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Artificial Intelligence (AI) Driven Dual-Loop Adaptive Learning In Economics Education: Evidence From A Quasi-Experimental Study

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Abstract

Artificial Intelligence-based Dual-Loop Adaptive Learning model designed to support differentiated economics learning in senior high schools. The model responds to a major limitation of conventional adaptive learning systems, which often adjust content and task difficulty without diagnosing students' learning strategies, misconceptions, or recurring error patterns. The proposed model integrates automatic content adaptation with reflective feedback to help students reconsider their assumptions, regulate their learning strategies, and strengthen metacognitive awareness. This study employed a Research and Development orientation combined with a quasi-experimental pretest-posttest control group design. Model feasibility was examined through expert validation, while its effectiveness was analyzed through comparative statistical procedures and AI classification performance metrics. The findings indicate that the model achieved a high level of validity and produced stronger improvement in cognitive learning outcomes, intrinsic motivation, and metacognition compared with conventional instruction. The AI component also demonstrated adequate capability in classifying student error patterns to support reflective feedback. These results suggest that the Dual-Loop Adaptive Learning model can function not only as a content personalization system but also as a pedagogical intervention that promotes reflective, differentiated, and data-informed economics learning. The model offers practical value for teachers in diagnosing learner needs, designing targeted interventions, and supporting more adaptive classroom decision-making.

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Keywords: Adaptive Learning; Artificial Intelligence; Differentiated Learning; Economics Education; Metacognition.

INTRODUCTION

Artificial intelligence has become an important catalyst in contemporary educational innovation because it enables learning systems to diagnose student responses, personalize instructional pathways, and provide feedback at a speed that conventional classroom mechanisms cannot easily match (Dino et al., 2025). In the context of school learning, AI-supported adaptive learning is particularly relevant because students rarely enter the classroom with the same prior knowledge, pace of learning, motivation, and strategy for solving problems (Juliastuti et al., 2025). The core pedagogical challenge is therefore not merely how to deliver digital content, but how to design an intelligent learning environment that can respond to learner differences without reducing learning into mechanical drill and answer correction (Romero-Rodríguez et al., 2024).

The current literature on AI in education shows that intelligent systems can assist learning analytics, personalization, and feedback processes (Fernhaber & Zou, 2022). Nevertheless, many adaptive learning systems still emphasize content-level adaptation. (Duan et al., 2024) they adjust difficulty, sequence, or recommendation based on correct and incorrect answers, but they do not always diagnose why students make errors or how students regulate their own thinking. This limitation is pedagogically important because students may improve their immediate answer accuracy while leaving their misconception, ineffective strategy, or low self-monitoring ability unresolved (B et al., 2025).

Differentiated learning requires more than the diversification of material formats. (S. Hu, 2024) explains that differentiation should respond to students' readiness, interests, and learning profiles. In a digital classroom, this principle can be strengthened by AI when the system not only changes content but also generates information about students' learning processes. At the same time, reflective feedback remains central because effective feedback should clarify learning goals, current performance, and next actions for improvement (Manurung, 2025). When feedback helps students plan, monitor, and evaluate their thinking, it supports self-regulated learning and metacognitive development (Molenaar, 2022).

The theoretical foundation of the present model draws on double-loop learning.(Chen et al., 2020) distinguish single-loop learning, which corrects action within existing assumptions, from double-loop learning, which examines the underlying assumptions that guide action. Translated into an AI-based learning system, single-loop adaptation occurs when the system changes task

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difficulty after a wrong answer (Feriyadi et al., 2025). Dual-loop adaptation occurs when the system identifies an error pattern and asks students to review the strategy, concept, or assumption that produced the error. This distinction becomes the central innovation of the Adaptive Learning Dual Loop model (Nabila & Rachman, 2025).

This This article aims to evaluate the validity and effectiveness of the Adaptive Learning Dual Loop model in economics education through a field-based quasi-experimental design. The study examines whether the model can improve cognitive learning outcomes, intrinsic motivation, and metacognition among senior high school students. The research questions are: (1) How valid is the AI-based Adaptive Learning Dual Loop model according to expert validation? (2) How effective is the model in improving students' cognitive learning outcomes, intrinsic motivation, and metacognition? (3) How well does the AI component classify student error patterns to support reflective feedback?

