
AN INTELLIGENT GAME-BASED LEARNING ARCHITECTURE BASED ON AN AI-IOT FRAMEWORK FOR SMART LEARNING ENVIRONMENTS

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ABSTRACT

The integration of Artificial Intelligence (AI), the Internet of Things (IoT), and Game-Based Learning (GBL) has the potential to create adaptive learning environments, yet existing studies rarely combine these technologies within a unified operational architecture. This study proposes the Intelligent Game-Based Learning (IGBL) Architecture as the operational realization of a previously developed AI-IoT Game-Based Learning framework. Using the Design Science Research methodology, a five-layer adaptive architecture was developed and evaluated through expert review and simulation-based assessment using 80 predefined student profiles. Two architectural configurations were compared: gameplay analytics only and gameplay analytics enriched with contextual learning information obtained through IoT-enabled connected learning technologies. The results showed that the proposed architecture improved learning-state classification accuracy (82.4% to 89.8%), adaptive decision accuracy (79.3% to 86.5%), and successful adaptation rate (80.7% to 88.7%) while maintaining near real-time processing performance. These findings demonstrate that the proposed architecture is conceptually valid and operationally feasible, providing a structured implementation model for integrating AI, IoT, and GBL in context-aware adaptive learning environments.

KEYWORDS

Artificial Intelligence; Internet of Things; Game-Based Learning; Adaptive Learning; Design Science Research



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INTRODUCTION

Game-based learning (GBL) has been shown meta-analytically to improve cognitive, motivational, and behavioural learning outcomes (Sailer & Homner, 2020; Zeng

et al., 2024), and its effectiveness depends heavily on how well the game mechanics match the needs of each learner (Krath et al., 2021; Manzano-León et al., 2021). In parallel, smart learning environments have evolved into context-aware and adaptive ecosystems (Demir, 2021), in which connected learning technologies and IoT-enabled devices support the collection of contextual learning data (Zhang et al., 2024), while AI transforms these data into pedagogical decisions (Hwang et al., 2020; Ouyang & Jiao, 2021).

The problem is that these three elements still operate separately. Reviews of IoT-enabled gamification conclude that the field lacks an established reference architecture (Xiao et al., 2022), while smart-classroom designs for GBL stop at the infrastructure layer without an adaptation engine (Petrović et al., 2022). On the analytics side, combining multiple data channels does improve the prediction of learning states (Emerson et al., 2020), yet current practice remains dominated by in-game data alone, such as scores, attempt counts, and completion times (Banihashem et al., 2024; Chiu et al., 2023; Daoudi, 2022). Recent studies have also shown that contextual data collected through connected learning technologies can improve the real-time identification of learning states (Ejaz & Shah, 2022). As a consequence, a uniform difficulty curve continues to cause boredom among faster learners and frustration among slower ones (Khaldi et al., 2023).

These limitations indicate that future smart learning environments require more than isolated AI or IoT applications; they require an integrated architecture capable of combining real-time contextual data acquisition, intelligent decision-making, and adaptive game mechanics. Building upon these research gaps, this study proposes the Intelligent Game-Based Learning (IGBL) Architecture as the technical realization of an integrated AI–IoT Game-Based Learning framework. Rather than treating AI and IoT as isolated technologies, the proposed architecture integrates them into a unified adaptive learning system that continuously acquires contextual learning information, supports AI-driven pedagogical decisions, and dynamically adapts gameplay.

Accordingly, this study aims to design and validate the Intelligent Game-Based Learning (IGBL) Architecture for smart learning environments. Specifically, the study seeks to (1) develop a five-layer adaptive architecture, (2) define the interaction among AI, IoT, and game-based learning components, and (3) evaluate the proposed architecture through expert validation and controlled simulation.

RESEARCH METHOD

Research Design

This study adopted the Design Science Research (DSR) methodology to address the need for an integrated AI–IoT Game-Based Learning architecture identified in our previous study. The previous study established the conceptual framework and highlighted the need for an architectural model capable of operationalizing adaptive instruction, automated assessment, and context-aware learner monitoring. Building on these findings, the present study focuses on designing, demonstrating, and evaluating the proposed architecture.

