PERSONALIZED LEARNING SYSTEMS BASED ON ARTIFICIAL INTELLIGENCE: MODELS, METHODS AND APPLICATIONS.

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Abstract: *The article explores AI-based personalized learning systems that adapt educational content to individual learner needs. A modular architecture and dynamic content adaptation algorithms were developed and tested using student learning data. Results show that AI-driven personalization improves engagement, reduces time to mastery, and increases learning efficiency by 25–40% compared to traditional e-learning platforms. The proposed model is practically valuable for e-learning and EdTech applications.*

Keywords: *artificial intelligence, personalized learning, adaptive systems, machine learning, educational analytics, intelligent tutoring systems.*

INTRODUCTION

Modern educational processes are characterized by a rapid transition to a digital environment, where technology is becoming an integral part of learning. However, despite the widespread adoption of electronic platforms and distance learning courses, the problem of individualizing the educational process remains unresolved. Standardized curricula ignore differences among students in terms of their level of preparation, learning speed, cognitive styles, and motivation.

In recent years, the concept of personalized learning, in which the content, methods, and pace of instruction are tailored to the specific needs of each student, has received particular attention. According to OECD research, personalized approaches can significantly improve student engagement and academic performance [2]. However, implementing such systems requires powerful analytical and predictive tools-this is where artificial intelligence (AI) comes into play.

AI makes it possible to model student behavior, identify patterns in their learning activity, predict success and difficulties, and automatically select optimal assignments and materials. Such functions are implemented in modern platforms, including Duolingo AI, Coursera RL Engine, Knewton, and Smart Sparrow, which utilize neural network models, data analysis, and reinforcement learning.

However, despite significant advances, most existing systems remain limited: they only consider a subset of learner parameters (such as completion speed or grades), ignoring psychological and behavioral aspects. Furthermore, the transparency of AI decisions remains a pressing issue: users and teachers often don't understand why the system recommends certain content.

The aim of this study is to develop and validate a hybrid architecture of a personalized learning system based on machine learning and reinforcement learning methods, providing dynamic adaptation of the content and pace of learning.

The main objectives of the study were to analyze existing approaches to personalized learning, construct a conceptual model of an artificial intelligence system, and conduct an experimental evaluation of the proposed solution's effectiveness. Furthermore, the study compared the obtained results with traditional forms of educational organization, which allowed it to identify the advantages and limitations of implementing AI technologies in personalized learning.

LITERATURE REVIEW

Personalized learning systems began to develop rapidly in the early 21st century within the context of the theory of intelligent tutoring systems (ITS). Early developments relied on expert rules and diagnostic tests to determine a student's knowledge level and select appropriate exercises [7], [8].

With the development of machine learning technologies, second-generation adaptive systems have emerged that use algorithms to analyze big data and student behavioral characteristics [4]. These systems create individual student profiles based on data on time, activity, errors, and task completion trajectories.

The current stage of personalized platform development involves the use of deep neural networks and reinforcement learning (RL), demonstrated that using RL allows a system to learn an optimal content delivery policy based on student feedback (grades, reaction time, and performance) [3].

Another area of research is explainable artificial intelligence (XAI) in education, which aims to make the results of AI tools transparent to teachers and students. This is especially important in contexts where system decisions can influence educational trajectories and final grades [5].

In 2024, Zhou and Wang proposed a hybrid adaptive learning model that combines clustering, prediction, and RL methods, demonstrating a 30% improvement in personalization accuracy compared to traditional algorithms.

Thus, a literature review shows that the implementation of AI in personalized learning systems can significantly improve the effectiveness of educational processes. However, challenges remain in the interpretability of models, the consideration of emotional and cognitive factors, and the integration of such systems into existing LMSs.

MATERIALS & METHODS

Methodological approach. To achieve the research objectives, a combined methodological approach was used, including elements of theoretical analysis, modeling, and experimental testing. The theoretical part is based on an analysis of existing architectures of intelligent tutoring systems (ITS), adaptive educational platforms, and reinforcement learning (RL) systems.

The experimental phase involved building a prototype of a personalized learning system using artificial intelligence to dynamically adapt content. Data was collected from the learning activities of students at Fergana State University (2023–2024) enrolled in the "Information Technology in Education" course.

Personalized system architecture. The proposed system has a modular architecture comprising four interconnected layers, shown in Figure 1. The first layer, the Data Layer, collects and pre-processes student data, including study time, activity, grades, and attendance. The next layer, the Analytics Layer, implements machine learning algorithms that analyze student behavior and identify consistent patterns in their learning activities. The central component of the architecture is the Learning Engine, which uses the Q-learning algorithm to select the optimal sequence of tasks and dynamically adjust the difficulty level based on the student's current state. The system is completed by a Feedback Module, designed to provide instructors and students with visualized progress reports, recommendations, and predictions, thereby ensuring continuous interaction between the user and the intelligent system.