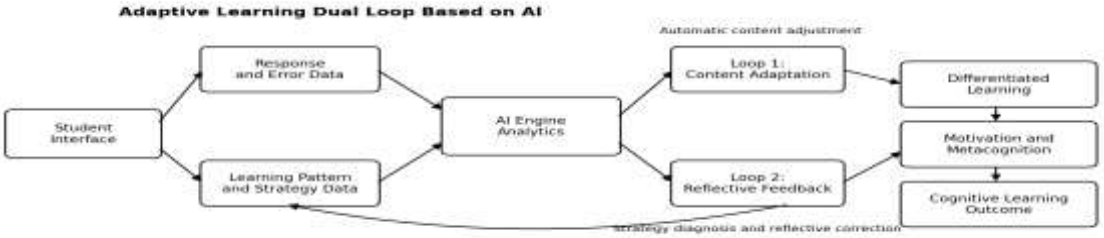


Figure 1. Operational Structure of the AI-Based Adaptive Learning Dual Loop Model

Figure 1 summarizes the model logic. The first loop processes student responses and adapts content, while the second loop processes learning patterns and produces reflective feedback. The expected learning effects are differentiated learning, stronger motivation and metacognitive regulation, and improved cognitive learning outcomes.

METHODOLOGY

The The study used a Research and Development orientation combined with a quasi-experimental pretest-posttest control group design. The developmental component focused on conceptualizing the model architecture, validation indicators, instructional flow, AI feedback mechanism, and evaluation instruments. The effectiveness component involved 200 senior high school students, with 100 students assigned to the experimental group and 100 students assigned to the control group. The experimental group learned through the AI-based Dual-Loop Adaptive

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Learning model, while the control group learned through conventional instruction. The study was conducted in the context of senior high school economics learning (Hair et al., 2019).

The model validation involved five validators who assessed five aspects: content feasibility, instructional design, technical AI quality, reflective feedback, and practicality. Each aspect was converted into a percentage score and interpreted using validity categories. Student outcomes consisted of cognitive learning outcomes, intrinsic motivation, and metacognition. Cognitive learning outcomes were measured using pretest and posttest scores. Intrinsic motivation and metacognition were measured using pretest and posttest questionnaire scores. Normalized gain was used to represent the magnitude of learning outcome improvement, following the logic of gain analysis in educational intervention studies (Muhammad Afifi Rahman, Satunggale Kurniawan, 2025).

The AI performance component used 1,000 local data points to classify student error patterns into four classes: misconception, carelessness, lack of conceptual understanding, and inappropriate strategy. Classification performance was evaluated using accuracy, precision, recall, F1-score, macro average, and weighted average (Lestari et al., 2024). These metrics were selected because the AI component is intended to support the second loop of reflective feedback; therefore, it must distinguish not only whether the answer is wrong, but also the likely structure of the error .

Data analysis was conducted through descriptive statistics, paired sample t-tests, Welch independent sample t-tests, MANOVA, normalized gain, and classification metrics. Paired sample t-tests examined within-group changes from pretest to posttest. Welch independent sample t-tests compared posttest scores, delta scores, and normalized gain between groups while providing a more robust approach when equal variance cannot be fully assumed. MANOVA tested whether group membership produced effect on the combined dependent variables of normalized gain, motivation improvement, and metacognition improvement. All numerical findings were interpreted as empirical evidence from the quasi-experimental implementation, while still considering the scope, sample characteristics, and contextual limitations of the study (R. Hu et al., 2024).

RESULTS AND DISCUSSION

The first analysis examined expert validation. The validation results indicate that the model achieved a high level of developmental feasibility. The overall average score reached 4.56, equivalent to 91.12%. The strongest aspect was instructional design, while the technical AI quality

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aspect received the lowest score although it remained in the valid category. This pattern is important because it suggests that the pedagogical architecture is already strong, but the technical AI component still requires careful refinement during field implementation, especially in relation to the quality of error classification, explainability of feedback, and system reliability.

