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A DESIGN FRAMEWORK FOR PERSONALIZED INTELLIGENT TUTORING SYSTEMS INTEGRATING KNOWLEDGE TRACING AND RETRIEVAL-AUGMENTED GENERATION

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ABSTRACT

This research presents a study on the design framework of an intelligent, personalized tutoring system to meet the individual needs of learners, overcoming the limitations of traditional learning management systems (LMS) that lack flexibility and brainstorming. The researchers designed a system architecture based on the Intelligent Tutoring System (ITS) concept, comprising seven main modules such as pre-assessment, intelligent learner grouping (AI-Classify), and blended learning, built on a cloud-based database structure. The developed system applies advanced techniques, including Retrieval-Augmented Generation (RAG) to increase accuracy and reduce AI hallucinations; Knowledge Tracing (KT) for continuous analysis of learner knowledge status; and an AI Chatbot to act as a continuous academic advisor. Expert evaluation of the conceptual framework's consistency showed an Index of Content Validity (IOC) for each module ranging from 0.89 to 0.97, with an average of 0.93, exceeding the acceptable criterion ($\geq$ 0.50), indicating the appropriateness and consistency of the content with the research objectives. The overall system suitability assessment was at the highest level ($\bar{x}$ = 4.71, S.D. = 0.45), and the technical suitability dimension of the AI innovation had a high average score of 4.73. In conclusion, this learning support system is designed to support deep learning, analytical thinking, and learner participation, with the potential to enhance educational practices aligned with 21st-century skills.

Keywords: *Intelligent Tutoring Systems, Personalized Learning, Knowledge Tracing, Retrieval-Augmented Generation, Artificial Intelligence in Education*

1. INTRODUCTION

The development of quality education in the 21st century requires adaptation to economic, social, and technological changes that directly affect student learning styles and the management of educational institutions. The National Education Plan 2017-2036 has set the direction for the development of Thai education, emphasizing the creation of educational opportunities and equality, the development of educational quality, the participation of all sectors, and the development of effective educational management mechanisms [1]. In the context of digital technology use, the government has emphasized the development of information and communication technology infrastructure (ICT Infrastructure), the creation of an Education Data Warehouse, the production and development of quality and standardized learning materials, as well as the development of teachers, lecturers and educational personnel to have knowledge, abilities and skills in using technology to manage learning that is appropriate for students at each level.

Learning Management Systems (LMS) [2] have become popular platforms for e-learning [3], being used in the teaching of various online courses. Studies on how LMS resources support student success are ongoing [4]. Data collection allows us to identify individual learners' learning styles and individual limitations, enabling us to personalize the learning environment, delivering content tailored to each learner's style and context, resulting in increased learner satisfaction, enhanced teaching effectiveness, improved course completion rates, and reduced learning time. The importance of delivering personalized resources to learners, taking into account their context, style, and learning duration, is crucial to ensuring high-quality educational services. However, LMSs have limitations in that the diverse and developed tools in the system are not adequately suited to brainstorming, discussion, and the exchange of learning experiences among learners. The teaching management is not flexible enough for the needs of modern instructors in designing learner-centered learning [5], and the developed systems often feature repetitive and unengaging learning, as well as insufficient responses to content questions or learning limitations. It does not respond to teaching as well as regular classroom learning. To address this limitation, Artificial Intelligence (AI) in the form of Chatbot applications has been used to enhance learning management using Retrieval-Augmented Generation (RAG) techniques [6] to solve learning management problems in the form of brainstorming (discussion) and to resolve learner difficulties. This is a novel approach in AI that integrates dynamic external data retrieval into the creation process of machine learning models. This technique enhances the system's creativity by allowing it to access a wider range of data beyond its initial training data, resulting in greater accuracy and relevance. RAG plays an important role in educational technology, especially in Learning Management Systems (LMS) [7]. The advantages of RAG are numerous. First, RAG enhances performance by bringing factual and up-to-date information from an external knowledge base into the Large Language Model (LLM). In addition, RAG maintains contextual relevance in responses, which makes the conversational Artificial Intelligence (AI) user experience more engaging [8].

Due to the limitations of traditional lecture-based teaching approaches that inadequately address individual learner needs and limit student engagement, there is a growing demand for educational innovations that enhance learning quality. Intelligent Tutoring Systems (ITS) [9], [10] offer a promising solution by adapting instructional content and learning strategies to learners' capabilities, thereby fostering analytical thinking, deep learning, and experiential learning. Prior studies indicate that AI-driven ITS can significantly improve learners' academic achievement and motivation [11], [12], particularly when combined with language models for personalized instruction or Reinforcement Learning techniques [13], [14] to dynamically optimize learning sequences. Furthermore, the integration of Retrieval-Augmented Generation (RAG) and learner intent recognition enhances the accuracy and interactivity of knowledge delivery. Accordingly, this study proposes "A Design Framework for Personalized Intelligent Tutoring Systems Integrating Knowledge Tracing and Retrieval-Augmented Generation" as a strategic guideline for the development of modern curricula and innovative instructional practices.

Despite the increasing adoption of Artificial Intelligence (AI) in Learning Management Systems (LMS), current implementations remain fragmented and lack systemic integration. Knowledge tracing models effectively estimate learners' mastery progression, while retrieval-augmented generation (RAG) enhances contextual accuracy and relevance in generative responses; however, these components are typically developed and deployed independently. Existing systems often provide predictive analytics without generative personalization, or conversely, offer generative tutoring without longitudinal learner modeling. Moreover, most RAG-based educational applications operate reactively and lack a closed-loop pedagogical architecture that systematically connects assessment, learner diagnosis, adaptive content generation, and performance feedback in a continuous instructional cycle. To address this gap, this study proposes an integrated design framework that unifies knowledge tracing and retrieval-augmented generation within a closed-loop intelligent tutoring system architecture. The proposed framework enables continuous learner state estimation, dynamic instructional adaptation, and data-driven decision-making across student, teacher, and administrative interfaces. By formalizing system-level integration and introducing architectural evaluation criteria—such as learning gain, predictive accuracy, and engagement indicators—this research advances the development of next-generation personalized intelligent tutoring ecosystems in a theoretically grounded and operationally scalable manner.

This study aims to:

1) Design a unified system-level framework integrating knowledge tracing, retrieval-augmented generation, and pedagogical decision-making.

2) Establish a closed-loop adaptive learning architecture that continuously connects assessment, learner modeling, generative instruction, and feedback mechanisms.

3) Evaluate the structural validity and expert-level appropriateness of the proposed framework using predefined architectural and validation criteria.

