

EduAI Personalized Learning System: A Large Language Model-Based Adaptive Learning System to Enhance the Effectiveness of Digital Education

Ahmad Fauzan Saputra^{a,1*}, Muhammad Rizky Pratama^{b,2}, Daniel James Anderson^{b,3}

^a Program Studi Informatika, Fakultas Teknik, Universitas Teknologi Indonesia, Jakarta, Indonesia

^b Program Studi Informatika, Fakultas Teknik, Universitas Teknologi Indonesia, Jakarta, Indonesia

^c Department of Computer Science, University of Melbourne, Melbourne, Australia

¹ ahmad.fauzan@example.com^{*}; ² m.rizkypratama@university.ac.id; ³ d.j.anderson@university.ac.id

^{*} Corresponding author

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Article history Received: 21 August 2026 Revised: 25 September 2026 Accepted: 26 September 2026 Published: 29 September 2026 Keywords adaptive learning large language models personalized learning artificial intelligence in education intelligent tutoring systems  License by CC-BY-SA Copyright © 2026, The Author(s).	Digital education has expanded access to learning resources, but conventional digital learning environments frequently provide standardized content that does not adequately accommodate differences in learners' knowledge, learning pace, interests, and proficiency levels. Recent advances in large language models (LLMs) provide opportunities to develop adaptive educational systems capable of dynamically generating learning materials, explanations, feedback, and learning pathways. This study aims to develop the conceptual architecture of EduAI Personalized Learning System, an LLM-based adaptive learning system designed to support individualized digital learning. The study employed a design-oriented developmental approach consisting of needs identification, literature-informed system design, adaptive learning architecture development, and functional analysis. The proposed system integrates learner profiling, learning-path recommendation, LLM-based content generation, formative assessment, personalized feedback, and continuous learner-model updating. The analysis indicates that LLMs can provide a flexible interaction layer for adaptive learning while analytics and learner models provide the personalization mechanism. However, issues concerning hallucination, bias, privacy, pedagogical alignment, and excessive dependence on automated tutoring require explicit governance mechanisms. The proposed EduAI architecture therefore combines generative capabilities with learner analytics, knowledge representation, assessment, and human oversight. The study contributes an integrated conceptual framework for implementing LLM-powered personalized learning in digital education and provides a foundation for subsequent empirical evaluation.

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INTRODUCTION

The rapid transformation of digital education has expanded opportunities for learners to access educational resources independently, continuously, and across diverse learning contexts. However, the availability of extensive digital content does not automatically ensure effective or individualized learning. Many digital learning environments continue to rely on standardized sequences of materials, identical assessments, and generalized feedback despite differences in learners' prior knowledge, learning pace, interests, abilities, and proficiency levels. This uniformity can limit the responsiveness of digital education to individual learning needs, particularly in online and blended environments where instructors may have limited opportunities to continuously monitor learner progress and provide individualized interventions. Adaptive learning has consequently emerged as an approach for adjusting learning experiences according to learner characteristics and demonstrated progress. Kabudi et al. (2021), through a systematic mapping of the literature, identified learner modeling, recommendation mechanisms, personalization, and automated decision-making as important components of AI-enabled adaptive learning systems. More recent systematic studies have likewise highlighted the increasing role of AI in personalized education while identifying challenges related to pedagogical integration, implementation, explainability, and responsible use (Farhood et al., 2025; Hariyanto et al., 2025).

The emergence of large language models (LLMs) provides additional technological capabilities for interactive educational systems. LLMs can process natural-language inputs and generate context-sensitive explanations, examples, questions, exercises, summaries, and feedback. In education, these capabilities have been explored for teaching assistance, content generation, question answering, and learning support (Li et al., 2024; Shen, 2024; Saiedian, 2024). However, the ability to generate context-sensitive responses should not be equated with adaptive learning itself. An LLM-based educational assistant primarily refers to a system that uses an LLM to interact with learners and provide educational assistance through natural language, whereas adaptive learning concerns the systematic adjustment of learning activities based on learner characteristics and evidence of learning progress. Therefore, integrating an LLM into an educational platform does not automatically establish a coherent personalized learning process.

