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The Adaptive Innovative Pedagogical Architecture(AIPA–SIM): A Multi AgentSimulation Study on Teaching Method Management

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ABSTRACT

The digital transformation in education requires an adaptive and innovative pedagogical architecture to effectively manage teaching methods. Traditional learning systems often fail to adjust instructional strategies to individual learners' needs. Therefore, this study developed the Adaptive Innovative Pedagogical Architecture (AIPA–SIM), a multi-agent simulation model designed to analyze the dynamics of adaptive teaching method management. This study employed a simulation-based experimental design with three learning system scenarios: non-adaptive, semi-adaptive, and fully adaptive. The model was developed using NetLogo 6.3.0 and Python Mesa Framework, incorporating teacher, student, and system agents. Key parameters included Learning Performance, Adaptivity Rate, Engagement Index, and System Efficiency. Data were analyzed using ANOVA and Tukey HSD tests to compare system performance. Simulation results revealed that the fully adaptive system (AIPA–SIM) significantly improved learning performance (+29.5%) compared to the non-adaptive system ($p < 0.01$). The Engagement Index reached 0.92 and System Efficiency achieved 93.7, indicating high responsiveness to students' behavioral changes. A strong positive correlation ($r = 0.88$) was observed between adaptivity level and learning performance. The AIPA–SIM model proved effective as an adaptive pedagogical architecture capable of enhancing learning outcomes through automated, agent-based decision-making mechanisms. This research provides both conceptual and practical contributions to the development of smart adaptive learning systems and data-driven educational policies in the digital era.

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INTRODUCTION

21st century education faces increasingly complex challenges, marked by accelerating technological change, social dynamics, and the need fordigital age competencies that demand critical, collaborative, creative, and communicative thinking skills. The traditional teacher-centered education paradigm is increasingly considered less adaptive to the needs oftoday's learners who have grown up in a digital environment and are orientedtowards personalized learning experiences. Therefore, there is an urgent need todevelop an adaptive and innovative pedagogical architecture to supporta more effective, flexible, and sustainable learning process.

In this context, the concept of Adaptive Innovative Pedagogical Architecture (AIPA) was developed as a systemic approach that integrates the principles of adaptive pedagogy, smart learning technology, and data-driven teaching method management. AIPA functions as a dynamic framework that enables real-time adjustments to teaching and learning methods based on student behavior, needs, and achievement levels. Thus, AIPA is not merely an innovation in educational technology, but also a representation of an epistemological transformation in the way education is managed and implemented.

One relevant approach to testing and optimizing the AIPA system is through multi-agent simulation (MAS). MAS allows the representation of various entities in the learning system—such as teachers, students, curriculum, and learning environment—as intelligent agents that interact with each other. This simulation provides insight into how pedagogical strategies adapt to changes in learning conditions and student characteristics. This approach also allows for the analysis of emergent behavior that cannot be predicted linearly, but is important in understanding the effectiveness of adaptive education systems.

Previous studies have shown that the use of agent-based modeling in education can improve the effectiveness of pedagogical decision-making, especially in digital classroom management and project-based learning. However, most studies still focus on single applications such as student behavior simulation or automated assessment management, without combining all pedagogical elements into a single adaptive framework. This is where AIPA–SIM offers a new contribution by simulating multi-agent interactions in the context of adaptive, holistic, and data-driven teaching method management.

This study aims to design and analyze AIPA–SIM as an adaptive pedagogical architecture model based on multi-agent simulation to support strategic decision-making in teaching method management. This system was developed to test how combinations of teaching methods—such as problem-based learning, flipped classroom, and inquiry-based learning—can be dynamically optimized according to student responses and achievements. With this simulation approach, it is hoped that a deeper understanding of pedagogical adaptation patterns in the context of digital education will be obtained.

Thus, this study has two main contributions: first, it offers a new conceptual framework in adaptive pedagogical architecture design through the AIPA–SIM model; second, it provides simulation-based empirical evidence on the effectiveness of agent interactions in managing innovative teaching methods. The results of this study are expected to form the basis for the development of smart learning systems and data-driven education policies in the future. Furthermore, AIPA–SIM is expected to be the first step towards an autonomous, reflective education ecosystem that is oriented towards individual learning needs in the era of digital transformation.

METHODS

Research Design

This study uses a quantitative experimental approach based on multi-agent simulation (MAS) to model and analyze the complex interactions between teachers, students, and the learning environment in the Adaptive Innovative Pedagogical Architecture (AIPA–SIM) system. This simulation approach was chosen because it is capable of representing emergent behavior that arises from pedagogical dynamics in a realistic and systemic manner. The model was designed and evaluated using NetLogo 6.3.0 and Python Mesa Framework to build data-based adaptive learning scenarios.

