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Design of an Intelligent Agent-Based Adaptive Learning System: A Literature-Based Model Proposal

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Abstract: The integration of artificial intelligence technologies into educational environments has accelerated the development of personalized and adaptive learning approaches. In this context, intelligent agent-based systems stand out with their potential to adapt learning processes according to students' individual characteristics, learning needs, and performance. The aim of this study is to examine the use of intelligent agents in education and to propose an integrated adaptive learning system model based on literature findings. The research was conducted with a literature-based qualitative approach, and studies on the use of intelligent agents in education in recent years were examined in terms of student modeling, content recommendation, performance evaluation and decision-making processes. As a result of the investigations, it was determined that intelligent agents are widely used in these components, but studies addressing these components in a holistic structure are limited. Accordingly, this study proposes a multi-agent adaptive learning model that integrates student modeling, personalized content recommendation, continuous assessment, and decision-making processes. Additionally, the model is enriched with a generative AI-powered agent component that provides real-time interaction, feedback, and dynamic personalization. The developed model will be evaluated through expert review, and the findings will be reported in future empirical studies. In conclusion, the proposed model is considered to have the potential to make learning processes more flexible, data-driven, and student-centered. The study is expected to contribute to the literature by providing an integrated conceptual framework for intelligent agent-based adaptive learning systems.

Keywords: Artificial intelligence, Intelligent agents, Adaptive learning, Learning analytics, Generative AI

Introduction

Rapid developments in artificial intelligence technologies lead to significant transformations in the design, implementation and evaluation processes of educational environments (Holmes, 2024; UNESCO, 2023). In particular, the spread of generative artificial intelligence technologies has enabled learning processes to be designed in a more personalized, flexible and data-based way; this has significantly increased the interest in adaptive learning approaches (Kasneci et al., 2023; Lo, 2023; Tlili et al., 2023). Traditional teaching approaches often fail to adequately take into account students' individual differences, learning speeds, readiness levels and learning preferences. On the other hand, artificial intelligence-supported learning systems make it possible to structure learning processes in a student-centered and dynamic manner by analyzing multidimensional data obtained from students (Holmes, 2024; UNESCO, 2023). In this regard, adaptive learning systems stand out as one of the important educational technologies that aim to personalize the learning experience by taking into account individual characteristics of students such as their knowledge level, learning speed, area of interest and learning preferences (Brusilovsky, 2001). In recent years, with the developments in artificial intelligence-supported technologies, these systems have turned into more flexible structures that can provide content, activities and feedback according to the immediate needs of students; thus, they

have begun to offer important opportunities in terms of increasing participation in learning processes, supporting motivation and improving learning outcomes (Crompton & Burke, 2023; Kasneci et al., 2023; Lo, 2023).

Effective design of adaptive learning systems depends not only on determining the individual characteristics of students, but also on continuous analysis of the data produced during the learning process. In this context, learning analytics is considered as one of the basic components that enable instructional decisions to be made in a data-based manner by making sense of students' cognitive, behavioral and performance-based data. In this process, intelligent agent-based systems stand out with their ability to make autonomous decisions in learning environments, monitor user behavior, identify learning needs and provide appropriate learning support (Franklin & Graesser, 1997; Russell & Norvig, 2021; Wooldridge, 2009). Intelligent agents are defined as software components that collect data from their environment for specific purposes, analyze the information obtained, make decisions and interact with the user when necessary (Nwana, 1996). Intelligent agents in educational environments can perform functions such as student modeling, content recommendation, performance monitoring, feedback, and instructional decision-making (Russell & Norvig, 2021).