In this study, personalized learning refers to an educational approach in which learning experiences are adjusted according to individual learner characteristics, needs, preferences, prior knowledge, and learning progress. Adaptive learning refers to the mechanism through which a system dynamically modifies learning content, sequence, difficulty, feedback, or learning activities in response to learner evidence. Intelligent tutoring refers to an AI-supported instructional approach that provides individualized guidance, explanations, feedback, or instructional assistance resembling selected functions of a human tutor. Meanwhile, an LLM-based educational assistant refers to a conversational educational system that uses an LLM to provide natural-language interaction and generative support. These concepts are related but are not interchangeable. Personalized learning represents the broader educational orientation, adaptive learning represents the mechanism for dynamic adjustment, intelligent tutoring emphasizes individualized instructional assistance, and an LLM-based educational assistant represents a technological means for delivering generative and conversational support.

Recent studies demonstrate the potential of LLMs to support different components of personalized education. Chen et al. (2024) developed GPTutor to generate personalized learning content and provide tutoring support, while Ng and Fung (2024) investigated personalized learning-path planning using LLMs. Li et al. (2025) applied LLMs to personalized programming education, and Lee and Eronen (2025) examined tailored English learning and skill development. Wang and Gao (2025) further emphasized the customization of language-learning content and feedback according to learner needs and proficiency levels. These studies demonstrate applications of LLMs across content generation, learning-path planning, tutoring, feedback, and skill development. However, these applications generally emphasize particular educational contexts or specific personalization functions rather than providing a unified architecture that connects multiple functions throughout the learning process.

Other studies have addressed supporting components required for broader personalization. Li et al. (2025) highlighted the role of LLM-powered learning analytics in personalized curriculum design, while Wasnik and Shrivastava (2025) proposed the integration of LLMs with knowledge graphs to support tailored education. Liu (2025) examined computational intelligence approaches for adaptive learning and personalized education, while Sari et al. (2024) emphasized the potential of AI-based adaptive learning systems for improving educational processes. In parallel, Bamnote et al. (2025) reviewed LLM-driven intelligent educational agents for adaptive learning, Bendraou et al. (2025) proposed LAMPAS as an LLM-driven adaptive multi-factor personalized learning system, and Spiteri and Dingli (2025) introduced DAVE as a personalized AI tutoring approach. These studies indicate a transition from relatively static digital learning applications toward interactive systems capable of responding dynamically to learner inputs. Nevertheless, the existing literature tends to emphasize particular functions, educational contexts, or system components rather than integrating learner profiling, analytics, knowledge representation, learning-path recommendation, content generation, assessment, feedback, and governance within a single coherent learning cycle.

The research gap therefore concerns the limited architectural integration of these capabilities into a unified framework for personalized digital learning. Existing studies have established the feasibility of personalized content generation (Chen et al., 2024), personalized learning-path planning (Ng & Fung, 2024), personalized programming education (Li et al., 2025), tailored language education (Lee & Eronen, 2025; Wang & Gao, 2025), intelligent educational agents (Bamnote et al., 2025), personalized AI tutoring (Spiteri & Dingli, 2025), learning analytics (Li et al., 2025), and knowledge-graph integration (Wasnik & Shrivastava,

2025). However, these contributions do not collectively establish a comprehensive architecture in which learner profiling, learning analytics, curriculum and knowledge representation, adaptive pathway recommendation, LLM-based content generation, formative assessment, personalized feedback, and responsible AI governance operate as interconnected components of a continuous personalization process. Thus, the gap is not the absence of LLM applications in education, but the limited conceptual integration of these functions into a coherent adaptive learning architecture.

Such integration is important because personalization involves more than generating responses that appear relevant to individual learners. An LLM may produce multiple explanations for the same concept, but this capability does not guarantee that the explanations correspond to the learner's prerequisite knowledge or intended learning outcomes. Similarly, a system may recommend learning activities dynamically without ensuring that the recommended sequence is consistent with curriculum objectives. Learning analytics and structured knowledge representation can therefore complement generative capabilities by providing information about learner performance, behavior, curriculum structures, and prerequisite relationships. Wasnik and Shrivastava (2025) emphasized the relevance of combining LLMs and knowledge graphs for tailored education, while Li et al. (2025) highlighted LLM-powered analytics for personalized curriculum design. These perspectives support an architecture in which the LLM operates within defined educational constraints and receives structured information about both learners and curriculum.