DSR was selected because the primary objective of this study is to develop and evaluate a technological artifact rather than to test an educational intervention. The proposed artifact takes the form of an adaptive learning architecture integrating Artificial Intelligence (AI), the Internet of Things (IoT), and Game-Based Learning (GBL). Following the Design Science Research Methodology (DSRM), the study comprised four main activities: (1) problem identification and objective definition based on the needs identified in the previous framework study and supported by current literature; (2) design and development of the five-layer IGBL Architecture based on the proposed AI–IoT Game-

Based Learning framework; (3) demonstration through a controlled simulation environment; and (4) evaluation through expert validation and performance analysis.

Architecture Development

The Intelligent Game-Based Learning (IGBL) Architecture was developed by translating the previously proposed AI–IoT Game-Based Learning framework into an operational system architecture for smart learning environments. The conceptual framework established the integration of Artificial Intelligence (AI), the Internet of Things (IoT), and Game-Based Learning (GBL) as the core foundation for adaptive learning. Building upon this foundation, the present study operationalizes these concepts into a technical architecture that supports real-time learner monitoring, intelligent decision-making, automated assessment, and adaptive gameplay within a unified system.

The architectural development was guided by four design principles. First, modularity was adopted to separate the major functional components of the system while maintaining interoperability among them. Second, real-time adaptability was incorporated by integrating gameplay analytics with contextual information obtained through IoT-enabled connected learning technologies. This enables the architecture to maintain continuous awareness of learner conditions while remaining adaptable to different technological environments. Third, AI-driven decision-making was embedded to analyse multimodal contextual learning data and determine appropriate pedagogical interventions, including difficulty adjustment, feedback generation, and learner support. Finally, human-centred supervision was maintained by incorporating teacher oversight as an integral component of the architecture, ensuring transparency and allowing instructional decisions to be overridden when necessary (Alfredo et al., 2024).

To implement these principles systematically, the proposed architecture was organised into five functional layers representing the complete adaptive learning cycle. The layers cover context acquisition, data processing, intelligent decision-making, adaptive game control, and teacher supervision. Information flows through these layers in a closed-loop process, enabling continuous monitoring of learner performance and engagement while dynamically adapting game activities to individual learning needs. This layered organisation improves scalability, facilitates future system development, and provides a clear separation between context acquisition, data processing, intelligent decision-making, adaptive learning, and instructional management.

Five-layer IGBL Architecture

Figure 1 illustrates the proposed five-layer Intelligent Game-Based Learning (IGBL) Architecture. The architecture comprises five functional layers: Context Acquisition, Data and Edge Processing, Intelligence Engine, Game Adaptation, and Learning Management & Reporting, which collectively form a closed-loop adaptive learning system. Contextual learning data flow upward through the architecture for processing and AI-driven analysis, while adaptive decisions flow downward to personalize gameplay and instructional support. This continuous feedback cycle enables the system to provide context-aware adaptive learning within smart learning environments.

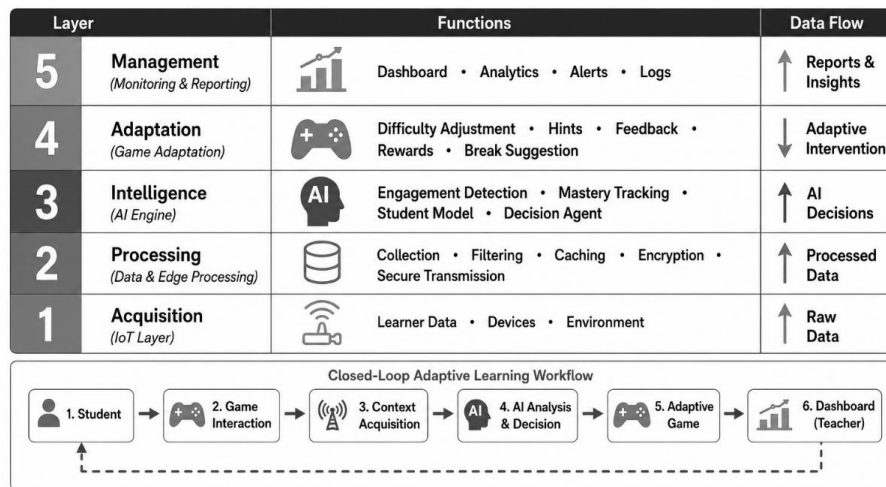


Figure 1. The Five-Layer IGBL Architecture

The proposed Intelligent Game-Based Learning (IGBL) Architecture consists of five interconnected functional layers that collectively support context-aware adaptive learning (Figure 1). Each layer performs a distinct function, beginning with contextual learning data acquisition and ending with learning management, reporting, and teacher supervision. Information flows upward from the Context Acquisition Layer through the Data and Edge Processing Layer to the Intelligence Engine, where the collected data are analysed to generate adaptive instructional decisions. These decisions are subsequently transmitted downward through the Game Adaptation Layer to personalize gameplay, feedback, and learning support.

