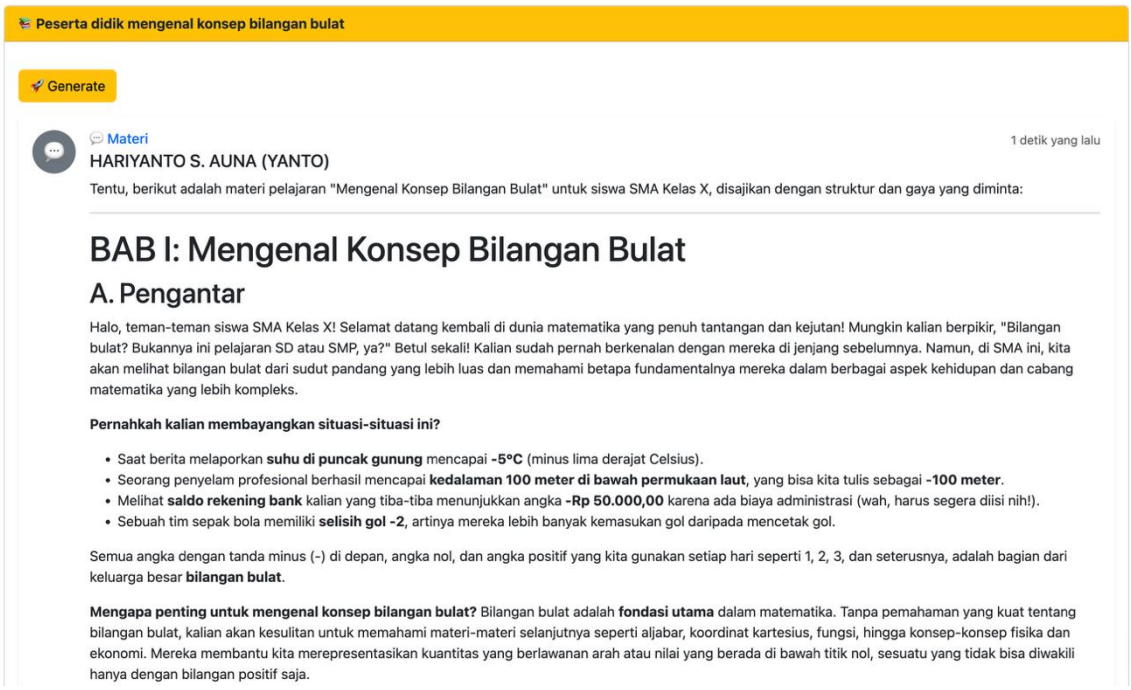


Figure 8. Examples of Learning Materials Display on AI-Generated Content

Figure 8 illustrates that learning topics are automatically generated through an AI-based system. Each individual receives materials presented differently, as the content is tailored to the characteristics and needs of each user. This reflects the implementation of personalized learning within the LMS. Thus, the system is capable of providing a more adaptive and relevant learning experience for each student.

Conclusion

This study shows that personalized learning supported by an AI-based recommendation system significantly improves students' C2 and C4. The adaptive system adjusts learning materials according to students' needs, making the learning process more focused and structured. These findings suggest that controlled personalization can enhance learning effectiveness. SRL did not have a significant effect on either understanding or analytical abilities. This suggests that the AI-based system may provide comparable learning support across students with different SRL levels.

The interaction between learning strategy and SRL does not influence students' C2, but it does affect their C4. This result indicates that C4 requires active student engagement in the learning process. The study suggests that controlled AI-based learning may help reduce gaps in students' learning outcomes. The integration of AI systems, teachers, and students may create a more effective learning environment. Therefore, AI-based adaptive learning has the potential to improve the quality of education.

Educational institutions should adopt AI-based recommendation systems as an integral component of personalized learning to improve learning effectiveness. Successful implementation requires a balanced integration of technology, pedagogy, and institutional support to ensure that AI functions as a learning facilitator rather than a substitute for instructional practice. Future implementation should prioritize adaptive and pedagogically guided AI applications that respond to students' learning needs. These efforts can promote

more effective, equitable, and sustainable personalized learning across diverse educational contexts.

Declarations

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Conflict of Interest: *The authors declare that there is no conflict of interest regarding the publication of this paper.*
Informed Consent: *Informed consent was obtained from all participants involved in this study prior to data collection.*
Data availability: *The data supporting the findings of this study are available from the corresponding author upon reasonable request.*

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