2. LITERATURE REVIEW

2.1 Literature Selection Criteria

To ensure that the literature sample used to justify the research problem is representative, up-to-date, and methodologically adequate, a structured selection process was adopted. Relevant studies were retrieved from international scholarly databases, including Scopus, IEEE Xplore, and Google Scholar, along with recent high-impact preprints from arXiv to capture emerging developments in generative AI. The selection was guided by the following criteria:

1) Thematic relevance involves the selection of studies related to Intelligent Tutoring Systems (ITS), Knowledge Tracing (KT), Retrieval-Augmented Generation (RAG), Large Language Models (LLMs) in educational contexts, learning analytics, or adaptive pedagogical architectures.

2) Recency emphasizes publications released between 2020 and 2025 to reflect the rapid advancement of LLM technologies in education.

3) Methodological rigor involves the selection of peer-reviewed journal articles or international conference proceedings that focus on architectural design, learner-state modeling, or system-level integration rather than isolated component-level algorithmic development.

Studies focusing solely on technical optimization without pedagogical application were excluded unless directly relevant to KT or RAG modeling. This structured selection process ensured that the reviewed literature adequately represents contemporary theoretical, technical, and architectural developments in AI-driven educational systems

2.2 Synthesis and Critical Analysis of Related Literature

Previous studies indicate that Retrieval-Augmented Generation (RAG) enhances Large Language Models (LLMs) by enabling the retrieval of relevant information from external knowledge bases during response generation, thereby improving accuracy and knowledge coverage, particularly in educational chatbot applications[15] In the context of Intelligent Tutoring Systems (ITS), RAG-based chatbots can support the learning of complex subjects by delivering context-aware and multimodal instructional content while dynamically adapting response complexity to individual learners. By analyzing learners' historical data, such systems can identify learning patterns, strengths, and weaknesses [16], and subsequently personalize instructional content, exercises, and assessments to enhance learner engagement and motivation [17] However, the effective deployment of RAG-based educational chatbots requires careful knowledge source selection, natural interaction design, and continuous system evaluation to ensure instructional effectiveness.

The architecture and components of an Intelligent Tutoring System (ITS) are fundamental to system development. Regardless of whether the system is implemented within the context of information systems, decision support systems, or intelligent systems, a clearly defined system architecture is essential to support integrated operations and facilitate future scalability. An effective architectural design enhances system flexibility, maintainability, and the structured management of complex components, reflecting the concept of the Cognitive Learning Cycle [18], which dynamically connects learners, knowledge, and instructional strategies. When the system is capable of efficiently linking learner data with instructional strategies and adapting them in real time, the ITS can closely approximate the instructional behavior of expert human tutors. Consequently, ITS architectures are commonly decomposed into functional subunits or modules [19], each serving a specific role and maintaining sequential and interdependent relationships. In general, a typical ITS consists of four core modules, namely:

1) Learner Model The Learner Model is responsible for collecting and analyzing learners' individual characteristics, such as prior knowledge levels, learning skills, learning behaviors, and cognitive deficiencies. These data serve as the foundation for determining appropriate instructional strategies. The Learner Model is regarded as the core component of an Intelligent Tutoring System (ITS), as it collects, integrates, and analyzes learner-specific information across multiple dimensions. These dimensions include prior knowledge, which is used to identify concepts or skills that learners have already mastered as well as areas of weakness; learning styles and skills, such as visual, auditory, and kinesthetic learning preferences; learning behaviors, encompassing patterns of interaction with the system, frequency of use, response time, and problem-solving approaches; and cognitive errors, including misconceptions or incorrect interpretations. The collected information is processed to construct a learner profile that is dynamically updated throughout the instructional process, enabling the system to deliver truly personalized and adaptive instructional strategies.

2) Expert/Domain Model The Expert or Domain Model represents the body of knowledge related to the subject matter, including problem-solving methods and potential errors that may occur, and is used to assess whether learners' understanding is correct or contains misconceptions. This module functions as a knowledge base that stores instructional content, theories, principles, rules, and problem-solving procedures relevant to the domain taught by the system. For example, in a mathematics tutoring system, this module contains mathematical formulas, problem-solving principles, and mechanisms for detecting common learner errors. In other words, the Expert Model serves as an expert teacher possessing comprehensive domain knowledge and the ability to

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evaluate learners' understanding and identify areas that require remediation. The key components of this module include: (1) core knowledge, consisting of essential facts, theories, and skills; (2) problem-solving rules, which define correct procedures or algorithms; and (3) error patterns, which describe common misconceptions and incorrect reasoning, enabling the system to provide targeted and accurate instructional guidance.

3) Tutoring/Pedagogical Model The Tutoring or Pedagogical Model is responsible for making strategic instructional decisions, such as content selection, instructional sequencing, and the provision of appropriate feedback or guidance, based on information obtained from the Learner Model and the Expert Model. This module functions as the strategic planning component of the ITS, integrating learner data and domain knowledge to determine the most effective presentation of instructional content and learning activities. Accordingly, the Tutoring Model can be viewed as an intelligent instructional designer that dynamically adapts to individual learners' conditions. Its primary functions include: (1) content selection, determining which topics learners should study next; (2) sequencing, organizing instructional materials according to learners' developmental progress and difficulty levels; (3) feedback and hints, providing constructive guidance or cues when learners make errors to encourage self-correction; and (4) dynamic adaptation, whereby the system adjusts instructional strategies when learners repeatedly encounter difficulties, such as shifting from text-based explanations to visual representations.

4) User Interface Module The User Interface Module serves as the communication channel through which learners interact with the system and may be implemented in the form of text, graphics, or natural language dialogue. This module acts as a bridge between learners and the system, enabling effective access to instructional content and feedback. The quality of the user interface has a significant impact on learner experience and is a key determinant of overall system success, as even a system with robust knowledge and instructional strategies may fail to support learning effectively if interaction is not smooth and intuitive. Interface designs may vary depending on the application context and include: (1) text-based interfaces, used for explanations, assessments, and written feedback; (2) graphical and multimedia interfaces, incorporating images, audio, video, or animations to enhance understanding; (3) natural language interfaces, employing Natural Language Processing (NLP) techniques to allow learners to interact with the system in a manner similar to conversing with a human teacher; and (4) interactive interfaces, such as dashboards or game-based learning environments, which help increase learner motivation and engagement.