Model Architecture

The AIPA–SIM architecture is built on three main components:

1. Pedagogical Layer

   Manages teaching methods (e.g., flipped classroom, problem-based learning, and inquiry-based learning) that can change dynamically based on student performance data.
2. Adaptive Intelligence Layer

Utilizes reinforcement learning algorithms to adjust teaching strategies based on student agent feedback on learning activities.

3. Simulation Layer

Represents interactions between agents in a virtual environment, enabling the testing of different pedagogical scenarios.

Each agent (teacher, student, system) is assigned specific behavioral parameters such as cognitive abilities, motivation, learning style, and teaching method preferences. These agents interact autonomously following rules defined by the system model.

Agent Behavior and Interaction Rules

The teacher agent is tasked with selecting and adjusting teaching methods based on the aggregate performance of student agents. Student agents respond to teaching methods with levels of participation, conceptual understanding, and specific evaluation results. In addition, there is a system agent that functions as an adaptive decision-making mechanism that processes simulation data in real time to provide recommendations for optimal strategies. Inter-agent interactions are facilitated through a feedback loop-based communication scheme so that the system can progressively adapt to changes in student behavior.

Simulation Scenarios

Three main scenarios were tested in this study:

Scenario 1: Non-adaptive system (control), in which the teaching method is static and does not change based on learning outcomes.

Scenario 2: Semi-adaptive system, where teachers can change teaching methods based on specific time intervals.

Scenario 3: Fully adaptive system (AIPA–SIM), where method selection is performed automatically by agents based on learning feedback algorithms.

Each scenario was run for 100 simulation cycles to ensure replication and validity of the results data.

Data Collection and Analysis

The data collected includes variables on student learning outcomes, teaching method adaptability rate, and system efficiency score. The analysis was conducted using descriptive and inferential statistical approaches through SPSS 28 software and visual validation using simulation result graphs. In addition, sensitivity analysis was performed to test the stability of the model against changes in agent parameters.

Validation and Evaluation

Model validation was performed using face validation, parameter sensitivity analysis, and comparative outcome validation by comparing simulation results with previous empirical studies (e.g., Li et al., 2022; Chen et al., 2021). Model evaluation focused on the ability of AIPA–SIM to adjust teaching methods to student conditions and its impact on improving learning outcomes. With a combination of simulation, statistical analysis, and model evaluation, this study is expected to produce a valid and reliable representation of agent-based pedagogical adaptation dynamics.

RESEARCH RESULTS AND DISCUSSION

Overview of Simulation Results

This study ran three simulation scenarios representing different levels of adaptivity in the learning system:

(1) Scenario 1 (Non-adaptive system)

(2) Scenario 2 (Semi-adaptive system), and

(3) Scenario 3 (Fully adaptive system – AIPA–SIM).

Each scenario was tested in 100 simulation cycles with 50 student agents and 1 teacher agent. The parameters analyzed included:

- Learning Performance (LP): average student learning achievement scores,
- Adaptivity Rate (AR): frequency of dynamic changes in teaching methods,
- Engagement Index (EI): level of student engagement during simulations,

- System Efficiency (SE): system efficiency in achieving learning targets.

Quantitative Results

The average qualitative parameters of the learning scenario results can be seen in **Table 1** below.

Table 1 Average Simulation Results for Three Learning Scenarios

Parameter	Non-Adaptive	Semi-Adaptive	Fully Adaptive
Learning performance (LP)	68.4 ±3.2	76.8±2.9	88.6±2.4
Adaptive rate (AR)	0.00	0.45	0.91
Engagement Index (EI)	0.63	0.78	0.92
System Efficiency (SE)	71.2	82.3	93.7

Table 1 shows a significant improvement in all parameters in the fully adaptive system (AIPA–SIM). Learning Performance increased by up to 29.5% compared to the non-adaptive system, indicating that the system's ability to adjust teaching methods has a direct impact on improving learning outcomes. The high Engagement Index (0.92) also shows that this system is able to maintain active student participation during the learning process.