Current research shows that intelligent agents have significant potential, particularly in creating personalized learning experiences. By analyzing students' learning history, academic achievement, learning preferences, interaction patterns, and performance data, it has become possible to recommend content, activities, and learning paths tailored to individual needs (Baker & Inventado, 2014). Furthermore, assessment agents can continuously monitor students' learning process and provide real-time feedback, while decision-making agents integrate data from different components to contribute to the formation of pedagogical decisions on how to adapt the learning process. In this way, the learning environment transforms into a dynamic and data-driven structure that can be continuously updated according to the student's needs (Siemens & Long, 2011). Existing studies reveal that intelligent agents are used for various purposes in educational settings. Some research focuses on student modeling processes, while others address content recommendation mechanisms, assessment processes, or generative AI-supported interactions. While these findings demonstrate significant progress in AI-based learning systems across different components, they also highlight the importance of holistic design approaches to how these components can work together within a single adaptive learning ecosystem. In particular, recent developments in generative AI have made the integration of next-generation agents—capable of interacting with learners using natural language, providing explanations, offering feedback, and supporting instructional decision-making processes—with learning analytics and adaptive learning mechanisms a prominent research topic in educational technologies. Based on this need, an integrated adaptive learning system model based on intelligent agents is proposed. The proposed model is structured on a multi-agent architecture consisting of a Student Modeling Agent, a Content Recommendation Agent, an Assessment Agent, a Decision-Making Agent, and a Generative AI-Powered Interaction Agent.

The proposed architecture aims to continuously analyze learning analytics data obtained from students, suggest appropriate learning content based on these analyses, monitor learning performance, and dynamically adapt the instructional process according to the results obtained. In addition, by incorporating a generative AI-powered interaction agent into the model, the aim is to transform students from mere content consumers into individuals who can request explanations, receive feedback, and actively participate in the learning process. The main contribution of the research is to propose a conceptual model that brings together learning analytics, intelligent agents, generative AI, and adaptive learning approaches under a holistic architecture. Consequently, it is considered that the proposed model will provide a theoretical framework for the design of AI-powered adaptive learning systems in education and will form a scientific basis for future expert evaluations and applied research.

Theoretical Framework and Literature Review

Artificial Intelligence and Adaptive Learning Systems in Education

The integration of artificial intelligence technologies into educational environments has significantly accelerated the transition from standardized teaching approaches to flexible and personalized learning models based on student data. AI-supported systems enable the adaptation of content, learning paths, and feedback to individual needs by analyzing students' interactions, performance, and learning behaviors. Recent review studies show that techniques such as machine learning, deep learning, natural language processing, and multimodal data analysis are increasingly used in creating student profiles, predicting performance, and adjusting instructional content in real time (Hariyanto et al.,

2025; Tan et al., 2025). Adaptive learning systems are systems that dynamically adjust the learning experience in line with students' knowledge levels, learning speeds, preferences, performance patterns, and learning needs (Brusilovsky, 2001). The primary goal of these systems is to create differentiated learning experiences based on the student's current situation and development throughout the process, rather than offering all students the same learning content and learning path. Contemporary adaptive learning platforms can continuously analyze student data to change the content level, task sequence, feedback format, and learning pace; thus transforming personalization from a one-time classification into a dynamic, continuously updated process (Hariyanto et al., 2025; Tan et al., 2025). In this context, learning analytics plays a fundamental role in interpreting data obtained from student interactions and transforming them into adaptation decisions. Through learning analytics, students' participation levels, performance trends, need for help, and difficulties encountered in the learning process can be determined; the findings can then be used for content recommendations, assessment processes, and instructional interventions. The integration of artificial intelligence with learning analytics supports the transformation of adaptive learning systems into structures that not only monitor student behavior but also generate data-driven interventions (Alfredo et al., 2024; Cukurova, 2024; Khosravi et al., 2025). This integration makes it possible to use data obtained from students for pedagogical purposes, but also requires consideration of design principles such as human supervision, student autonomy, and the reliability of system decisions. Generative AI applications have further expanded the interaction and feedback capacity of adaptive learning systems. These technologies have the potential to generate explanations, examples, guidance, and personalized feedback by considering the student's learning context and previous interactions. However, using generative AI in conjunction with learning analytics is not just about producing more content; it also requires evaluating whether the support generated supports the student's cognitive engagement, self-regulation, and learning goals (Khosravi et al., 2025). Therefore, in the design of adaptive systems, pedagogical suitability, student control, and human-centered design principles should be taken into account, in addition to technological functionality (Alfredo et al., 2024; Cukurova, 2024). AI-supported adaptive learning systems offer significant opportunities in terms of delivering personalized content, providing timely feedback, identifying at-risk students, and supporting instructional decisions. However, recent research shows that problems such as data privacy, algorithmic bias, explainability, scalability, reliability, and limited stakeholder participation in the design process persist (Alfredo et al., 2024; Hariyanto et al., 2025; Tan et al., 2025). Consequently, the success of adaptive learning systems depends not only on their ability to provide a high level of personalization but also on their design as ethically sound, transparent, pedagogically grounded structures that maintain human oversight.