Table 1. Model Validation Results

Validation aspect	Mean	Percentage	Category
Content feasibility	4.56	91.20%	Highly valid
Instructional design	4.66	93.20%	Highly valid
Technical AI quality	4.46	89.20%	Valid
Reflective feedback	4.58	91.60%	Highly valid
Practicality	4.52	90.40%	Highly valid
Overall average	4.56	91.12%	Highly valid

The descriptive statistics show a clear difference in improvement patterns between the experimental and control groups. The experimental group increased from 55.40 to 77.93 in cognitive learning outcomes, while the control group increased from 54.57 to 63.58. The normalized gain of the experimental group was 0.525, compared with 0.206 in the control group. The same tendency appeared in intrinsic motivation and metacognition. This descriptive pattern supports the basic assumption that dual-loop adaptation may provide stronger learning support than conventional instruction because it combines content personalization with reflective strategy correction.

Table 2. Descriptive Statistics of Learning Outcomes

Outcome	Group	Pretest M (SD)	Posttest M (SD)	Delta	N-gain
Cognitive learning outcome	Experimental	55.40 (8.78)	77.93 (10.29)	22.53	0.525
Cognitive learning outcome	Control	54.57 (8.28)	63.58 (9.82)	9.01	0.206
Intrinsic motivation	Experimental	63.96 (7.10)	79.85 (8.18)	15.89	-
Intrinsic motivation	Control	63.84 (7.50)	69.79 (8.64)	5.95	-
Metacognition	Experimental	44.89 (6.03)	59.74 (6.87)	14.85	-
Metacognition	Control	46.53 (6.09)	52.42 (7.35)	5.89	-

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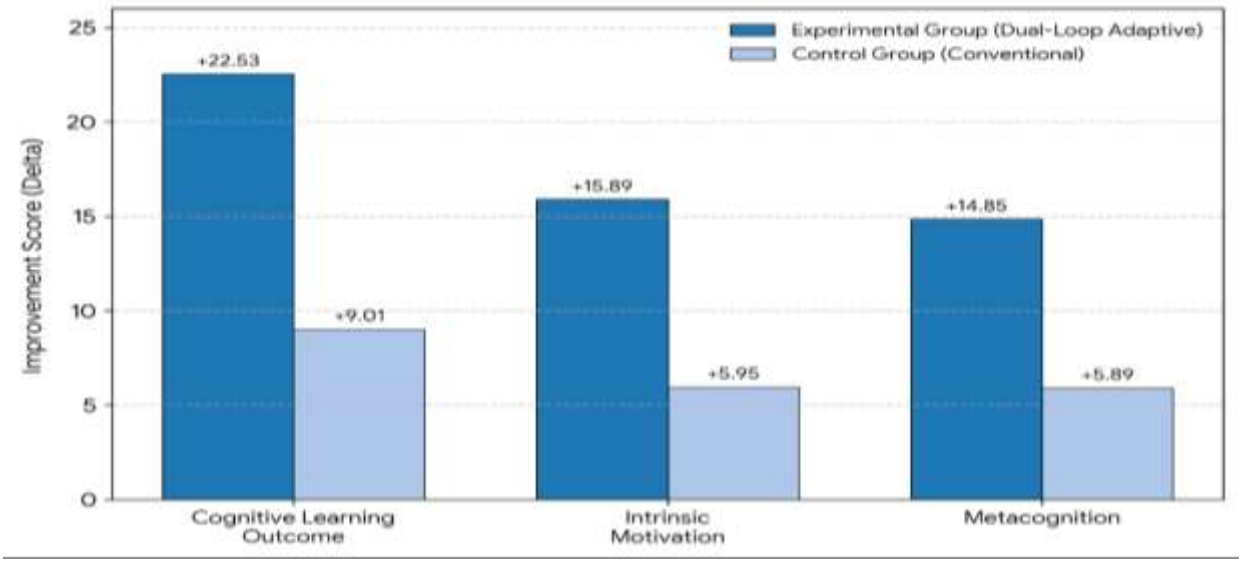


Figure 2. Comparison of Improvement Scores Between Experimental and Control Groups

Figure 2 presents the comparison of improvement scores between the experimental and control groups across three main learning outcomes. The experimental group showed higher improvement in cognitive learning outcomes, intrinsic motivation, and metacognition. The largest difference appeared in cognitive learning outcomes, where the experimental group improved by 22.53 points, while the control group improved by 9.01 points. Similar patterns were also observed in intrinsic motivation and metacognition. This visual comparison strengthens the statistical results by showing that the dual-loop adaptive learning model produced a consistently higher improvement pattern across cognitive, motivational, and metacognitive domains (Bo, 2024).