Layer 1. The Context Acquisition Layer

The Context Acquisition Layer is responsible for collecting contextual learning data from connected sources within the learning environment. The architecture integrates two complementary categories of information. The first consists of gameplay analytics, including response time, response accuracy, help requests, and interaction logs generated during gameplay. The second comprises contextual information obtained through IoT-enabled connected learning technologies, including mobile devices, personal computers, learning management systems, and other available connected platforms. Together, these data provide the contextual input required for AI-driven adaptive decision-making. Because the proposed architecture is modular, the specific data sources may vary according to the technological resources available in different implementation environments (Dhouib et al., 2025).

Layer 2. Data and Edge Processing

The Data and Edge Processing Layer prepares the collected contextual learning data for intelligent analysis. The acquired data are filtered, validated, integrated, anonymized where appropriate, encrypted, buffered, and securely transmitted to the Intelligence Engine. Where edge computing resources are available, preliminary processing is performed locally to reduce communication latency, enhance privacy protection, and improve the responsiveness of the adaptive learning system (Ejaz & Shah, 2022). This layer ensures that only reliable, secure, and well-structured contextual data are forwarded for subsequent AI analysis.

When contextual information is obtained from connected learning devices, preliminary processing may be conducted locally before transmission. Rather than

transmitting raw activity records, the architecture forwards only the contextual indicators required for adaptive decision-making whenever appropriate. This approach reduces bandwidth requirements, strengthens data privacy, and minimizes the exposure of personally identifiable information while maintaining the quality of information required for intelligent adaptation.

Layer 3. Intelligence Engine (AI)

The Intelligence Engine functions as the analytical core of the proposed architecture. AI algorithms integrate multimodal contextual learning data to detect student engagement, monitor mastery progress, construct student profiles, and generate learning analytics. Based on these analyses, the adaptive decision agent determines the most appropriate instructional actions for each student. Rather than relying solely on gameplay performance, the AI engine combines gameplay analytics with contextual learning information to support more accurate and personalized adaptive decisions.

The AI engine analyses ten multimodal learning indicators derived from gameplay analytics and contextual learning information collected through connected learning technologies. Indicators 1–4 are obtained directly from gameplay logs and represent students' cognitive and behavioural performance during gameplay. Indicators 5–10 represent contextual learning information obtained through connected learning devices and IoT-enabled connected platforms, including learning participation, interaction patterns, and contextual learning conditions. Combining these complementary sources of information enables the AI engine to construct a more comprehensive representation of students' learning states than would be possible using gameplay analytics alone (Emerson et al., 2020).

Table 1. Indicators Monitored by The System

Indicator	Source	Contribution to AI Decision
Response time	Gameplay analytics	Identifies processing speed and possible confusion
Response accuracy	Gameplay analytics	Estimates mastery level
Help requests	Gameplay analytics	Indicates need for instructional support
Consecutive incorrect responses	Gameplay analytics	Detects persistent learning difficulty
Session duration	Connected learning device	Measures learning persistence
Interaction frequency	Connected learning device	Indicates level of active participation
Learning progress	LMS / Learning platform	Tracks completion of learning objectives
Learning continuity	LMS / Learning platform	Detects interrupted or irregular learning sessions
Task completion status	LMS / Learning platform	Identifies unfinished learning activities
Learning activity history	LMS / Learning platform	Provides context for personalized recommendations

The first six indicators are derived directly from gameplay analytics and are available in most game-based learning systems. The remaining four indicators represent contextual learning information obtained through connected learning platforms and IoT-enabled devices. This distinction allows the contribution of contextual information to be evaluated independently by comparing the performance of the architecture using gameplay analytics alone with its performance when additional contextual learning information is incorporated.