Intelligent Agents and Their Use in Educational Environments

Intelligent agents are defined as software components that can perceive their environment, process the information they obtain, make decisions, and act independently when necessary, for specific purposes (Franklin & Graesser, 1997; Wooldridge, 2009). Their autonomy, reactivity, proactivity, and ability to interact with other systems make intelligent agents important for the distributed execution of complex tasks. Intelligent agents used in educational environments combine these general characteristics with pedagogical purposes, taking on different roles such as student support, instructional guidance, and management of the learning process. Recent research examines the functions of pedagogical artificial intelligence agents under different categories such as providing direct instruction, supporting students' cognitive and metacognitive processes, developing motivation and self-efficacy, and facilitating instructional or managerial tasks (Yusuf et al., 2025). Intelligent agents used in educational environments differ according to the functions they undertake. Student modeling agents create dynamic student profiles by analyzing students' knowledge levels, performance patterns, learning preferences, and interactions with the system. Content recommendation agents utilize these profiles to identify learning materials, tasks, and learning pathways appropriate to the student's needs. Assessment agents generate feedback on learning levels by analyzing process and outcome data, while decision-making agents integrate information from different components of the system to make decisions about how to adapt the learning process. This functional specialization allows for the distribution of teaching, learning, assessment, and guidance tasks among interconnected agents rather than a single component. Indeed, in recent multi-agent education applications, architectures are being developed where different roles such as instructor, learner, interaction manager, and evaluator are performed by separate agents (Pei et al., 2025; Shi et al., 2025).

Traditional pedagogical agents mostly operate according to predefined rules, limited data sources, and mechanical interaction patterns. While these systems can perform certain instructional tasks, they may be limited in their ability to generate contextually sensitive explanations, respond instantly to the changing needs of the student, and maintain a natural interaction. Pedagogical agents powered by generative AI, on the other hand, can interact with students

through natural language, generate explanations and examples, provide adaptive feedback, and change the form of support according to the learning context. Experimental studies conducted with generative AI-powered pedagogical agents show that these systems can support students' conceptual understanding and cognitive engagement; however, it is also observed that the effects obtained can vary depending on the agent's representational style, pedagogical design, and the quality of student-agent interaction (Wu et al., 2026). The distinguishing feature of next-generation agents supported by large language models is not only their ability to generate responses, but also their ability to plan towards a specific goal, break down tasks into sub-stages, utilize information resources and tools, consider previous interactions, and collaborate with other agents. These features enable agent systems in education to evolve from a single chat interface to multi-agent structures with different expertise roles. In multi-agent learning environments, agents representing different roles such as teacher, peer, learner, and evaluator can contribute to the student's knowledge construction and self-regulation processes in different ways. A recent application examined the interactions of students with multiple AI agents and determined that knowledge construction and collaborative regulation patterns differed depending on the level of prior knowledge; in particular, students with low prior knowledge were able to gain more learning from multi-agent interactions (Hao et al., 2026). Another advantage of multi-agent architectures is the ability to bring together different expertise within the same system. For example, while one agent analyzes the student's current state, another agent can identify appropriate content, a third agent can perform evaluation, and yet another agent can interact with the student using natural language. Similarly, a study on mathematical task design showed that AI agents with different expertise perspectives collaborated to evaluate and reorganize tasks. However, multi-agent collaboration does not automatically guarantee the accuracy and pedagogical quality of the content produced; it has also been emphasized that human expert evaluation, clear job descriptions, and appropriate control mechanisms are necessary (Schorcht et al., 2025). The use of intelligent agents in educational settings offers significant opportunities in terms of personalized support, instant feedback, automation of instructional tasks, and more detailed monitoring of students' learning processes. However, the educational value of these systems is not determined solely by their technical capabilities. Agents must be compatible with pedagogical purposes, process student data securely, produce verifiable responses, reduce the risk of algorithmic bias and misleading content, and maintain teacher supervision. Moreover, it is argued that overall reasoning success in major language models does not directly translate to higher teaching competence; skills such as adaptive feedback, appropriate questioning, and pedagogical interaction must be evaluated separately for effective teaching (Shi et al., 2025). In conclusion, intelligent agents in education should move beyond single-function and rule-based software components; instruction is evolving towards more flexible structures that can share tasks such as student modeling, content recommendation, assessment, and interaction. While current studies reveal the potential of multi-agent systems to create personalized and interactive learning environments, existing applications often focus on a specific course, task, or agent function. Therefore, developing models that integrate different agent roles within a common architecture through learning analytics and adaptation mechanisms is considered a significant research need.