The within-group test confirms that both groups improved significantly from pretest to posttest. However, the magnitude of change was consistently larger in the experimental group. The paired sample t-test for cognitive learning outcomes in the experimental group produced $t(99) = 35.655$, $p < .001$, Cohen's $d = 3.565$. Motivation and metacognition also increased significantly with very large effect sizes. The control group also improved, but the deltas were substantially smaller. This pattern suggests that ordinary learning exposure can generate improvement, but the dual-loop model produces a stronger projected effect when adaptive content and reflective feedback operate together.

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Table 3. Paired Sample T-Test Summary

Group	Outcome	Mean delta	t	df	p	Cohen's d
Experimental	Cognitive learning outcome	22.53	35.655	99	< .001	3.565
Experimental	Intrinsic motivation	15.89	31.496	99	< .001	3.150
Experimental	Metacognition	14.85	39.706	99	< .001	3.971
Control	Cognitive learning outcome	9.01	15.622	99	< .001	1.562
Control	Intrinsic motivation	5.95	13.746	99	< .001	1.375
Control	Metacognition	5.89	14.481	99	< .001	1.448

Between-group testing provides stronger evidence for the projected effectiveness of the model. Welch independent sample t-tests showed that the experimental group outperformed the control group on posttest score, improvement score, normalized gain, motivation improvement, and metacognition improvement. The N-gain comparison was significant, $t = 14.321$, $df = 188.41$, $p < .001$, Cohen's $d = 2.025$. This effect size is very large in the dataset. The practical interpretation is that the experimental condition did not simply raise scores; it produced a higher rate of learning progress relative to initial achievement (Dario Lombardi, 2025).

Table 4. Welch Independent Sample T-Test Summary

Variable	Experimental M (SD)	Control M (SD)	t	df	p	d
Posttest learning outcome	77.93 (10.29)	63.58 (9.82)	10.088	197.56	< .001	1.427
Delta learning outcome	22.53 (6.32)	9.01 (5.77)	15.803	196.37	< .001	2.235
N-gain learning outcome	0.525 (0.174)	0.206 (0.139)	14.321	188.41	< .001	2.025
Posttest motivation	79.85 (8.18)	69.79 (8.64)	8.460	197.41	< .001	1.196

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Variable	Experimental M (SD)	Control M (SD)	t	df	p	d
Delta motivation	15.89 (5.05)	5.95 (4.33)	14.953	193.53	< .001	2.115
Posttest metacognition	59.74 (6.87)	52.42 (7.35)	7.275	197.07	< .001	1.029
Delta metacognition	14.85 (3.74)	5.89 (4.07)	16.216	196.62	< .001	2.293

The multivariate analysis strengthens the interpretation because the model was expected to influence several learning outcomes. MANOVA was performed on normalized gain in cognitive learning outcomes, motivation improvement, and metacognition improvement. The results showed a significant multivariate effect of group membership. Pillai's Trace reached 0.765, $F(3, 196) = 213.216$, $p < .001$. Wilks' Lambda also indicated a strong multivariate separation between groups, lambda = 0.235. These results support the conceptual claim that the model works as an integrated learning intervention, not merely as a score-improvement tool.

Table 5. MANOVA Results for Group Effect

Multivariate statistic	Value	F	Hypothesis df	Error df	p
Wilks' Lambda	0.235	213.216	3	196	< .001
Pillai's Trace	0.765	213.216	3	196	< .001
Hotelling-Lawley Trace	3.264	213.216	3	196	< .001
Roy's Greatest Root	3.264	213.216	3	196	< .001

The AI performance analysis focused on whether the system could classify error patterns that are needed for reflective feedback. The classification model achieved accuracy of 0.884, macro precision of 0.883, macro recall of 0.882, and macro F1-score of 0.882. The strongest F1-score appeared in the misconception class, while the inappropriate strategy class obtained the lowest score. This result is meaningful for development because strategy-related errors are often more complex than surface-level mistakes. In future field implementation, the inappropriate strategy category should receive more training data, clearer annotation criteria, and additional teacher review.