Although Intelligent Tutoring Systems (ITS) and Retrieval-Augmented Generation (RAG) techniques have advanced significantly recently, most existing systems remain architecturally fragmented. Knowledge Tracing (KT) is typically employed for learner state prediction without being tightly integrated into dynamic content generation mechanisms, while RAG- and LLM-based tutoring systems largely function as reactive response engines that do not incorporate continuously updated learner diagnostics. Consequently, adaptation often lacks a true closed-loop learning cycle and fails to achieve deep personalization. Moreover, the literature reveals a clear absence of unified architectural frameworks that systematically integrate KT, RAG, and pedagogical decision-making processes. Existing studies tend to evaluate isolated AI components rather than assessing system-level interactions and their impact on personalization and learning gain. To address these limitations, this study proposes an integrated design framework that embeds learner modeling, generative content adaptation, and pedagogical decision mechanisms within a closed-loop intelligent tutoring architecture. This contribution advances AI deployment from modular implementation toward system-level integration, providing a structured foundation for next-generation personalized intelligent tutoring systems.

2.3 Key Conceptual Definitions

To ensure conceptual clarity and alignment with the design-oriented framework of this study, the following constructs are defined in relation to the proposed system architecture.

2.3.1 Intelligent Tutoring System (ITS)

An intelligent tutoring system is an AI-driven instructional environment that integrates learner analytics, adaptive decision-making, and generative feedback within a structured pedagogical architecture.

2.3.2 System-level Integration

System-level integration refers to the coordinated interaction of learner modeling, retrieval mechanisms, generative processing, and pedagogical decision-making within a unified instructional architecture, forming an interdependent closed-loop tutoring structure.

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2.3.3 Closed-loop Learning Architecture

A closed-loop learning architecture is a continuous instructional cycle linking assessment, learner-state estimation, adaptive content generation, and feedback, enabling iterative adjustment of instructional decisions.

2.3.4 Longitudinal Learner Modeling

Longitudinal learner modeling refers to the continuous updating of a learner's knowledge state over time using knowledge tracing, providing the basis for adaptive instructional decisions and generative constraints.

2.3.5 Instruction-aware Generative AI

Instruction-aware generative AI is a generative module guided by learner-state estimates and pedagogical policies, producing responses aligned with learner proficiency and adaptive instructional goals.

2.3.6 Personalized Learning

Personalized Learning is an adaptive learning process in which instructional content and pedagogical support are tailored to individual learners based on dynamic modeling of their knowledge state and learning behavior, enabled in this study through Knowledge Tracing and Retrieval-Augmented Generation.

3. CONCEPT OF DESIGNING

3.1 Research Design Rationale

This study adopts a design and development research approach grounded in Design Science Research (DSR). The primary objective is not to measure immediate learning outcomes but to propose and validate a system-level architectural framework integrating knowledge tracing and retrieval-augmented generation within a closed-loop intelligent tutoring system.

Design Science Research is appropriate when the research contribution lies in artifact creation, architectural innovation, and structured framework development rather than experimental intervention. Accordingly, this study focuses on the systematic design, structural validation, and expert-based evaluation of the proposed framework.

Given that the framework represents a conceptual and architectural integration of multiple AI components, expert validation was employed to assess content validity, structural coherence, and technical feasibility prior to large-scale empirical deployment. This approach ensures theoretical rigor and design soundness before proceeding to experimental effectiveness studies in future research phases.

3.2 System Architecture Design

The concept of developing smart teaching innovations to support the needs of individual learners by enhancing the efficiency of the Learning Management System (LMS) by using digital media and Artificial Intelligence (AI) to design learning [20] is a concept that focuses on arranging the learning environment and learning content to suit the knowledge and abilities of each learner [21], as well as using digital media to improve teaching to suit the needs and potential of learners. This system helps learners to receive more effective learning, and to be able to apply the acquired knowledge and skills to solve learning problems effectively. In addition, the system helps teachers to monitor and evaluate learners' learning thoroughly and continuously, enabling them to improve and develop teaching to better suit learners. The aim is for learners to have knowledge and skills that can be used in teaching and learning and can be applied in real work in a quality and efficient manner, with the format as shown in Figure 1.

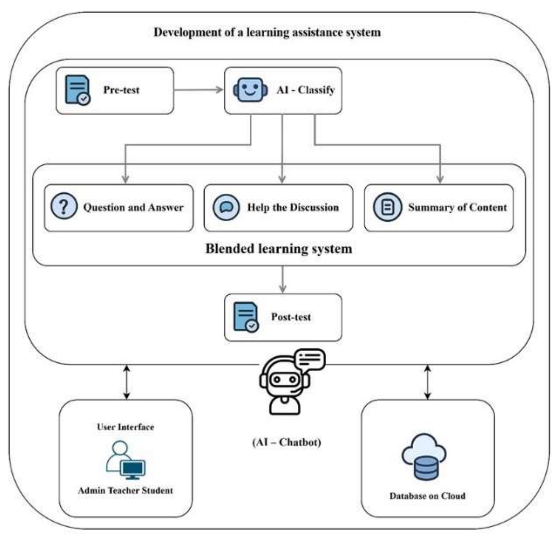

Figure 1: Architecture of the Personalized Intelligent Learning Assistance System

The learning assistance system, using artificial intelligence (AI) tailored to individual learner needs, is an intelligent teaching system that integrates AI technology to support systematic individualized learning. It begins by assessing learner background knowledge with a pre-test, providing initial data for analysis and learner grouping using AI techniques and Knowledge Tracing. This helps customize learning paths to match each learner's ability level and needs. The blended learning system is enhanced with intelligent tools such as a Q&A system, discussion support system, and automated content summary system, utilizing Natural Language Processing (NLP) techniques to promote deep learning and learner engagement. After each lesson, the system evaluates achievement with a post-test to measure progress and learning effectiveness. Furthermore, an AI-powered academic advisor (AI Chatbot) provides guidance and answers learner questions at all times. The entire system is designed with a user-friendly interface and supports data storage and processing on a cloud (Database on Cloud) for flexibility, security, and future scalability. This can be described in detail across seven sub-modules as follows:

3.2.1 Pre-Test Module

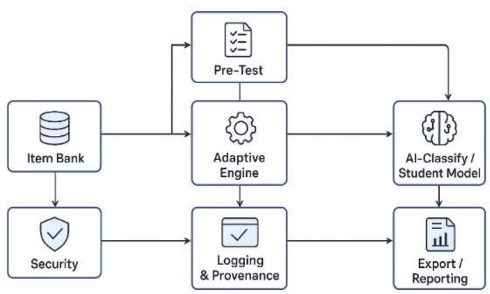

Figure 2: Architecture of the Pre-Test Module

Pre-Test Module [22] is a process of testing students' knowledge and understanding before learning the subject matter. It is to assess students' initial knowledge before starting the lesson, helping teachers to plan the teaching appropriately, focusing on areas where students lack understanding. If students already understand, they can skip to the next lesson. This results in teaching that is effective and aligns with the students' knowledge base and needs. It consists of:

1) Item Bank is a test bank that stores a set of questions [23] such as difficulty level, learning indicators and cognitive parameters (IRT parameters) to enable the system to select appropriate questions and support adaptive testing.