Generative Artificial Intelligence and Next-Generation Learning Agents

Advances in generative AI technologies and large language models have led to a significant transformation in the functions of AI systems used in educational environments. While traditional AI applications are mostly designed as systems that perform specific tasks or generate responses to user queries, next-generation agents based on large language models have transformed into structures that can plan, execute multi-stage tasks, utilize different tools, take previous interactions into account, and make autonomous decisions in line with defined goals. This transformation has enabled the emergence of generative AI-supported learning agents in the field of educational technologies and has added a new dimension to the development of personalized learning environments (Chu et al., 2025; Kamalov et al., 2025; Yusuf et al., 2025). In the literature, this new approach is frequently discussed within the framework of Agentic AI, LLM Agents, Educational AI Agents, and Pedagogical AI Agents concepts. These systems are more than just chat systems that respond to student questions; they are defined as integrated structures that can analyze learning objectives, plan tasks, utilize different tools, recall previous learning processes, and collaborate with other agents. Recent research shows that large language model-based agents are beginning to be used in a wide range of educational processes such as instructional design, feedback generation, content development, assessment, teacher support, and learning guidance (Chu et al., 2025; Yusuf et al., 2025). The fundamental contribution of generative AI-powered learning agents to education lies in their ability to dynamically adapt the learning process to the individual needs of the student, rather than simply providing information. These agents can interpret student performance, identify learning gaps, generate personalized explanations and feedback, suggest alternative learning paths, and reorganize the teaching process according to the student's progress. With these features, generative AI agents are considered pedagogical components

that support students' cognitive and metacognitive processes, increase learning motivation, and enrich teaching processes (Chu et al., 2025; Yusuf et al., 2025). One of the notable developments in the field of generative AI is the increasing use of multi-agent architectures in educational environments. In these structures, agents with different areas of expertise work collaboratively towards a common learning goal. The collaboration of agents assuming different roles such as instructor, learner, evaluator, and interaction manager allows for a more flexible, scalable, and pedagogically comprehensive management of the learning process. Recent research addressing multi-agent workflows shows that the collaboration of different agent roles can provide significant advantages in assessing instructional quality, managing learning interactions, and offering learning support tailored to students' individual needs (Kamalov et al., 2025; Pei et al., 2025).

However, the effective use of generative AI-powered learning agents in educational settings is not solely dependent on technological advancements. Current research emphasizes that issues such as reliability, explainability, algorithmic bias, data privacy, ethical use, and the preservation of human oversight should be considered as fundamental principles in the design of next-generation learning agents. Furthermore, it is stated that the pedagogical effectiveness of large language model-based agents should be evaluated not only by technical performance but also by their alignment with instructional objectives, the quality of feedback, and their contribution to the student's learning process (Chu et al., 2025; Kamalov et al., 2025; Yusuf et al., 2025). A general review of the existing literature reveals that generative AI-powered learning agents have made significant progress in areas such as student support, content generation, instructional design, assessment, and learning interaction. However, a significant portion of research focuses on specific tasks, single-agent applications, or limited instructional scenarios; and multi-agent adaptive learning architectures integrating learning analytics, student modeling, content recommendation, assessment, decision-making, and generative AI-powered interaction processes are considered a developing research area (Chu et al., 2025; Pei et al., 2025; Yusuf et al., 2025). Accordingly, the proposed model offers a holistic conceptual framework for a generative AI-powered multi-agent adaptive learning system by linking these components through the learning analytics layer.