Layer 4. Game Adaptation

The Game Adaptation Layer translates AI-generated decisions into adaptive instructional interventions within the learning environment. Based on each student's

cognitive performance, behavioural patterns, and contextual learning information, the system dynamically adjusts game difficulty, provides intelligent hints, generates personalized feedback, awards achievements, or recommends appropriate learning support, such as a short break when sustained interaction indicates declining engagement. These adaptive mechanisms aim to maintain student engagement while supporting individual learning progress through personalized gameplay experiences.

The system aims to maintain an optimal level of challenge consistent with Flow Theory by adjusting task difficulty according to students' ongoing performance, which suggests that learning is most effective when tasks are sufficiently challenging without causing excessive frustration (Zainuddin et al., 2020). Recommendations for additional learning support are generated by analysing gameplay analytics together with contextual learning information rather than relying solely on performance scores. By integrating these complementary sources of information, the proposed architecture can deliver more responsive and personalized adaptive interventions than conventional game-based learning systems that rely primarily on gameplay analytics. The pedagogical basis for these adaptive strategies is supported by previous research on stealth assessment and in-game learning support (Cai et al., 2022; Chen & Chang, 2024; Min et al., 2020; Shute et al., 2021; Yang et al., 2021).

Table 2. Actions the System can Take

Adaptive Action	Trigger Condition	System Response
Lower difficulty	Correct response rate below 60% or three consecutive incorrect responses	Simplifies the task and extends the time limit by 25%
Increase difficulty	Correct response rate above 80% across two monitoring windows	Presents more complex tasks and reduces the time limit by 20%
Provide adaptive hints	Two help requests or low mastery level	Displays progressively more specific hints
Generate reinforcing feedback	Engagement indicators decline below the predefined threshold	Presents encouraging messages and visual progress updates
Recommend a short break	Prolonged gameplay combined with declining engagement or repeated unsuccessful attempts	Pauses the game for 60 seconds and recommends a short break before continuing

Layer 5. Learning Management and Reporting

The Learning Management and Reporting Layer provides teachers with comprehensive information to support instructional monitoring and decision-making. Through dashboards, learning analytics, early warning notifications, and audit logs, teachers can monitor student progress, identify students requiring additional instructional support, and review the adaptive interventions generated by the AI engine. This layer preserves human oversight by enabling teachers to validate, modify, or override AI-generated recommendations whenever necessary, thereby ensuring that adaptive decisions remain pedagogically appropriate and transparent (Alfredo et al., 2024).

Table 3. The Function Summary of the Layer

Layer	Primary Function	Main Output
Layer 1 Context Acquisition	Collect gameplay analytics and contextual learning data	Contextual learning data
Layer 2 Data and Edge Processing	Process, integrate, secure, and prepare contextual data	Clean, integrated, and protected data
Layer 3 Intelligence Engine	Analyse contextual learning data and generate adaptive decisions	AI-generated adaptive decisions

Layer	Primary Function	Main Output
Layer 4 Game Adaptation	Deliver adaptive instructional interventions	Personalized adaptive gameplay
Layer 5 Learning Management & Reporting	Monitor learning progress and support instructional decision-making	Dashboards, learning analytics, and reports

Evaluation Procedure

The proposed Intelligent Game-Based Learning (IGBL) Architecture was evaluated through a simulation-based approach to examine its functional feasibility and adaptive performance. Rather than conducting a classroom intervention, the evaluation employed simulated student profiles representing diverse learning conditions, performance levels, and engagement patterns. This approach enabled the proposed architecture to be assessed under controlled, repeatable, and reproducible scenarios while minimizing external variables that could influence system performance.

Two simulation configurations were designed to examine the contribution of contextual learning information to the adaptive decision-making process. The first configuration utilized gameplay analytics only, whereas the second combined gameplay analytics with contextual learning information obtained through connected learning technologies. Comparing these two configurations enabled the incremental contribution of contextual information to AI-driven adaptation to be evaluated independently.

The simulation dataset consisted of 80 predefined student profiles representing diverse combinations of cognitive performance, behavioural engagement, and contextual learning conditions. The profiles were designed to represent representative learning scenarios based on the functional requirements of the proposed architecture rather than to model a real student population. During each simulation run, the AI engine analysed gameplay analytics together with contextual learning information, generated adaptive instructional decisions, and updated game interventions according to the simulated student profiles. The resulting system responses were analysed to evaluate the operational feasibility, consistency, and adaptive behaviour of the proposed architecture (Alonso-Fernández et al., 2020; Marengo et al., 2025; Udeozor et al., 2023).