2) Security controls the security of data and the accuracy of the testing process [24] such as encryption, identity verification and protection against unauthorized access to questions or data to maintain the reliability of the assessment results.

3) Pre-Test is a pre-test designed to measure the learner's initial knowledge level [25] by linking it to the same learning indicators as the post-test so that learning gain can be accurately assessed.

4) Adaptive Engine is a Computerized Adaptive Testing (CAT) [26] mechanism that uses data from the Item Bank and learner responses to dynamically adjust the difficulty of the questions to increase the accuracy of knowledge assessment.

5) AI-Classify/Student Model is a system that analyzes test results and classifies learners according to their ability level [27] by possibly using models such as Bayesian/Deep Knowledge Tracing to create a knowledge profile of the learner and determine the appropriate learning path for the next step.

6) Logging and Provenance records all activities [28], such as the choice of questions, question order, response time, and model parameters, to support retrospective verification, detailed analysis of results, and future improvement of the test and model quality.

7) Export/Reporting module summarizes results and exports data [29], such as individual scores, skill reports, and class statistics, for teachers and administrators to use for further analysis or to determine learning activities.

3.2.2 AI Classify Module

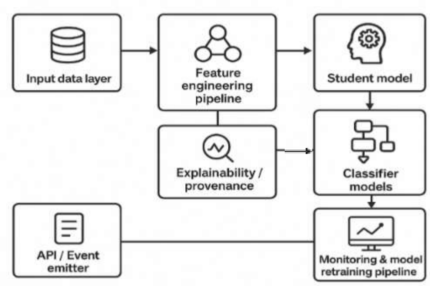

Figure 3: Architecture of the AI-Based Learner Classification Module

Intelligent Learner Grouping (AI Classify Module) [30] This system uses AI to group learners based on their abilities and needs, tracking their knowledge and personalizing their learning experience. Knowledge Tracing (KT) Effective KT solutions will unlock the potential of computer-assisted education applications such as intelligent tutoring systems, curriculum design, and appropriate learning media recommendations. Furthermore, KT can be extended to a wider range of machine teaching scenarios where "learners" may refer to either humans or artificial intelligence.

1)Input The data layer is responsible for collecting data from the pretest, LMS, learning behavior, and activity logs [31] to be used as a basis

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for systematic analysis of learners. The data is organized into standard formats such as JSON so that other modules can easily process it. Having multidimensional data helps make the analysis model more accurate, especially in knowledge tracing and learning analytics tasks.

2) Feature Engineering Pipeline is the process of extracting key information from raw data [32], such as topic accuracy, response time, frequency of repeated errors, and hint behavior, to create behavioral signals that the model can understand. Good feature design improves the accuracy of the learner classification model. Analysis of patterns of errors (misconceptions) is an important trend in modern adaptive learning systems.

3) Student Models (BKT/DKT/Transformer-based KT) are designed to assess the learner's knowledge status continuously. BKT employs Bayesian principles to track skill learning, whereas DKT and Transformer-based KT utilize deep learning [33] to capture patterns of forgetting, learning, and skill relationships. These types of models can predict responses and help identify missing knowledge.

4) Classifier Models (Logistic/Tree/Neural/ Clustering) divide learners into groups such as remedial, on-track, or advanced using the results of the student model + features. Supervised learning (e.g., logistic regression) or unsupervised learning (e.g., k-means) can be used [34] to find groups based on the learners' actual behavior. Good classification helps determine the appropriate learning path for each individual.

5) Explainability/Provenance is the explanation of the reasoning behind the classification, such as which feature has the greatest impact or what type of error caused the system to decide it was a remedial group. Tools like SHAP or LIME [35] make it easier for instructors to verify and help increase the transparency of AI-powered learning systems. Adding explainability enhances confidence and fairness in learner analysis.

6) API/Event Emitter is responsible for sending classification results to other modules [36], such as Q&A Generator, Summary Generator, or LMS via REST API or event-based messaging, enabling real-time system connectivity and future scalability. A well-designed API allows for a highly flexible architecture.

7) Monitoring & Model Retraining Pipeline monitors the accuracy of the model [37], such as data drift, concept drift, or model performance degradation with new learners, and retrains it periodically or when processing detects abnormalities, helping to keep the model up-to-date and relevant to the actual learner's context.

3.2.3 Blended Learning System

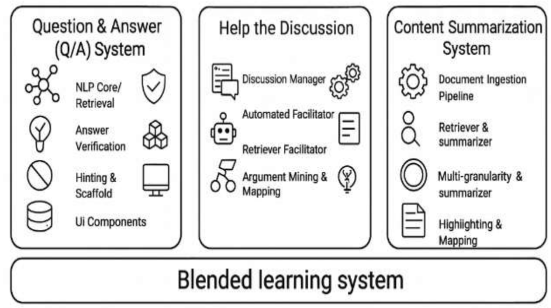

Figure 4: Architecture of the AI-Based Blended Learning System

A blended learning system can take advantage of large language models (LLMs) to develop a platform that integrates functions to support question solving/intelligent question answering [38], [39], discussion support (by detecting and analyzing forum messages or creating a discussion prompt), and content generation/summarization. These innovation-driven LLMs have the potential to revolutionize educational practices and foster a more personalized and effective learning environment, finding that early student support can help increase learning engagement and effectiveness, and LLMs can also be used to create personalized learning content. This enhances student engagement and learning outcomes. It consists of three sub-modules:

1) Question & Answer (Q/A) System is a question-answering system that helps learners search for and understand content immediately [40]. Its main objective is to provide access to original knowledge sources and support the learning process by using NLP techniques such as Retrieval-Augmented Generation (RAG) and semantic retrieval (e.g., using cosine similarity with dense representations in a mathematical context) [40] to retrieve accurate information from databases. RAG is used to overcome the main obstacle for LLM chatbots in education, namely, hallucinations.

2) Help the Discussion: This module supports discussions to enhance learners' reasoning exchanges by using Argument Mining (AM) techniques [41] Working in conjunction with discourse analysis and LLM-based facilitation, it analyzes argument structures (e.g., claim and evidence). The LLM system is used to analyze conversations and provide timely feedback to instructors [42]. This feedback helps instructors refine strategies to increase the number of high-quality (non-mechanical) questions and feedback, resulting in more structured conversations and fostering reasoning and critical thinking skills.