Method

Research Design

This study is a conceptual model development study conducted within the scope of a qualitative research approach, based on the document analysis method. Based on this review, the current literature on artificial intelligence in education, adaptive learning systems, learning analytics, intelligent agents, and generative AI-supported learning agents was systematically examined; the theoretical findings obtained were synthesized and a multi-agent adaptive learning system model was developed. Document analysis is one of the qualitative data collection methods that enables the systematic examination and interpretation of written sources and the obtaining of meaningful inferences towards the solution of the research problem (Bowen, 2009). In the model development process, the conceptual framework creation approach was used, and the components suggested in the literature were re-related within a holistic structure (Jabareen, 2009).

Literature Review Process

Within the scope of this research, the current literature on artificial intelligence in education, intelligent agents, adaptive learning systems, learning analytics, and generative AI-supported learning agents was reviewed. The literature search primarily utilized the Web of Science, Scopus, ERIC, and ScienceDirect databases, and Google Scholar was used as a supporting resource to access relevant studies when necessary. The keywords used in the searches were artificial intelligence in education, adaptive learning systems, learning analytics, intelligent agents, educational AI agents, multi-agent systems, generative artificial intelligence, large language models, AI agents, and agentic AI, both individually and in various combinations. Priority was given to studies directly related to the research problem, published in peer-reviewed journals, and reflecting current developments. Moreover, classical studies forming the theoretical basis of the field were also included in the review to establish the conceptual framework. The reviewed studies were evaluated in terms of content; adaptive learning systems, learning analytics, intelligent agents, generative AI-powered learning agents, and multi-agent architectures were analyzed thematically. Based on the findings, the basic components of the proposed model were determined, the relationships between the components were defined, and a multi-agent adaptive learning system model was created.

Model Development Process

The model development process was carried out in line with the approach of systematically synthesizing theoretical findings obtained from the literature review and developing a conceptual framework (Jabareen, 2009; Snyder, 2019). In this context, theoretical and current studies on artificial intelligence in education, adaptive learning systems, learning analytics, intelligent agents, and generative AI-assisted learning agents were examined, and the findings were synthesized thematically to determine the basic components of the model and the relationships between these components (Thomas & Harden, 2008). The model development process was carried out in three main stages. In the first stage, the functions of student modeling, content recommendation, assessment, decision-making, learning analytics, and generative AI-supported interaction processes in adaptive learning systems were analyzed in line with the literature. In the second stage, the functional relationships between the determined components, data flow, and task sharing were structured, and the learning analytics layer was positioned at the center of the model. In the final stage, all components were reorganized within an integrated system architecture, and the proposed multi-agent adaptive learning system model was created. The developed model consists of six core components: a Student Modeling Agent, a Content Recommendation Agent, an Assessment Agent, a Decision-Making Agent, a Generative AI-Powered Interaction Agent, and a Learning Analytics Layer that manages the data flow between these agents. The model aims to continuously analyze learning data obtained from students, share it among different agents, and dynamically adapt the learning process to students' individual characteristics and performance based on the results obtained. In this respect, the model synthesizes the approaches found in the literature by integrating adaptive learning, learning analytics, and generative AI-supported agent approaches under a common architecture, and proposes a holistic conceptual model for the design of personalized learning processes (Chu et al., 2025; Holmes, 2024; Yusuf et al., 2025).