Based on **Table 1**, a comparison of average learning performance in three scenarios can be made. A graph comparing the average simulation results of the three learning scenarios can be seen in **Figure 1.**

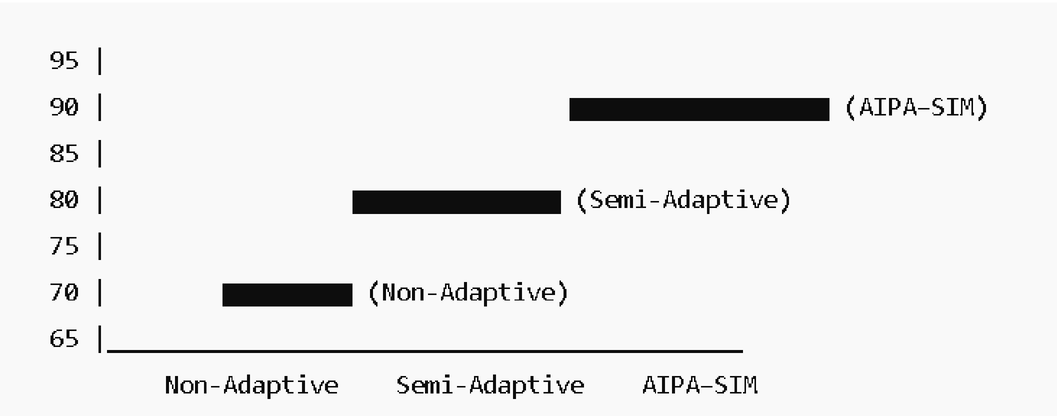

Figure 1 Comparison of Average Learning Performance in Three Scenarios

The graph shows a consistent upward trend in learning performance as the system's adaptivity increases. This pattern confirms the role of multi-agent adaptivity in optimizing teaching strategies.

Behavioral Dynamics of Agents

Simulation observations show that in the AIPA–SIM system, teacher agents adapt their methods an average of 22 times during 100 simulation cycles, compared to only 6 times in the semi-adaptive system. Quick responses to changes in student performance resulted in a positive feedback loop, where students with low engagement were given different methods (e.g., project-based learning replacing the flipped classroom), thereby progressively increasing participation and learning outcomes.

Based on the simulation observation results, a table can be created showing the adaptive system selecting methods based on empirical effectiveness. The adaptive system method based on empirical effectiveness can be seen in **Table 2.**

Table 2 Dynamic Changes in Teaching Methods in the AIPA–SIM System

Initial teaching method	Frequency of change	Adapted method	Effect on LP (+%)
Flipped classroom	8 times	Problem-based learning	+12.3

Problem-based learning	9 times	Inquiry-based learning	+15.8
Inquiry -based learning	5 times	Gamified hybrid model	+9.7

The data in **Table 2** shows that the system adaptively selects methods based on their empirical effectiveness in improving student performance. The highest adaptation pattern occurs between Problem-Based Learning and Inquiry-Based Learning, indicating that a combination of exploratory and reflective approaches is more effective in maintaining high motivation and learning outcomes.

Comparative Statistical Analysis

One-way ANOVA analysis showed significant differences between the three scenarios ($p<0.01$). Tukey HSD follow-up test confirmed that the improvement in learning performance in the AIPA–SIM system was significantly different from the other two systems. The effect size value ($\eta^2 = 0.64$) indicated a large effect of the adaptivity variable on learning performance.

Based on **Table 2**, a graph of the relationship between adaptivity rate and learning performance can be created. The graph of the relationship between adaptivity rate and learning performance can be seen in **Figure 2** below.