3) Content Summarization System is a system that manages and summarizes large documents into essential information by using retriever-based summarization techniques in conjunction with Transformer abstractive models such as PEGASUS or LLM summarizer to summarize large documents into essential information that is accurate and retains the original context [43], [44]. The system also supports long context models, such as Longformer, to handle large amounts of data, and applies highlighting techniques to extract essential lesson content to help learners understand the content structure more quickly.

3.2.4 Post-Test Module

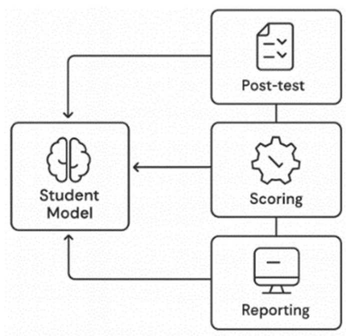

Figure 5: Architecture of the Post-Test Module

The Post-test Module [45] is a test of students' knowledge and understanding and is an assessment of learning after studying the subject matter of each lesson. It also measures student progress, helps measure the effectiveness of teaching and learning, and provides feedback for improving teaching in the next session. It consists of:

1) A post-test is a post-learning assessment to evaluate the learner's level of understanding and to use as a basis for improving instruction. This module uses AI techniques such as Automatic Item Generation (AIG) from Transformer models (GPT, PEGASUS, T5) to generate diverse and accurate test items and analyzes metadata such as response time and click patterns to assess the learner's confidence level. The results are then fed into the Scoring and Student Model to analyze and personalize learning [46].

2) Scoring performs the function of automatically checking both objective and essay answers using advanced NLP techniques such as Automated Essay Scoring (AES) through Transformer models (BERT, RoBERTa, and DeBERTa) and LLM that evaluate the quality of answers according to a rubric. The hybrid scoring technique combines rule-based with deep learning [47] to increase accuracy and reduce bias. The system can also detect cognitive errors and generate automatic feedback before sending scores to the Reporting and Student Model.

3) Reporting summarizes student scores and behaviors into easily understandable reports using learning analytics, such as clustering, classification, and predictive analytics to identify weaknesses, strengths, and risk trends. AI also uses NLP summarization techniques to create personalized feedback and uses a dashboard connected to the LLM to allow learners to interactively ask questions [48]. All data form the basis for the student model to predict learning behavior and progress.

4) Student Models (BKT/DKT/Transformer-based KT) are designed to continuously assess the learner's knowledge status. BKT uses Bayesian principles to track learning skill by skill, while DKT and transformer-based KT use deep learning [33] to capture patterns of forgetting, learning, and skill relationships. These types of models can predict responses and help identify missing knowledge.

3.2.5 AI - Chatbot Module

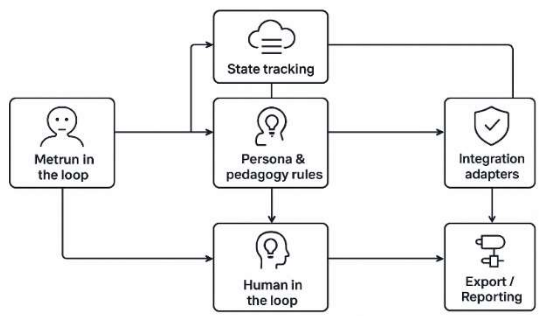

Figure 6: Architecture of the AI Chatbot Component

The AI-powered academic advisory system (AI Chatbot Module) [5] uses AI technology to provide academic advice, helping to solve problems that students may encounter during each lesson by answering students' questions about the content they are learning. Students can ask questions about the lesson at any time. It consists of:

1) State Tracking (Dynamic State Tracking Model) is used to track conversation context, user intent, and ongoing conversational state information so that AI chatbots can understand previous content and respond accordingly. Techniques used include Dialogue State Tracking (DST) on Transformer architectures such as BERT-DST, TripPy-DST, and GPT-DST [49]], as well as Reinforcement Learning (RL) for learning states in complex contexts. Memory-augmented LLMs are also used to store long-term conversation memory [50] to accurately analyze intent and slot value.

2) Persona & Pedagogy Rules This module controls the chatbot's personality, response characteristics,

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and teaching philosophy to align with its objectives, such as being a trainer, psychologist, or AI mentor. Techniques used include Persona-Conditioned LLM, Instruction Fine-Tuning (IFT), Prompt Engineering, and RLHF (Reinforcement Learning from Human Feedback) [51], as well as Pedagogical Modeling such as Intelligent Tutoring Systems (ITS), Mastery Learning, and Scaffolding to ensure the AI responds in a way that is appropriate and safe.

3) Human-in-the-Loop (HITL) allows humans to monitor, decide, or control parts of the conversation to ensure accurate, reliable, and accountable results. It uses techniques such as Human Feedback Reinforcement Learning (HF-RL, RLHF), Active Learning, Expert Feedback Loops, and Uncertainty Estimation, which allows humans to only monitor when the AI is unsure, reducing workload and increasing efficiency. It also supports multiple roles, such as teachers, experts, or system administrators [52].

4) Metrun-in-the-Loop performs an automated evaluation of the quality of chatbot results, such as accuracy, appropriateness, and teacher level. AI uses techniques such as Automatic Evaluation Models, LLM-as-a-Judge [53]], Rubric-Based Scoring, Toxicity Detection Models (BERT-TC, RoBERTa-TC), and Reward Models to analyze quality in real-time without human intervention.

5) Integration adapters serve to connect AI chatbots with other systems such as LMS, CRM, student systems, online classrooms, or databases [54] using techniques such as API orchestration, knowledge-level retrieval (RAG), vector embedding models (FAISS, Chroma, Milvus), and ontology alignment to answer knowledge-based questions accurately and reference real data.

6) Export/Reporting is responsible for displaying results, such as behavior reports, learning performance reports, or chatbot analysis results. It uses techniques such as learning analytics, data visualization, clustering/classification, predictive modeling, and NLP summarization to create automated reports, such as summarizing learner behavior, weaknesses, strengths, or risks of not passing [55].