Content Validity Study

To evaluate the content validity of the developed multi-agent adaptive learning system model, field experts will be consulted. The content validity study will be conducted with the participation of academics specializing in educational technologies, artificial intelligence, Computer Education and Instructional Technology, learning analytics, and artificial intelligence in education. The selection of experts will be based on criteria such as holding a doctoral degree in a relevant field, having relevant peer-reviewed publications on the subject, and possessing research experience in the field. Experts will be asked to evaluate each component of the developed model in terms of its necessity. For this purpose, the evaluation form prepared in accordance with the content validity approach proposed by Lawshe (1975) will include the options "Necessary," "Useful but not necessary," and "Unnecessary" for each component. In addition, experts will be invited to provide comments and suggestions through open-ended questions to contribute to the improvement of the proposed model. The quantitative data obtained from expert evaluations will be analyzed by calculating the Content Validity Ratio (CVR) for each item, and the resulting values will be interpreted according to the critical values proposed by Lawshe (1975) and Ayre and Scally (2014). The overall content validity of the model will be determined by calculating the Content Validity Index (CVI). Furthermore, the qualitative data collected through the open-ended questions will be analyzed using content analysis, and the proposed model will be revised and finalized based on the experts' feedback.

Data Analysis

The data obtained within the scope of the research will be analyzed in two dimensions: qualitative and quantitative. The findings obtained from the literature review were evaluated in accordance with the thematic synthesis approach and used to determine the basic components of the model and the relationships between these components (Thomas & Harden, 2008). For each item, the Content Validity Ratio (CVR) and the Content Validity Index (CVI), which represents the model as a whole, will be calculated from the quantitative data obtained from expert opinions. The qualitative data obtained through open-ended questions will be analyzed using the content analysis method and evaluated in line with the suggestions for improving the model. Finally, the quantitative and qualitative findings will be evaluated together, necessary adjustments will be made to the proposed model, and the final version of the model will be created.

Proposed Intelligent Agent-Based Adaptive Learning System Model

Model Design and General Architecture

The Intelligent Agent-Based Adaptive Learning System proposed in this study is designed as a multi-agent learning architecture that can dynamically adapt learning processes by considering the individual characteristics of students, generate data-driven decisions, and offer generative AI-supported interaction mechanisms within an integrated structure. In the development of the system, theoretical frameworks presented in the current literature on adaptive learning systems, learning analytics, intelligent agents, and generative AI-supported learning approaches were utilized (Chu et al., 2025; Holmes, 2024; Yusuf et al., 2025). The proposed architecture is based on five fundamental principles. First, the system adopts a personalized learning approach that takes into account the individual differences in students' knowledge level, learning speed, interests, learning preferences, and performance characteristics. Secondly, a continuous adaptation approach has been adopted, ensuring that the system updates itself according to the changing needs of the student by continuously analyzing the data generated throughout the learning process. Thirdly, all recommendations and instructional decisions made within the system are based on the analysis of data obtained from students, thus adopting a data-driven decision-making approach. Fourthly, a multi-agent architecture is created by distributing tasks in the learning process among specialized agents, increasing the flexibility, scalability, and sustainability of the system. Finally, thanks to the Generative AI-Powered Interaction Agent integrated into the system, natural language-based interaction can be established with students, and personalized explanations, guidance, and instant feedback can be provided. The proposed model consists of six main components: Student Modeling Agent, Content Recommendation Agent, Assessment Agent, Decision-Making Agent, Generative AI-Powered Interaction Agent, and a Learning Analytics Layer that manages the data flow between these components. In the system, all agents interact with each other through the Learning Analytics Layer, and the learning data obtained from students is evaluated within a common data processing process. The analysis results are shared with the relevant agents, thus continuously updating the student model, suggesting appropriate learning content, evaluating learning performance, and dynamically generating instructional decisions. The Generative AI-Powered Interaction Agent provides personalized learning support, explanations, and real-time feedback by interacting with the student through natural language-based interaction at every stage of the learning process. The overall architecture of the proposed model and the interaction between its components are presented in Figure 1.