The proposed architecture was evaluated through two complementary procedures. First, expert validation was conducted to assess the conceptual validity, technical feasibility, and pedagogical appropriateness of the architecture. The validation involved three experts representing educational technology, game-based learning, and AI–IoT systems. Second, a simulation-based evaluation was performed using the predefined student profiles to examine the operational behaviour of the adaptive learning system under diverse learning scenarios. The evaluation focused on the consistency of AI-driven adaptation, the contribution of contextual learning information, and the functional feasibility of the proposed architecture.

RESULT AND DISCUSSION

Expert Review Result

The proposed IGBL Architecture was reviewed by three experts representing AI–IoT systems, educational technology, and game-based learning. Overall, the experts agreed that the proposed architecture provides a coherent integration of Artificial Intelligence (AI), the Internet of Things (IoT), and Game-Based Learning (GBL) to support context-aware adaptive learning.

The experts particularly highlighted the modular organization of the five-layer architecture, the clear separation of functional responsibilities across layers, and the

integration of AI-driven adaptive decision-making into the game environment. Several recommendations were provided to improve the clarity of the architecture, including refining the responsibilities of the Learning Management and Reporting Layer, clarifying the flow of contextual learning data across layers, and strengthening the description of data privacy and security mechanisms within the Data and Edge Processing Layer. These recommendations were incorporated into the final version of the architecture before the simulation-based evaluation was conducted.

A. Simulation Result

The proposed Intelligent Game-Based Learning (IGBL) Architecture was evaluated through a controlled simulation using 80 predefined student profiles representing diverse combinations of learning performance, engagement levels, and contextual learning conditions. The simulation compared two architectural configurations. The first configuration relied solely on gameplay analytics, whereas the second incorporated additional contextual learning information obtained through IoT-enabled connected learning technologies. The comparison was conducted to examine the contribution of contextual information to AI-driven adaptive decision-making.

Table 4. The Performance of the Two Simulation Configurations

Performance Indicator	Gameplay Only	Gameplay + IoT
Learning-state classification accuracy	82.4%	89.8%
Adaptive decisions accuracy	79.3%	86.5%
Average processing time	0.70 s	0.79 s
Successful adaptation rate	80.7%	88.7%

As shown in Table 4, incorporating contextual learning information consistently improved the adaptive performance of the proposed architecture. Learning-state classification accuracy increased from 82.4% to 89.8%, while adaptive decision accuracy improved from 79.3% to 86.5%. Although the context-aware configuration required slightly longer processing time (0.79 s compared with 0.70 s), the increase was minimal and remained compatible with real-time adaptive learning. These findings suggest that enriching gameplay analytics with contextual learning information enables the AI engine to make more accurate and responsive instructional decisions.

To further examine the adaptive capability of the proposed architecture, representative simulation profiles were analyzed. These examples illustrate how the AI engine generated different instructional interventions based on the combination of gameplay analytics and contextual information.

Table 5. Representative Adaptive Decision Scenarios

Profile	Gameplay Observation	Contextual Learning Information	Learning State Identified	Adaptive Intervention
P01	Slow response	Regular learning activity	Conceptual difficulty	Provide additional hints
P17	Slow response	Prolonged session duration and declining interaction	Reduced engagement	Recommend a short break
P32	High accuracy	High participation and consistent activity	High mastery	Increase challenge level
P49	Frequent failures	Interrupted learning progress	Learning difficulty	Reduce task complexity and recommend additional practice
P70	Low engagement	Low interaction frequency	Reduced motivation	Introduce motivational game elements

The representative simulation profiles demonstrate that similar gameplay behaviours do not necessarily represent the same learning condition. For example, two students may exhibit comparable gameplay performance while differing in their contextual learning information, resulting in different adaptive instructional decisions. By integrating contextual learning information with gameplay analytics, the proposed architecture enables the AI engine to distinguish among these situations and generate more context-aware adaptive interventions. These findings complement the quantitative improvements presented in Table 4 and demonstrate the value of incorporating contextual learning information into adaptive game-based learning.