3.2.6 User Interface

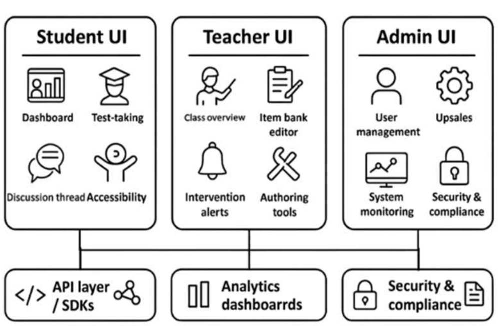

Figure 7: Architecture of the User Interface for the AI-Based Learning Assistance System

User interface module refers to the parts of a program or application that interact with the user [56]. It is designed to make it easy and convenient for the user to perform tasks or operations. It consists of various elements such as buttons, text fields, display formats, and others that are used to guide the user to understand and use the system for the desired purpose. It consists of:

1) Student UI is a system that integrates AI to provide comprehensive support for learners through core modules such as Dashboard, Test-taking, Discussion Thread, and Accessibility. It applies Adaptive/Personalized Learning, which relies on machine learning, deep learning, and multimodal analytics to analyze learning behavior and outcomes to tailor content and feedback to each learner [57], as well as Chatbot/Conversational Agent, which uses Generative AI + NLP combined with retrieval-based methods to provide explanations, answer questions, and support learning through the Discussion thread in real-time [58], and Real-time Feedback & Engagement Monitoring, which uses behavioral analytics and predictive modeling to track learning behavior and provide automated feedback when a learner is at risk or falling behind, ensuring learners receive continuous and contextually appropriate support.

2) Teacher UI is an AI-assisted system that systematically supports teaching by integrating an AI-assisted Item Bank & Parameterization to help analyze difficulty and create appropriate test questions to reduce the workload of teachers [59]. It uses intervention alerts & early-warning models from learning analytics and predictive modeling to detect at-risk students and offer immediate assistance [60]. It also uses an Analytics Dashboard to give teachers an overview of class, student behavior, and error patterns, helping to improve teaching planning efficiency and make more accurate, data-driven decisions.

3) Admin UI is an AI-powered system to support centralized management through System-wide Analytics & Resource Management, which uses machine learning to analyze system usage and performance to optimize resource management [61]; Model Management & Security Oversight, which uses MLOps, monitoring, and data-governance approaches to track model drift, fairness, and data security; and Automated Reporting & Insights Generation, which uses AI to automatically generate statistical reports and policy information for

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executives, enabling more accurate and transparent decision-making.

3.2.7 Database on Cloud

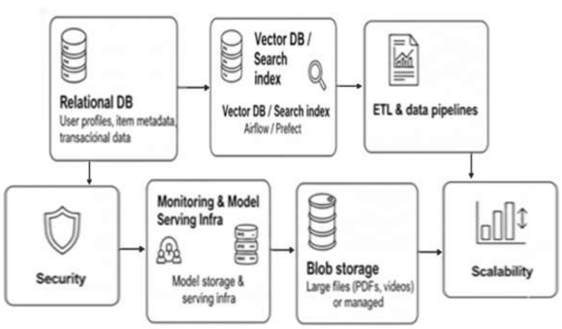

Figure 8: Architecture of the System Database and Cloud Infrastruct

Cloud-based database architecture [62] is designed to handle a wide variety of data types, from structured and semantic data to big and unstructured data, by integrating relational databases, vector databases, data pipelines, and object storage into a secure, verifiable, and scalable structure. This type of system is a cornerstone of modern analytics and AI platforms. It includes:

1) Relational DB stores structured data such as user profiles, item metadata, and transactional data, which is the main database of the learning analytics system. This data is used with predictive modeling, clustering, and knowledge tracing techniques with supervised and unsupervised learning to systematically analyze student achievement and behavior [63].

2) Vector DB/Search Index stores embeddings of text, documents, and learning materials to support semantic retrieval and Retrieval-Augmented Generation (RAG) using Transformer-based embeddings and Approximate Nearest Neighbor (ANN) for accurate and efficient semantic retrieval [64].

3) ETL & Data Pipelines are responsible for collecting, transforming, and preparing data from multiple sources into the cloud, applying AI in automated data cleaning, anomaly detection, and feature engineering to improve data quality before training and using models [65].

4) Security is responsible for protecting data and system access, using AI techniques for anomaly detection and behavioral security analytics to identify attacks or abnormal behavior in the cloud in real time [66].

5) Monitoring & Model Serving Infrastructure is responsible for supporting the storage and service of AI models in real-world environments, using MLOps, model performance monitoring, and drift detection concepts to maintain long-term model reliability and stability [67].

6) Blob Storage is used to store large files such as PDFs, videos, and multimedia. AI is used in multimodal representation learning to transform unstructured data into embeddings for analysis and knowledge retrieval [68].

7) Scalability is designed to support the growth of users and data volumes by using AI for predictive autoscaling and workload forecasting, such as LSTM or Transformer-based time-series models, to allocate cloud resources appropriately and efficiently [69].

4. METHODOLOGY

The proposed conceptual framework for designing a personalized intelligent learning management system was evaluated to examine the appropriateness, validity, and reliability of the technologies and techniques employed in the platform development. Expert-based evaluation was conducted to verify the conceptual soundness, model stability, and alignment of system components with the research objectives. Three assessment dimensions were applied as follows.

4.1 Content Validity

Content validity was examined by a panel of at least five experts to assess the relevance and accuracy of each evaluation item. The Index of Item–Objective Congruence (IOC) index was calculated for each item to determine the degree of alignment between system components and research objectives. This measure was used to ensure the suitability, correctness, and credibility of the proposed system framework.

4.2 Appropriateness of the Conceptual Framework

The appropriateness of the overall conceptual framework was evaluated using a structured questionnaire administered to 15 experts. The experts assessed the suitability of each system component, and the collected data were analyzed using descriptive statistics, including the mean ($\bar{x}$) and standard deviation (S.D.), to summarize quantitative trends and overall evaluation outcomes.

4.3 Appropriateness of AI Innovation and Techniques

The suitability of the proposed AI-based innovations and techniques was further evaluated through expert opinions collected from the same

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group of 15 experts. The evaluation focused on the applicability, feasibility, and technical soundness of the AI components. Descriptive statistical analysis, including the mean ($\bar{x}$) and standard deviation (S.D.), was employed to interpret the quantitative assessment results.

5. ANALYTICAL RESULTS

5.1 This section presents the results of the expert evaluation of the proposed conceptual framework for the AI-based learning system. The assessment focused on examining the alignment between the system components and the research objectives. The evaluation was conducted by five experts, and the results are summarized in Table 1.