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Table 6. AI Classification Metrics for Student Error Patterns

Error class	Precision	Recall	F1-score	Support
Misconception	0.896	0.912	0.904	284
Carelessness	0.875	0.889	0.882	244
Lack of conceptual understanding	0.913	0.883	0.898	248
Inappropriate strategy	0.848	0.844	0.846	224
Macro average	0.883	0.882	0.882	1000
Weighted average	0.884	0.884	0.884	1000

The main research output is an AI-based Dual-Loop Adaptive Learning model for differentiated economics instruction. The model consists of five integrated components: student response input, AI-based learning analytics, automatic content adaptation, reflective feedback, and learning outcome monitoring (B et al., 2025). The first loop supports differentiated instruction by adjusting learning materials, task difficulty, and learning pathways based on student performance. The second loop supports metacognitive regulation by diagnosing repeated error patterns and generating reflective prompts that guide students to review their assumptions, strategies, and conceptual understanding (Putranti et al., 2024).

(Dalila et al., 2022) in practical use, the model can assist teachers in identifying students who require remedial support, enrichment tasks, or reflective intervention. The AI component does not replace teacher judgment; rather, it functions as a decision-support system that provides diagnostic information about misconception, carelessness, lack of conceptual understanding, and inappropriate learning strategy (Juliastuti et al., 2025). Therefore, the model output is not limited to a digital learning tool, but also includes a pedagogical framework for differentiated instruction, reflective feedback design, student progress monitoring, and data-informed teacher intervention.

The validated model can be developed further into a prototype learning platform, teacher guidebook, student learning module, assessment instrument, and AI-assisted feedback dashboard. These outputs are relevant for strengthening economics learning in senior high schools, particularly in classrooms with heterogeneous levels of prior knowledge, motivation, and learning strategy(Şerban et al., 2025).

Pedagogically, the findings support the need to move from adaptive content toward adaptive cognition. Content adaptation can help students receive tasks at a suitable difficulty level, but reflective feedback is needed to help students understand why their strategy fails and how they can regulate subsequent learning (Moreira et al., 2025). This explains why motivation

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and metacognition are important outcomes. If students perceive that the task is reachable and the feedback is diagnostically useful, they are more likely to sustain effort. If they are guided to examine their reasoning, they are more likely to develop metacognitive control rather than depend passively on AI-generated answers (Zhang et al., 2024).

The model also has practical implications for teachers. In conventional classrooms, teachers often see only final answers and scores. The dual-loop system provides additional diagnostic information about misconception, carelessness, conceptual weakness, and inappropriate strategy (Duan et al., 2024). This information can support remedial grouping, differentiated tasks, and targeted classroom discussion (Hamilton, 2024). However, AI should not replace teacher judgment. The system should function as decision support, while teachers remain responsible for interpreting context, validating feedback, and protecting students from over-automation or inaccurate classification.

The main limitation of this study lies in the scope of implementation and the characteristics of the research sample. Although the quasi-experimental results showed significant improvement in the experimental group, the findings should be interpreted within the context of senior high school economics learning and the specific implementation setting of the study. Further research should involve broader school contexts, longer intervention periods, stronger longitudinal tracking, and additional validation of AI-generated reflective feedback (Hasibuan et al., 2025); (Umali, 2024). Future studies also need to examine data privacy safeguards, teacher acceptance, system explainability, and the sustainability of model implementation in regular classroom practice

CONCLUSION

The Artificial Intelligence-based Adaptive Learning Dual Loop model offers a valid and effective framework for differentiated economics learning because it combines automatic content adaptation with reflective feedback. The validation results showed that the model achieved a high validity score of 91.12%, indicating that its content, instructional design, feedback structure, and practical implementation logic are feasible for classroom use.

The empirical statistical results showed stronger improvement in the experimental group than in the control group across cognitive learning outcomes, intrinsic motivation, and metacognition. The MANOVA result also indicated a significant multivariate effect, suggesting that the model functions as an integrated intervention for academic and regulatory learning outcomes. The AI classification component showed acceptable performance, with an accuracy of 0.884 and

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a macro F1-score of 0.882, indicating its potential to support reflective feedback based on student error patterns.

Overall, the findings demonstrate that the AI-based Dual-Loop Adaptive Learning model can strengthen differentiated economics instruction by helping students learn at an appropriate level of difficulty while also encouraging them to evaluate their learning strategies. The model can support teachers in identifying student needs, designing targeted interventions, and promoting more reflective, adaptive, and data-informed learning practices.

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