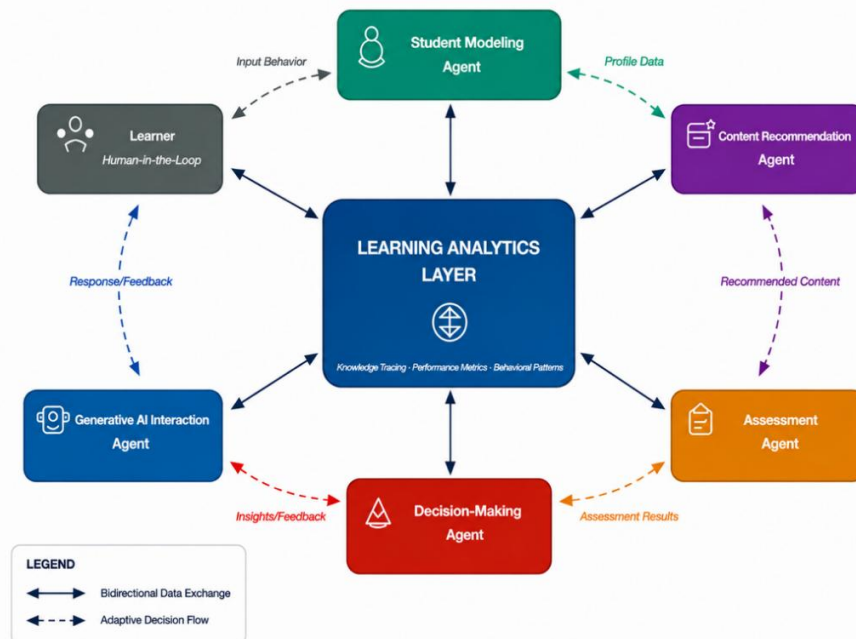


Figure 1. Conceptual architecture of the proposed intelligent agent-based adaptive learning system

Figure 1 shows that the system is structured around the Learning Analytics Layer. All learning data obtained from the student is collected, analyzed, and shared with the relevant agents through this layer. This allows the student's learning

process to be continuously monitored, the student model to be updated in line with new data obtained, and the learning experience to be dynamically adapted. The core components of the system and their roles within the system are summarized in Table 1. While each agent is responsible for a specific function, the continuous data sharing between agents and the coordination of the Learning Analytics Layer enable the system to operate as an integrated structure. This integrated structure allows for the continuous and dynamic adaptation of the learning process, based not only on the student's current performance but also on the interaction data obtained throughout the process.

Table 1. Core components and functions of the proposed intelligent agent-based adaptive learning system

Component	Function	Input	Output	Related Components
Student Modeling Agent	Creates and continuously updates the learner model.	and Student updates interactions, performance data	Updated learner model	Learning Analytics Layer, Content Recommendation Agent, Decision-Making Agent
Content Recommendation Agent	Recommends personalized learning content and activities.	Learner model, analytics results	Personalized learning content	Student Modeling Agent, Decision-Making Agent, Generative AI-Powered Interaction Agent
Assessment Agent	Evaluates learning performance and generates feedback.	Student responses, and performance records	Assessment results and feedback	Learning Analytics Layer, Decision-Making Agent
Decision-Making Agent	Generates adaptive instructional decisions based on integrated learning data.	Learner model, analytics results, assessment results	Adaptive instructional decisions	All system components
Generative AI-Powered Interaction Agent	Provides natural language interaction, personalized guidance, and adaptive feedback.	Student queries, system decisions	Explanations, recommendations, and feedback	Student, Content Recommendation Agent, Decision-Making Agent
Learning Analytics Layer	Collects, analyzes, and coordinates learning data across the system.	Learning data, system logs	Analytics results	All system components

How the Model Works

The proposed intelligent agent-based adaptive learning system is based on constantly analyzing the learning data obtained from students and dynamically adapting the learning process in line with the results of this analysis. All components in the system interact with each other through the Learning Analytics Layer, and the data produced during the learning process is evaluated within a common data processing mechanism. Thanks to this structure, the system offers a personalized and constantly updated learning experience by taking into account not only the student's current performance but also all their interactions in the learning process (Holmes, 2024; Siemens & Long, 2011). The functioning of the system begins when the student enters the learning environment. The student's participation in learning activities, content usage behaviors, evaluation results and other interactions within the system are recorded and transferred to the Learning Analytics Layer. In this layer, data obtained from different sources are integrated, analyzed and transformed into meaningful information that can be used by other agents in the system. In line with the analyzed data, the Student Modeling Agent creates a dynamic student profile regarding the student's knowledge level, learning preferences, learning speed and performance and constantly updates this profile in line with new interactions. The created student model forms the basis for all adaptation decisions to be made in the system (Baker & Inventado, 2014; Brusilovsky, 2001). The Decision-Making Agent integrates information obtained from other agents and the Learning Analytics Layer to determine the most appropriate teaching strategy for the student's current learning situation. Based on these decisions, the Content Recommendation Agent creates a personalized learning experience by identifying learning materials, activities, and learning paths suitable for the student's needs. The suggested content is also dynamically updated depending on changes in the learning process.