The integration of LLMs into personalized learning also requires attention to reliability, educational validity, learner data, and responsible implementation. Generative AI systems may produce inaccurate information, provide responses insufficiently aligned with instructional objectives, or reproduce biases present in training data. These risks become more consequential when generated outputs influence learning decisions or are treated by learners as authoritative explanations. Li et al. (2024) emphasized challenges involving reliability, evaluation, and educational alignment, while Sonkar et al. (2024) identified a student-data paradox and potential unintended consequences associated with personalization based on learner information. Parker et al. (2025) demonstrated the potential of LLMs to analyze educational survey feedback, but automated interpretation requires appropriate validation when it contributes to decisions concerning learner progression or intervention. Sharma et al. (2025) similarly emphasized that technological capability should not automatically be equated with educational effectiveness. Accordingly, learner data and generative capabilities need to be connected to pedagogical objectives, evaluation mechanisms, and responsible governance rather than being treated as independent technological features.

Based on this gap, the present study proposes the EduAI Personalized Learning System, an LLM-based adaptive learning architecture designed to support individualized digital education. The proposed architecture integrates learner profiling, learning analytics, structured knowledge and curriculum representation, LLM-based content generation, adaptive learning-path recommendation, formative assessment, personalized feedback, and governance mechanisms. Personalization is conceptualized as a continuous process in which learner interactions and assessment results update the learner model, which subsequently informs the selection and generation of learning activities. In this architecture, the LLM functions as a generative and conversational intelligence layer within a broader adaptive learning system rather than as an autonomous decision-maker or replacement for educators. This positioning connects the flexibility of natural-language interaction with structured learner information, educational objectives, knowledge representation, assessment, and evaluation mechanisms.

The objective of this study is to develop and conceptually analyze an integrated architecture for an LLM-based adaptive learning system that supports individualized learning experiences in digital education. Specifically, the study aims to organize key AI-enabled educational functions into a coherent personalization framework and to establish conceptual relationships among learner modeling, learning analytics, adaptive pathways, content generation, assessment, feedback, and responsible AI governance. The resulting EduAI architecture is intended to provide a conceptual foundation for subsequent empirical evaluation while maintaining a clear distinction between generative AI capabilities and the pedagogical responsibilities of educators.

METHOD

Research Design

This study employed a design-oriented developmental research approach to develop and conceptually analyze the EduAI Personalized Learning System, an adaptive learning architecture based on large language models (LLMs). The research focused on designing an integrated system architecture rather than empirically testing learning outcomes. This approach was selected because the primary objective was to formulate a scientifically grounded framework that integrates existing AI capabilities into a coherent personalized learning environment.

The research process consisted of five sequential stages: (1) literature identification, (2) literature screening and selection, (3) thematic literature synthesis, (4) system requirements analysis and architecture development, and (5) functional conceptual evaluation. The first three stages were used to establish the evidence base for the proposed architecture, while the subsequent stages translated the synthesized findings into system requirements, architectural components, and functional relationships. The overall research flow is presented as follows:

Literature Identification → Literature Screening and Selection → Thematic Synthesis → System Requirements Analysis → Architecture Development → Functional Conceptual Evaluation

This sequential process was designed to ensure that the proposed system components were derived from the identified educational and technological requirements and remained connected to evidence reported in the scientific literature.

Literature Identification and Selection

The literature used in the development process consisted of scientific references included in the article's reference list. The literature addressed AI-enabled adaptive learning, personalized education, LLM applications, intelligent educational agents, AI tutoring, learning analytics, knowledge representation, and responsible use of generative AI.

Literature identification was guided by the conceptual focus of the study. References were considered relevant when they contributed to at least one of the following areas: learner modeling, learning analytics, content personalization, learning-path adaptation, knowledge representation, formative assessment, personalized feedback, or AI governance. Particular attention was given to studies that described educational applications, system functions, personalization mechanisms, architectural components, or limitations relevant to the development of an integrated adaptive learning system.