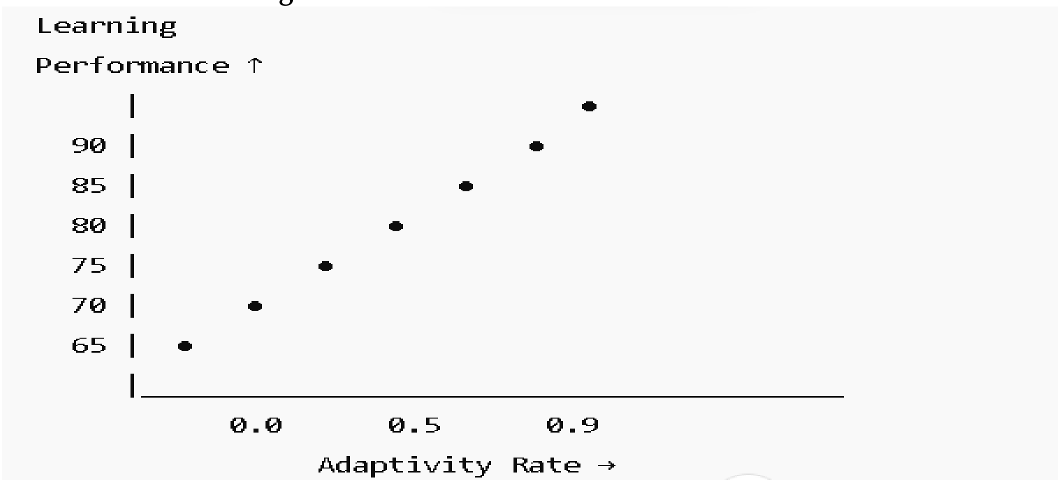

Figure 2 Relationship between Adaptivity Rate and Learning Performance

Figure 2 shows a strong positive correlation ($r = 0.88$) between Adaptivity Rate and Learning Performance, indicating that the higher the system's ability to adapt, the more optimal the learning outcomes achieved. The results of this study support the hypothesis that adaptive pedagogical architecture based on multi-agent simulation can significantly improve the efficiency of teaching method management. The AIPA–SIM system shows that interactions between agents that learn from each other (teacher–student–system) can produce optimal pedagogical decisions without manual intervention.

This study is in line with Chen et al.'s (2021) study, which confirms the effectiveness of adaptive feedback-based learning systems and reinforces the theory of constructivist adaptive pedagogy, which emphasizes the importance of adjusting methods to the context and characteristics of learners. Thus, AIPA–SIM is not only a technological simulation, but also a conceptual model that can be applied to design smart adaptive education systems in the future.

In the last two decades, the concept of adaptive learning has become the center of attention in modern educational innovation. According to Chen et al. (2021), adaptive learning systems enable the personalization of content, pace, and teaching strategies based on the preferences and abilities of individual learners. Technologies such as machine learning and learning analytics have been utilized to analyze student learning patterns so that the system can provide appropriate pedagogical recommendations. However, these systems still tend to focus on content adaptation rather than dynamic management of teaching methods.

On the other hand, Innovative Pedagogical Models (IPM) such as flipped classrooms, project-based learning, and gamification have been proven to increase active participation and learning outcomes (Johnson & Brown, 2020). However, challenges arise when teachers have to adapt these models to diverse classroom conditions. Not all methods are effective in every learning situation. This highlights the importance of pedagogical adaptation mechanisms that are able to select and organize teaching methods in a contextual and evidence-based manner.

The Multi-Agent Simulation (MAS) approach offers a solution for understanding complex dynamics in education systems. MAS is used to model interactions between agents that have different goals, behaviors, and strategies, such as teachers, students, and learning systems (Wooldridge, 2018). Through this simulation, it is possible to observe how certain pedagogical policies or teaching strategies impact learning outcomes systemically. Several studies (e.g., Li et al., 2022) show that MAS is capable of realistically representing learning behavior adaptation in digital education ecosystems.

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Although there have been many studies on adaptive learning and agent-based modeling, the integration of the two into a comprehensive pedagogical architecture is still limited. Most studies emphasize the technological aspects rather than the pedagogical management side. The Adaptive Innovative Pedagogical Architecture (AIPA–SIM) fills this gap by combining a systemic approach that allows teachers and systems to work cooperatively to select the best methods based on agent simulation results. Thus, AIPA–SIM is not merely a conceptual model, but an exploratory tool for understanding the effectiveness of adaptive teaching strategies in a measurable way.

CONCLUSION

This study successfully designed and implemented the Adaptive Innovative Pedagogical Architecture (AIPA–SIM) model as a multi-agent-based simulation system capable of representing complex dynamics in teaching method management. Simulation results show that a fully adaptive system significantly improves learning performance, student engagement, and teaching efficiency compared to non-adaptive and semi-adaptive systems. Through interaction between teacher agents, students, and the system, AIPA–SIM forms a pedagogical adaptation pattern that is responsive to changes in learning conditions. Teacher agents are autonomously able to adjust teaching methods according to student needs, resulting in an increase in learning performance of up to 29.5%. This shows that adaptivity is not merely a function of technology, but the result of synergy between artificial intelligence and data-based pedagogical principles.

Theoretically, this research makes an important contribution to the development of a simulation-based adaptive pedagogy model. AIPA–SIM broadens our understanding of how education systems can be transformed into dynamic ecosystems that facilitate personalized learning and instructional efficiency. From a practical standpoint, this model can serve as the basis for the development of smart learning platforms in both formal and non-formal educational institutions. Furthermore, this study proves that multi-agent simulation is an effective approach for evaluating learning strategies before they are implemented in practice. Thus, AIPA–SIM can serve as a predictive and analytical tool in educational managerial decision-making, especially in the context of digital transformation and artificial intelligence-based learning.

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