The Generative AI-Powered Interaction Agent supports the learning process by communicating with students using natural language. This agent answers students' questions, provides conceptual explanations, offers guidance on the learning process, and provides personalized feedback. In this way, students move from being passive individuals who only use suggested content to actively participating learners who are continuously supported by artificial intelligence (Kasneci et al., 2023; Lo, 2023). The student's learning performance is continuously monitored by the Assessment Agent, and the results are transferred back to the Learning Analytics Layer. This process updates the student model, re-evaluates instructional decisions, and adapts the learning process to the student's current needs. Thanks to this continuous feedback loop, the system can monitor the learning process in real time and constantly update itself in parallel with the student's development. This process integrates data collection, data analysis, student model updating, instructional decision-making, personalized content recommendations, generative AI-supported interaction, and performance evaluation. This integrated approach ensures that the learning environment is continuously adapted to the student's individual characteristics, offering a more flexible, data-driven, and interaction-oriented learning experience.

Discussion, Conclusion and Recommendations

The intelligent agent-based adaptive learning system model proposed in this study offers a holistic approach to adaptive learning systems by bringing together personalized learning, learning analytics, multi-agent systems, and generative artificial intelligence technologies within an integrated architecture. While existing research mostly treats student modeling, content recommendation, learning analytics, or generative artificial intelligence applications as independent components, the proposed model integrates the data flow and interaction between these components within a single system architecture. In this respect, the proposed model aims to continuously adapt the learning process not only according to the student's current performance but also in line with the multidimensional data generated throughout the learning process. One of the prominent features of the proposed model is that it places the Learning Analytics Layer at the center of the system, ensuring data sharing and coordination among all agents. Thus, interaction data obtained from the student can be used not only in performance evaluation but also in updating the student model, creating personalized content recommendations, and making instructional decisions. Moreover, the integrated inclusion of a Generative AI-Powered Interaction Agent into the model enables natural language-based interaction with students, provides personalized feedback, and continuously supports the learning process. This approach positions generative AI not merely as a content-generating tool, but as an active system component that guides and supports the learning process.

The model proposed in this research has been developed as a theoretical framework. Therefore, the effectiveness of the model has not been tested in real learning environments, and it does not present application-oriented results. Furthermore, details regarding the technical implementation of the model, the AI algorithms to be used, system performance, and software architecture are outside the scope of this study. However, this allows the proposed structure to be developed using different technological infrastructures and adapted to different learning environments. As a next step, the proposed model will be evaluated through expert review to examine its content validity, and the model will be revised in line with the findings obtained. In future research, it is recommended that the proposed model be applied in different educational levels and disciplines, and its effects on learning success, student participation, and user experience be examined through experimental studies.

Furthermore, in line with developments in large language models and next-generation AI agents, integrating the model with different AI services and evaluating it in terms of dimensions such as ethical use, data privacy, explainable AI, and system reliability will provide significant contributions. In conclusion, the proposed intelligent agent-based adaptive learning system model offers a contemporary approach that integrates student modeling, content recommendation, assessment, decision-making, learning analytics, and generative AI-supported interaction processes within a single architecture. It is considered that the model will provide a theoretical framework for the development of AI-supported adaptive learning systems and will form a guiding basis for future applied research.

Scientific Ethics Declaration

* The author declares that the scientific ethical and legal responsibility of this article published in EPSS journal belongs to the author.

* This study was conducted based on a literature review and did not involve data collection from human participants; therefore, ethics committee approval was not required.

Conflict of Interest

* The author declares that there is no conflict of interest regarding this study.

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