The selection process followed three steps. First, the identified references were examined for their relevance to the research focus. Second, studies that addressed one or more of the defined functional categories were retained for thematic analysis. Third, the retained literature was compared according to its educational function, AI technique, personalization mechanism, potential contribution, and identified limitation.

Literature was excluded from the conceptual synthesis when it did not have a substantive connection to AI-supported personalized or adaptive learning, did not provide an identifiable educational or technological function relevant to the proposed architecture, or only discussed general AI capabilities without relevance to the system requirements under investigation.

Because the study was designed as a literature-grounded conceptual architecture study rather than a systematic review, the selection process was not intended to estimate the prevalence or effect size of findings across the literature. Instead, the purpose was to identify complementary functions and architectural requirements that could be integrated into the proposed EduAI system.

Thematic Literature Synthesis

The selected literature was analyzed thematically to identify recurring educational and technological functions relevant to personalized learning. The analysis focused on eight categories: learner modeling, learning analytics, content personalization, learning-path adaptation, knowledge representation, formative assessment, personalized feedback, and AI governance.

Each selected reference was examined based on its reported educational function, AI technique, personalization mechanism, potential contribution, and identified limitation. Findings from individual studies

were then compared across the eight analytical categories to identify common capabilities, complementary functions, and limitations.

The synthesis also distinguished between functions that could be directly supported by LLMs and functions requiring additional computational, data-analytic, structured knowledge, or pedagogical mechanisms. This distinction was important because the study did not conceptualize the LLM as a complete adaptive learning system. Instead, the LLM was positioned as one component within a broader architecture in which learner information, curriculum structures, assessment results, adaptive mechanisms, and governance provide contextual constraints.

System Requirements Analysis

The system requirements were derived from the thematic synthesis of the selected literature. The analysis established that an adaptive learning system requires information about individual learners, mechanisms for interpreting learning progress, structured educational resources, adaptive recommendations, content-generation capabilities, and continuous evaluation.

These requirements were organized into functional system layers. The Learner Profile Layer represents learner characteristics, prior learning experiences, preferences, proficiency, and performance information. The Learning Analytics Layer processes learner interactions and assessment information to identify learning progress and potential learning needs. The Knowledge and Curriculum Layer provides structured educational information and curriculum objectives that constrain the generation and selection of learning materials. The LLM Intelligence Layer provides natural-language interaction and generates explanations, examples, questions, summaries, and feedback. The Adaptive Learning Layer uses learner-state information to support individualized learning-path recommendations. Finally, the Evaluation and Governance Layer supports quality monitoring, output validation, and human oversight.

Architecture Development

The proposed architecture was developed by mapping the identified requirements to system components and defining the information flow among those components. The architecture follows a continuous adaptive cycle.

First, learner information and learning interactions are collected to establish or update the learner model. Second, learning analytics interpret available evidence regarding learner performance and progress. Third, the adaptive learning component uses the learner state and curriculum information to determine an appropriate learning activity. Fourth, the LLM generates or adapts the required educational content and interaction. Fifth, the learner completes the activity and produces new performance evidence. This evidence is subsequently returned to the learner model to support further adaptation.

This closed-loop structure ensures that personalization is treated as an ongoing process rather than a single recommendation event. The architecture also separates generative functions from pedagogical and adaptive decisions. The LLM is primarily responsible for natural-language generation and interaction, whereas learner modeling, structured knowledge, assessment information, and adaptive mechanisms provide contextual constraints for the generated outputs.

Functional Conceptual Evaluation

The proposed system was evaluated conceptually through functional traceability. Each major component was examined to determine whether its function could be connected to an identified educational requirement and supported by the reviewed literature.

The evaluation considered four aspects: (1) functional relevance of each architectural component, (2) consistency of information flow between components, (3) alignment between system functions and personalized learning objectives, and (4) support for responsible implementation through validation and human oversight. Particular attention was given to the relationships among learner profiling, analytics, knowledge representation, LLM interaction, adaptive recommendation, assessment, feedback, and governance.