The simulation also verified the operational workflow of the five-layer IGBL Architecture. During each simulation cycle, gameplay analytics and contextual learning information were collected through the Context Acquisition Layer and transmitted to the Data and Edge Processing Layer, where the data were prepared for analysis. The Intelligence Engine subsequently identified the current student learning state and generated adaptive instructional decisions. These decisions were implemented through the Game Adaptation Layer, while the Learning Management and Reporting Layer recorded system activities and provided instructors with access to student progress, learning analytics, and adaptive recommendations. The successful interaction among the five functional layers demonstrates the operational feasibility of the proposed architecture in supporting context-aware adaptive learning.

Discussion

The findings of this study demonstrate that the proposed IGBL Architecture provides a feasible approach for integrating Artificial Intelligence (AI), the Internet of Things (IoT), and Game-Based Learning (GBL) within a unified adaptive learning environment. Expert review confirmed the conceptual appropriateness of the architecture, while the simulation results demonstrated its capability to perform adaptive instructional decision-making under diverse simulated learning conditions. Collectively, these findings indicate that the proposed architecture is not merely a conceptual framework but an operational design capable of supporting intelligent and context-aware learning.

A major contribution of the proposed architecture lies in its integration of contextual learning information with conventional gameplay analytics. Traditional adaptive game-based learning systems typically rely on interaction logs, such as response time, task accuracy, and completion behaviour, to estimate student performance. However, the simulation demonstrated that similar gameplay behaviours may represent different learning conditions when contextual information is also considered. By integrating gameplay analytics with contextual learning information obtained through connected learning technologies, the proposed architecture enables the AI engine to generate more accurate and context-aware adaptive instructional interventions. This capability represents an important advancement toward intelligent and human-centred adaptive learning systems.

The findings are consistent with previous studies highlighting the potential of AI for adaptive learning and IoT for smart educational environments (Emerson et al., 2020; García et al., 2024; Xiao et al., 2022). However, much of the existing literature has examined these technologies independently or has focused primarily on infrastructure development rather than pedagogical adaptation. The proposed IGBL Architecture extends previous work by integrating contextual learning information, AI-driven decision-making, adaptive gameplay, and instructional monitoring within a single operational architecture. In this respect, the present study contributes not only a conceptual integration of AI, IoT,

and GBL but also a structured implementation model that can guide the development of future intelligent learning systems.

The proposed architecture provides a foundation for future implementation in authentic educational settings. Its modular design facilitates integration with learning management systems, educational games, and connected learning technologies while allowing additional AI models or connected devices to be incorporated as needed. Nevertheless, the present study is limited to simulation-based evaluation and therefore does not examine the impact of the architecture on actual learning outcomes. Future research should implement the architecture in classroom environments to evaluate its effectiveness in improving student engagement, adaptive instructional support, and academic performance.

The proposed architecture may also serve as a reference model for future AI–IoT educational systems beyond game-based learning, including intelligent tutoring systems and adaptive learning platforms.

Overall, this study successfully achieved its three research objectives by (1) developing the five-layer Intelligent Game-Based Learning (IGBL) Architecture, (2) defining the interaction among Artificial Intelligence, the Internet of Things, and Game-Based Learning components, and (3) demonstrating its functional feasibility through expert review and simulation-based evaluation.

CONCLUSION

This study developed and evaluated the Intelligent Game-Based Learning (IGBL) Architecture as the operational realization of the previously proposed AI–IoT Game-Based Learning framework. Using the Design Science Research methodology, the study successfully achieved its objectives by developing a five-layer adaptive architecture, defining the interaction among Artificial Intelligence (AI), the Internet of Things (IoT), and Game-Based Learning (GBL), and evaluating the proposed architecture through expert review and simulation-based assessment.

The findings indicate that the proposed architecture is both conceptually valid and operationally feasible. The simulation results demonstrate that integrating gameplay analytics with contextual learning information enhances learning-state classification and AI-driven adaptive decision-making while maintaining near real-time system performance. Furthermore, the proposed architecture provides a structured implementation model that integrates AI, IoT, and Game-Based Learning into a unified context-aware adaptive learning environment.

Although this study was limited to simulation-based evaluation, the proposed architecture provides a practical foundation for future implementation in authentic educational settings. Future research should implement and validate the architecture in classroom environments to examine its effectiveness in improving student engagement, adaptive instructional support, and learning outcomes.

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