Table 1: Expert Evaluation Results on the Alignment of the Conceptual Framework

Assessment Items	Description	IOC
Pre-test Module (Item Bank, CAT, Security)	Assesses learners' prior knowledge accurately through an item bank, computer adaptive testing (CAT), and secure assessment mechanisms to ensure validity and reliability.	0.95
AI-Classify/Student Model (KT, Classifier)	Analyzes learner performance and behavior using Knowledge Tracing (KT) and classification models to identify learning levels and individual needs.	0.93
Blended Learning System (Q&A, Discussion, Summarization)	Supports blended learning through intelligent Q&A, discussion facilitation, and content summarization to enhance understanding and interaction.	0.90
Post-test Module (AIG, Scoring, Reporting)	Evaluates learning outcomes using automated item checking (AIC), scoring, and reporting to measure learning achievement effectively.	0.96
AI-Chatbot Module (DST, Persona, HITL)	Provides intelligent learning assistance using dialogue state tracking (DST), adaptive personas, and human-in-the-loop (HITL) mechanisms to ensure reliability and appropriateness.	0.92
Student UI (Adaptive Learning, Feedback, Engagement)	Delivers adaptive learning content, personalized feedback, and engagement support tailored to individual learner characteristics.	0.94
Teacher UI (Item Bank, Alerts, Dashboard)	Enables instructors to manage assessment items, monitor learner progress through alerts, and analyze learning data via dashboards.	0.91
Admin UI (Analytics, MLOps, Reporting)	Supports system administration, learning analytics, MLOps management, and comprehensive reporting for system monitoring and optimization.	0.89
Cloud Database & AI Infrastructure	Provides scalable cloud-based data storage and AI infrastructure to support system performance, security, and reliability.	0.97
Overall		0.93

Table 1 presents the results of the expert evaluation of the proposed AI-based learning system framework, which comprises nine core modules covering the entire instructional management process. These modules span pre-learning assessment, adaptive and personalized learning management, intelligent learning support, learning outcome evaluation, and systematic system administration.

The results indicate that the content validity of the evaluation instrument was rigorously examined by a panel of experts to determine the degree of alignment between each assessment item and the research objectives, using the Index of Item–Objective Congruence (IOC) as the evaluation criterion. The findings reveal that all assessment items achieved high IOC values, ranging from 0.89 to 0.97, with an overall mean IOC of 0.93, which clearly exceeds the acceptable threshold (≥ 0.50). These results demonstrate a strong correspondence between the assessment items and the research objectives, indicating that the developed instrument possesses high content accuracy and relevance. Moreover, the consistently high IOC values confirm that the evaluation instrument is appropriate and reliable for assessing the proposed conceptual framework and system components.

Overall, the content validity results indicate a strong alignment between the evaluation items and the research objectives. The high IOC values confirm the conceptual consistency and reliability of the assessment criteria, thereby reinforcing the credibility and theoretical validity of the proposed AI-based learning system framework.

5.2 The evaluation results of the conceptual framework by 15 experts reflect their opinions on the consistency, completeness, and appropriateness of the components and architecture of the proposed system. This assessment helps confirm the reliability and conceptual validity of the developed framework while also demonstrating the suitability of each module in supporting the systematic and efficient development of an intelligent teaching system. The evaluation results are summarized in Table 2.

Table 2: Results of the Evaluation of the Appropriateness of the Conceptual Framework by Experts

Assessment Items	$\bar{x}$	S.D.	Suitability Level
Pre-test Module (Item Bank, CAT, Security)	4.78	0.42	Very High
AI-Classify / Student Model (KT, Classifier)	4.72	0.45	Very High
Blended Learning System (Q&A, Discussion, Summarization)	4.65	0.50	High
Post-test Module (AIG, Scoring, Reporting)	4.82	0.38	Very High
AI-Chatbot Module (DST, Persona, HITL)	4.60	0.53	High
Student UI (Adaptive Learning, Feedback, Engagement)	4.75	0.41	Very High
Teacher UI (Item Bank, Alerts, Dashboard)	4.68	0.47	High
Admin UI (Analytics, MLOps, Reporting)	4.55	0.56	High
Cloud Database & AI Infrastructure	4.85	0.35	Very High
Overall	4.71	0.45	Very High

Table 2 indicates that the proposed AI-powered learning system, comprising nine interrelated sub-modules, has been validated by expert evaluation as a comprehensive and coherent framework supporting the full learning process, including pre-assessment, adaptive learning, intelligent instruction, post-assessment, and system management. The very high suitability ratings across all modules ($\bar{x}$ = 4.71, SD = 0.45) provide strong evidence of the conceptual validity and practical relevance of the framework, underscoring its contribution as a structured and extensible reference model for the development of intelligent and personalized learning systems.

5.3 The evaluation results of the proposed AI innovations and techniques were obtained based on the opinions of the same group of 15 experts. The assessment focused on the applicability, feasibility, and technical soundness of the artificial intelligence components integrated into the system. Quantitative data were analyzed using descriptive statistics, including the mean ($\bar{x}$) and standard deviation (S.D.), to interpret the evaluation outcomes. These results provide empirical validation of the suitability of the proposed AI techniques for practical implementation. The evaluation findings are summarized in Table 3.

Table 3: Results of the Evaluation of the Appropriateness of AI Innovations and Techniques

System Modules	Assessment Items	$\bar{x}$	S.D.	Suitability Level
1. Pre-Test & AI-Classify	1.1 The appropriateness of applying Knowledge Tracing techniques (BKT/DKT) in analyzing learners' prior knowledge.	4.72	0.46	Very High
	1.2 The capability to explain the results of learner classification (Explainability) through tools such as SHAP/LIME.	4.65	0.50	High
2. Blended Learning (RAG)	2.1 The suitability of applying Retrieval-Augmented Generation (RAG) to reduce hallucinations in AI-generated responses.	4.78	0.42	Very High

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	2.2 The suitability of applying Argument Mining techniques to analyze and support learning-related reasoning.	4.60	0.53	High
System Modules	Assessment Items	$\bar{x}$	S.D.	Suitability Level
3. Post-Test & Scoring	3.1 The suitability of using Automated Essay Scoring (AES) based on Transformer models and Rubric-based assessment.	4.82	0.38	Very High
	3.2 The appropriateness of integrating AI-generated feedback (AI-generated feedback).	4.70	0.45	Very High
4. AI-Chatbot Module	4.1 The suitability of using Persona and Pedagogical Rules (rule-based teaching strategies).	4.68	0.47	High
	4.2 The suitability of applying a Human-in-the-Loop (HITL) approach to enhance reliability and ethical use of AI.	4.85	0.35	Very High
5. User Interface (UI)	5.1 Intervention Alerts in the Teacher UI to support timely instructional decision-making.	4.66	0.49	High
	5.2 The suitability of accessibility features in the Student UI to support diverse learner needs.	4.73	0.44	Very High
6. Cloud & Infrastructure	6.1 The suitability of using a Vector Database for efficient knowledge retrieval and semantic search.	4.80	0.40	Very High
	6.2 The suitability of applying MLOps practices for continuous model management and handling model drift.	4.83	0.37	Very High
Overall		4.73	0.45	Very High

As shown in Table 3, the expert evaluation results demonstrate that the proposed AI-based learning system framework exhibits a very high level of appropriateness, with an overall mean score of 4.73 (S.D. = 0.45). This outcome provides strong empirical support for the conceptual robustness and structural validity of the proposed framework. Notably, key architectural components—such as the automated assessment and grading mechanism, the human-in-the-loop intelligent assistant, and the cloud-based infrastructure—received the highest ratings. These findings indicate that the integration of these components effectively strengthens the framework's capability to support adaptive learning, system scalability, and reliable AI-driven instructional processes.