The evaluation did not involve human participants, experimental intervention, or statistical hypothesis testing. Therefore, the study does not claim empirical improvement in learning achievement, engagement,

retention, or other learner outcomes. Instead, the methodological outcome is a literature-grounded system architecture that provides a basis for subsequent implementation and empirical validation.

Data Analysis

The collected literature information was analyzed using thematic synthesis. Relevant findings were grouped according to technological function and pedagogical purpose, followed by comparison across studies to identify common capabilities, complementary functions, and limitations.

The results of the synthesis were subsequently translated into architectural requirements. Each identified requirement was mapped to one or more proposed system components, and the relationships among the components were defined according to the continuous adaptive learning cycle. The final architecture was considered conceptually appropriate when each major component had a defined function, a clear relationship with other components, and a direct connection to personalized learning objectives.

This analytical procedure provides a transparent basis for tracing how findings from the selected literature were transformed into system requirements and architectural components. It also establishes a methodological foundation for subsequent empirical implementation and evaluation of the EduAI Personalized Learning System.

RESULTS AND DISCUSSION

Results of the EduAI Personalized Learning Architecture

The development process resulted in an integrated architecture for the EduAI Personalized Learning System that combines learner profiling, learning analytics, knowledge and curriculum representation, large language model (LLM)-based interaction, adaptive learning, formative assessment, personalized feedback, and governance. The architecture was derived from the functional requirements identified through the thematic synthesis of the literature. The resulting system does not position the LLM as an autonomous learning system. Instead, the LLM functions as an intelligence layer within a broader adaptive learning cycle in which learner information, learning evidence, curriculum structure, and assessment results determine the context in which generative capabilities are applied.

The architecture consists of six interconnected functional layers. The Learner Profile Layer maintains information relevant to individual learning characteristics and learning history. The Learning Analytics Layer interprets available learning evidence to identify learner progress and learning needs. The Knowledge and Curriculum Layer provides structured educational knowledge and curriculum-related information. The LLM Intelligence Layer generates context-sensitive educational content and natural-language interaction. The Adaptive Learning Layer uses learner-state information to support individualized learning-path recommendations. Finally, the Evaluation and Governance Layer provides mechanisms for output monitoring, validation, and human oversight.

Table 1. Functional Components of the EduAI Personalized Learning System

No.	System Component	Main Function	Relationship with Personalization
1	Learner Profile Layer	Represents learner characteristics, learning history, preferences, and performance information	Provides the learner context required for individualized adaptation
2	Learning Analytics Layer	Interprets learner interactions and learning performance	Identifies learner progress and current learning needs
3	Knowledge and Curriculum Layer	Organizes educational knowledge and curriculum objectives	Maintains alignment between generated content and learning objectives
4	LLM Intelligence Layer	Generates explanations, examples, questions, summaries, and feedback	Adapts educational interaction to learner context
5	Adaptive Learning Layer	Determines appropriate learning activities and pathways	Supports individualized sequencing of learning activities

6	Evaluation and Governance Layer	Supports validation, monitoring, and human oversight	Reduces risks associated with inappropriate or unreliable AI outputs
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The results indicate that personalization in EduAI operates as a continuous adaptive process rather than a single recommendation mechanism. Learner information and learning interactions provide evidence for updating the learner model. The resulting learner state informs the adaptive learning component, which determines the appropriate learning activity. The LLM subsequently generates or adapts the educational response according to the available learner and curriculum context. New learner responses and assessment evidence are then returned to the learner model. This structure establishes a feedback loop between learning behavior and subsequent instructional adaptation.

This architecture is consistent with the adaptive learning framework described by Kabudi et al. (2021), which identifies learner modeling, personalization, recommendation, and automated decision-making as important components of AI-enabled adaptive learning systems. It also corresponds with more recent systematic evidence emphasizing that AI-based personalized learning requires integration between technological capabilities and pedagogical requirements (Farhood et al., 2025; Hariyanto et al., 2025).

Integration of LLM-Based Personalization

A major result of the architectural development is the integration of LLM-based generation with learner-specific information. The system is designed to support personalization at both the content level and the learning-path level. At the content level, the LLM can generate explanations, examples, questions, summaries, and feedback based on the learner's context. At the pathway level, learner performance and learning-state information can inform the selection or recommendation of subsequent learning activities.

This distinction is important because content personalization and pathway personalization address different educational requirements. Chen et al. (2024) demonstrated the potential of GPTutor to generate personalized learning content using LLMs, whereas Ng and Fung (2024) focused on personalized learning-path planning. Li et al. (2025) further demonstrated the application of LLMs to personalized programming education. In language education, Lee and Eronen (2025) demonstrated tailored learning through LLMs, while Wang and Gao (2025) emphasized customization of content and feedback according to learners' needs and proficiency levels.

Table 2. Personalization Functions Identified in the EduAI Architecture

Personalization Dimension	Learner Information Used	System Function	Resulting Adaptation
Content	Learning needs and learner context	LLM-based generation	Individualized explanations and learning materials
Learning pathway	Learning progress and performance	Adaptive recommendation	Individualized sequence of activities
Feedback	Learner responses and demonstrated difficulties	LLM-based feedback	Context-sensitive formative feedback
Assessment	Learning responses and performance evidence	Formative assessment	Updated information about learner progress
Interaction	Learner input and learning context	Natural-language interaction	Personalized educational dialogue

The integration of these functions represents an important distinction between an LLM-enabled educational assistant and a comprehensive adaptive learning system. An educational assistant may provide a personalized response to an individual question, but such interaction does not necessarily modify the learner's subsequent learning pathway. EduAI instead connects the interaction with learner modeling and adaptive recommendation. This design is supported by the literature showing that LLMs have potential across personalized content generation, pathway planning, and individualized educational interaction (Chen et al., 2024; Ng & Fung, 2024; Li et al., 2025).

Learning Analytics and Knowledge Representation

The third result concerns the integration of learning analytics and structured knowledge representation. The architecture recognizes that LLM-based personalization cannot rely exclusively on the learner's immediate conversational input. Learning history and performance evidence must also be considered when determining the learner's current needs.

Learning analytics therefore functions as an intermediate mechanism between learner activity and adaptive decision-making. Li et al. (2025) identified LLM-powered analytics as a mechanism for personalized curriculum design, while Liu (2025) demonstrated the relevance of computational approaches to adaptive personalized education. Within EduAI, these capabilities are conceptually connected to the learner profile so that learning evidence can contribute to subsequent adaptation.

Knowledge representation provides a complementary function. Wasnik and Shrivastava (2025) emphasized the integration of LLMs with knowledge graphs for tailored education. In the EduAI architecture, structured knowledge and curriculum information provide contextual constraints for LLM-generated outputs. This mechanism is important because linguistic fluency alone does not guarantee curriculum alignment. A generated explanation may be grammatically correct and contextually plausible while remaining inappropriate for the intended learning objective. Structured knowledge therefore provides an additional mechanism for maintaining educational relevance.

Table 3. Relationship Between System Inputs, Processing, and Adaptive Outputs

System Input	Processing Component	Adaptive Output
Learner profile	Learner modeling	Learner-specific context
Learning history	Learning analytics	Learning-progress information
Assessment response	Formative assessment	Evidence of learning needs
Curriculum objectives	Knowledge and curriculum layer	Curriculum-aligned context
Learner question	LLM intelligence layer	Context-sensitive response
Learning evidence	Adaptive learning layer	Recommended subsequent activity
AI-generated output	Evaluation and governance layer	Validated educational response

The results suggest that learning analytics and knowledge representation provide the structural context required to make LLM-based personalization more coherent. The LLM supplies generative flexibility, whereas structured information supplies constraints and context. This division of functions supports the proposition that effective adaptive learning should not depend solely on generative AI.

Intelligent Tutoring and Personalized Feedback

The fourth result concerns the role of EduAI as an intelligent tutoring environment. The architecture allows learners to interact with the system using natural language and receive explanations, examples, questions, summaries, and feedback. This function corresponds with the development of LLM-driven intelligent educational agents reported by Bamnote et al. (2025). Bendraou et al. (2025) similarly proposed an LLM-driven adaptive multi-factor personalized learning system, while Spiteri and Dingli (2025) described personalized AI tutoring as a mechanism for supporting individualized and engaging learning. Kayyali (2025) further positioned AI agents as an emerging component of LLM-based educational environments.