Overall, the results confirm that the proposed framework contributes a well-validated and practically applicable architectural model for the design and development of intelligent tutoring systems, offering a systematic foundation for future AI-enhanced learning environments in higher education.

5.4 Evaluation Criteria and Validation Metrics To ensure that the study's conclusions are grounded in empirical and methodological rigor rather than conceptual interpretation, a multi-layered evaluation framework was established at both the model and system architecture levels. The proposed intelligent tutoring framework was validated using quantitative, behavioral, and architectural performance indicators as follows.

1) Predictive Modeling Performance. The effectiveness of the Knowledge Tracing (KT) component was assessed using standard predictive metrics, including Area Under the ROC Curve (AUC), Root Mean Square Error (RMSE), and Accuracy. Improvements over baseline models (e.g., standalone KT or non-adaptive systems) were used to determine whether the integrated framework enhances learner state estimation reliability. Statistically significant improvements ($p < .05$) indicate superior mastery prediction capability.

2) Learning Gain and Instructional Effectiveness. Instructional impact was measured through pre-test and post-test comparisons, employing normalized learning gain (g), percentage improvement, and effect size (Cohen's d). The framework is considered pedagogically effective if it demonstrates statistically significant learning improvements compared to control or baseline instructional conditions. This criterion ensures that architectural integration translates into measurable academic outcomes.

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3) Learner Engagement and Behavioral Analytics. User engagement was evaluated through log-based behavioral indicators, including session duration, interaction frequency, task completion rate, and participation in adaptive or discussion modules. Increases in engagement metrics relative to traditional LMS environments provide evidence that the closed-loop adaptation mechanism enhances learner involvement and sustained interaction.

4) System Performance and Scalability. Operational efficiency of the integrated KT–RAG architecture was assessed through system latency, throughput, and computational resource utilization. The framework must maintain acceptable real-time responsiveness under concurrent user loads, demonstrating feasibility for institutional deployment.

5) Comparative Architectural Validation. Beyond model-level metrics, architectural contribution was validated through comparative analysis against (1) traditional LMS systems, (2) standalone ITS implementations, and (3) reactive RAG-based tutoring systems. Evaluation focused on the degree of functional integration among assessment, learner modeling, adaptive content generation, and feedback refinement. The proposed closed-loop architecture is validated if it demonstrates coherent system-level orchestration and measurable cross-module performance enhancement.

These evaluation criteria provide a conceptual basis for examining how the proposed framework supports intelligent tutoring beyond algorithmic development toward systemic and pedagogical integration, defining key dimensions for assessing next-generation personalized AI-driven education systems. It should be noted that these criteria are intended to guide future empirical validation and were not applied in the present study. As this research focuses on architectural design and expert-based conceptual validation, empirical measures such as predictive accuracy, learning gain, engagement analytics, and system performance were not tested. Future research should operationalize these metrics through experimental or longitudinal studies involving real learners.

6. DISTINCTION FROM PRIOR LITERATURE

Despite continuous advancements in Intelligent Tutoring Systems (ITS), Knowledge Tracing (KT), Retrieval-Augmented Generation (RAG), and learning analytics, most prior studies have focused on developing isolated technological components rather than integrating them at the architectural level. In particular, existing works rarely connect longitudinal learner-state modeling, generative AI mechanisms, and pedagogical decision-making within a unified closed-loop learning cycle. To clarify the system-level distinction of the proposed framework, this study synthesizes and compares relevant prior research, as shown in Table 4.

Table 4: System-Level Distinction of the Proposed Framework from Prior Literature

Research Group	Uses KT	Uses RAG	Closed-Loop Adaptation	Architecture-level Integration
Group A: AI-based/Adaptive ITS [5], [9], [10], [12], [16], [17], [18], [19], [22], [45], [56], [58]	Partial	x	Limited / Partial	x
Group B: Knowledge Tracing-Focused Research [27], [29], [32], [33], [35]	/	x	x	x
Group C: RAG / LLM-Based Educational Systems [6], [7], [8], [15], [38], [40], [41], [50], [54], [57], [68]	x	/	Mostly Reactive	x
Group D: Adaptive Testing & Learning Analytics [24], [25], [26], [31], [55], [60], [63]	Partial	x	Partial	x
Group E: System Architecture & Infrastructure [36], [61], [64], [65], [67], [69]	x	x	x	x
Proposed Framework (This Study)	/	/	/	/

Table 4 indicates that prior research has predominantly focused on isolated components of intelligent learning systems—such as knowledge tracing algorithms, RAG/LLM-based tutoring agents, or learning analytics—without achieving architecture-level integration within a unified closed-loop pedagogical framework. While these

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studies contribute to advancements in predictive modeling, generative response quality, or adaptive assessment, they generally operate at the algorithmic or module level. In contrast, the proposed framework differs at the system-architecture level rather than the component level, integrating longitudinal learner-state modeling (KT), retrieval-augmented generative reasoning (RAG), and pedagogical decision-making into a coherent closed-loop ITS architecture. This systemic integration enables continuous diagnosis, adaptive content generation, and feedback optimization within a structurally unified and pedagogically governed intelligent learning ecosystem.

7. CONCLUSION AND FUTURE RESEARCH

This study proposed a novel design framework for a personalized intelligent learning assistance system that advances prior ITS and RAG-based approaches by integrating Knowledge Tracing, Retrieval-Augmented Generation, and pedagogical decision-making within a unified learning-cycle architecture. Unlike existing systems that treat generative AI as a standalone tutor, the framework positions it as an instruction-aware component guided by continuous learner-state modeling across nine modules. Expert evaluations demonstrate strong empirical support, with high content validity (IOC = 0.93; Table 1), overall appropriateness ($\bar{x}$ = 4.71; Table 2), and technical suitability of AI mechanisms ($\bar{x}$ = 4.73; Table 3). Future research should empirically evaluate learning gains, engagement, and adaptive accuracy through large-scale deployments, while extending the framework with multimodal learning analytics, explainable and ethical AI mechanisms, and cross-domain generalization to enhance scalability and long-term sustainability.

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