The distinguishing feature of EduAI is that tutoring interaction is connected to the adaptive learning cycle. The response generated by the LLM is not treated as the final stage of the learning process. Instead, the learner's subsequent response can provide additional evidence for updating the learner model. Consequently, tutoring, assessment, and adaptation operate as interconnected functions.

Personalized feedback is also important because generic feedback may not adequately address individual learning difficulties. Parker et al. (2025) demonstrated the potential of LLMs for analyzing educational feedback, indicating that language models can process educational information expressed in natural language. In EduAI, this capability is conceptually applied to formative interaction. However, the system should not assume that generated feedback is automatically accurate or pedagogically appropriate. Validation and human oversight remain necessary, particularly when feedback affects learner progression.

Continuous Adaptation and Responsible Implementation

The final result is the formulation of a continuous adaptation mechanism that connects assessment evidence with subsequent learning recommendations. In this architecture, formative assessment serves not only to document learner performance but also to generate information for further personalization. This principle is consistent with the adaptive learning literature, which emphasizes continuous adjustment based on learner information and performance (Kabudi et al., 2021; Hariyanto et al., 2025).

However, the conceptual architecture also identifies important limitations associated with LLM-based personalization. Li et al. (2024) highlighted concerns regarding reliability, evaluation, and educational alignment. Sonkar et al. (2024) demonstrated potential unintended effects associated with personalized LLM-based tutoring and learner data. Sharma et al. (2025) similarly emphasized the importance of evaluating the actual educational impact of LLM-based personalized learning rather than assuming that technological capabilities automatically produce improved learning outcomes. Mimoudi (2025) further discussed the potential of generative AI to support personalized learning while identifying challenges related to quality and responsible implementation.

These findings have direct implications for the governance component of EduAI. The LLM should support, rather than replace, educators. Educators remain important for curriculum interpretation, pedagogical judgment, validation of learning materials, and high-stakes decisions. The system should therefore maintain a clear distinction between automated assistance and educational authority.

Conceptual Flow of the EduAI System

The results can be represented through the following architecture:

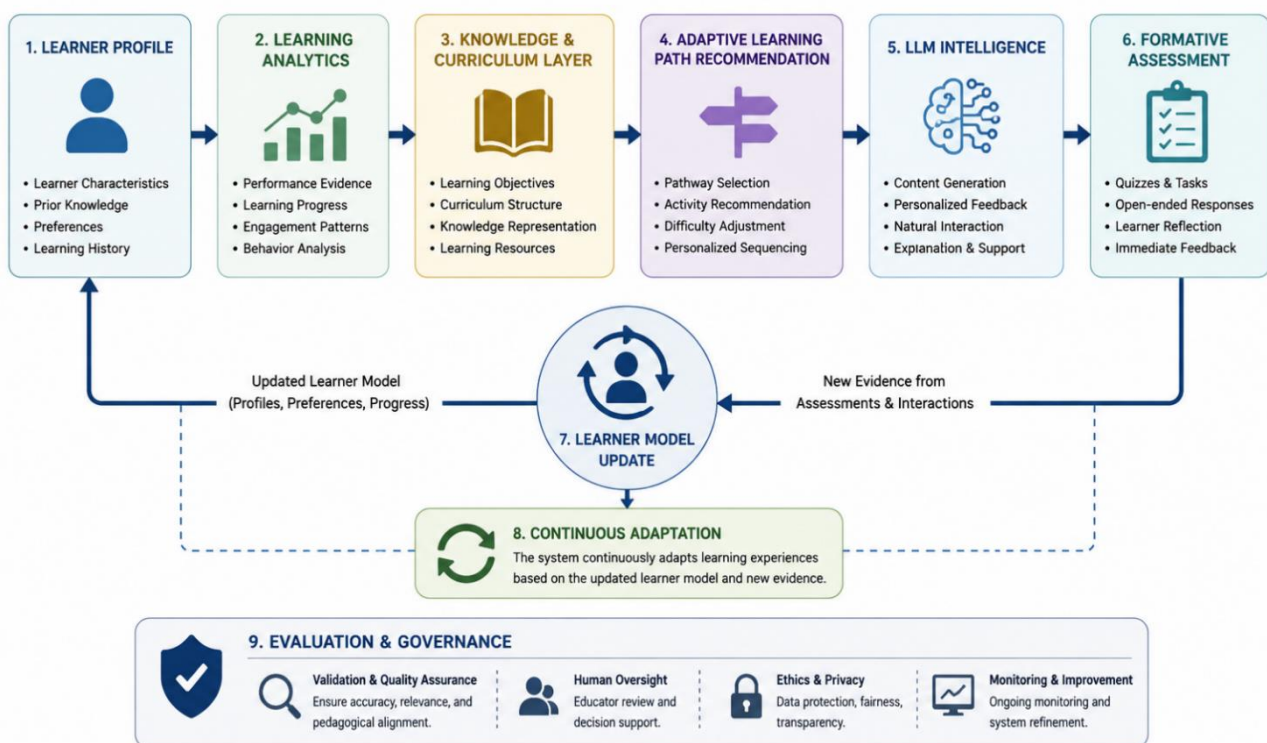


Figure 1. Conceptual architecture and adaptive learning cycle of the EduAI Personalized Learning System.

Figure 1 summarizes the central result of the study. The architecture establishes a closed-loop relationship between learner information, analytics, curriculum context, adaptive recommendation, LLM-based interaction, and formative assessment. The learner model is continuously updated through new learning evidence, enabling subsequent adaptation.

Importantly, Figure 1 is an architectural representation rather than an empirical performance diagram. Similarly, Tables 1 to 3 represent the results of the system-development and literature-synthesis process

rather than measurements obtained from experimental participants. Therefore, no numerical learning gains, accuracy percentages, satisfaction scores, or effectiveness claims are presented.

Overall, the results indicate that EduAI provides an integrated conceptual architecture that addresses the fragmented nature of existing LLM-based educational applications. Previous studies have established the feasibility of personalized content generation (Chen et al., 2024), personalized learning-path planning (Ng & Fung, 2024), programming education (Li et al., 2025), tailored language learning (Lee & Eronen, 2025; Wang & Gao, 2025), intelligent educational agents (Bamnote et al., 2025), adaptive multi-factor personalization (Bendraou et al., 2025), and AI tutoring (Spiteri & Dingli, 2025). EduAI integrates these functions with learning analytics, knowledge representation, formative assessment, and governance. The resulting architecture provides a basis for future empirical implementation, but its actual effectiveness in improving learning outcomes must be established through subsequent experimental or field-based research.

CONCLUSION

This study developed and conceptually analyzed the EduAI Personalized Learning System, an integrated large language model (LLM)-based adaptive learning architecture designed to support personalized digital education. The proposed architecture integrates learner profiling, learning analytics, structured knowledge and curriculum representation, LLM-based content generation, adaptive learning-path recommendation, formative assessment, personalized feedback, and evaluation and governance mechanisms within a continuous adaptive learning cycle. The results indicate that effective personalization requires more than the ability of an LLM to generate context-sensitive educational content. Personalization also depends on learner evidence, curriculum alignment, structured knowledge, assessment information, and mechanisms for continuously updating the learner model.

The proposed architecture contributes to the development of AI-supported education by connecting functions that have frequently been examined separately, including personalized content generation, learning-path planning, intelligent tutoring, learning analytics, and knowledge representation. From a practical perspective, EduAI provides a conceptual foundation for developing digital learning environments that can deliver individualized content, feedback, and learning recommendations while maintaining the role of educators in pedagogical decision-making and quality control.

However, this study does not provide empirical evidence of improved learning outcomes because the research focused on architectural development and conceptual analysis. Therefore, the effectiveness of EduAI should not be interpreted as empirically established. Future research should implement the proposed system in authentic educational settings and conduct empirical evaluation of learning achievement, engagement, usability, personalization quality, and long-term learning effects.

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