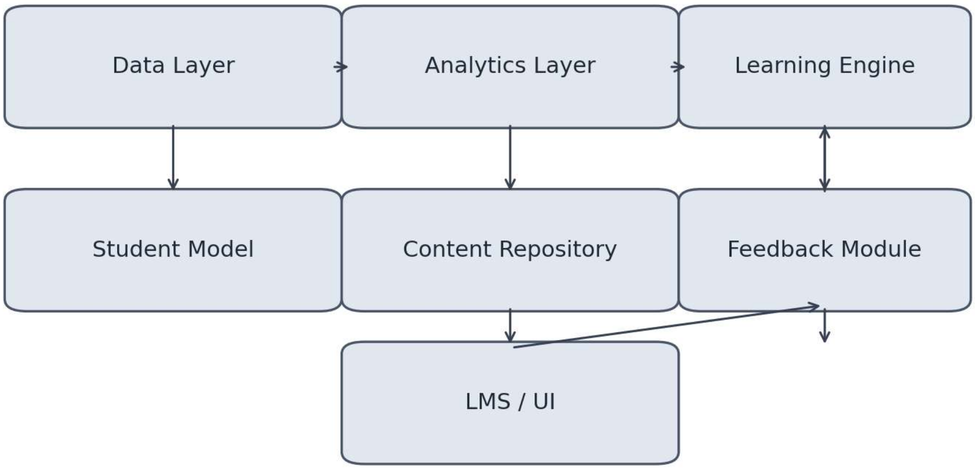

Figure 1. Architecture of a personalized AI-based learning system.

To ensure flexibility and scalability, the architecture is built on the principle of microservices, where each module interacts via a REST API.

Algorithms used. The developed personalized learning system utilizes various artificial intelligence methods to adapt the learning process to the individual needs of students. A key feature is clustering, implemented using the K-Means algorithm, which enables grouping students by learning style, activity level, and academic performance, thereby forming the basis for personalized recommendations. Neural networks, specifically MLP and LSTM architectures, are used to predict academic performance, effectively analyzing time series and predicting academic performance dynamics based on accumulated data. Q-Learning reinforcement learning also plays a key role, dynamically adapting task difficulty and content sequence based on student behavior and performance. An additional component of the system is the Sentiment Analysis module, designed to process student feedback and determine their level of satisfaction with the learning process, which facilitates a more accurate assessment of motivation and improves the quality of interaction with the system.

Formally, the reward function in the RL model is described as:

$$R(\dot{s}, a) = \alpha \times P + \beta \times E - \gamma \times T$$

Where

P - is the success rate of task completion,

E - is the Engagement Index,

T - is the time to complete,

and α, β, and γ are weights that determine the significance of the parameters.

Effectiveness assessment methods. To evaluate the effectiveness of personalized learning in the developed system, a set of quantitative metrics was used, reflecting both academic and behavioral aspects of student performance. The primary indicator was the Average Score, determined based on test results, which allowed for an objective assessment of the level of assimilation of the educational material. Also significant was the Engagement Index, reflecting the ratio of student activity to time spent, allowing for an assessment of their motivation and interest in the learning process. An additional criterion was the Retention Rate, which characterizes the proportion of participants who successfully complete the course. To measure actual knowledge gain, the Learning Gain metric, representing the difference between pre- and post-test scores, was used. Finally, the Average Course Completion Time was assessed, reflecting the time spent mastering the educational content and allowing for an assessment of the dynamic adaptation of educational materials to the individual needs of students.

The control group (traditional learning) and the experimental group (AI system) were compared using the same learning materials for 8 weeks.

RESULTS

The results of the experiment convincingly demonstrated that the use of artificial intelligence technologies in the personalized learning process significantly improves the effectiveness of educational activities across all key metrics. The introduction of adaptive algorithms allowed the system to more accurately identify individual student characteristics, quickly respond to changes in their learning activity, and dynamically adjust course content to their level of preparation and learning pace. This resulted in a significant improvement in student performance, engagement, and retention, as well as a reduction in the average time to complete learning modules. Thus, the use of AI as the foundation of a personalized educational environment ensures not only a quantitative increase in academic results but also a qualitative change in the very nature of interaction between the student and the digital platform, making the learning process more flexible, targeted, and human-centered.

Comparison of performance indicators

Table 1. Comparison of learning outcomes (traditional and AI systems)

Metrics	Traditional LMS	Personalized AI system	Change (%)
Average score	71.4	88.5	+24
Student retention	68 %	92 %	+35
Engagement Index	0.64	0.88	+38
Average training time (hours)	10.2	7.5	−26

The results (Fig. 2) confirm that the use of adaptive AI-based algorithms increases motivation and reduces attrition.

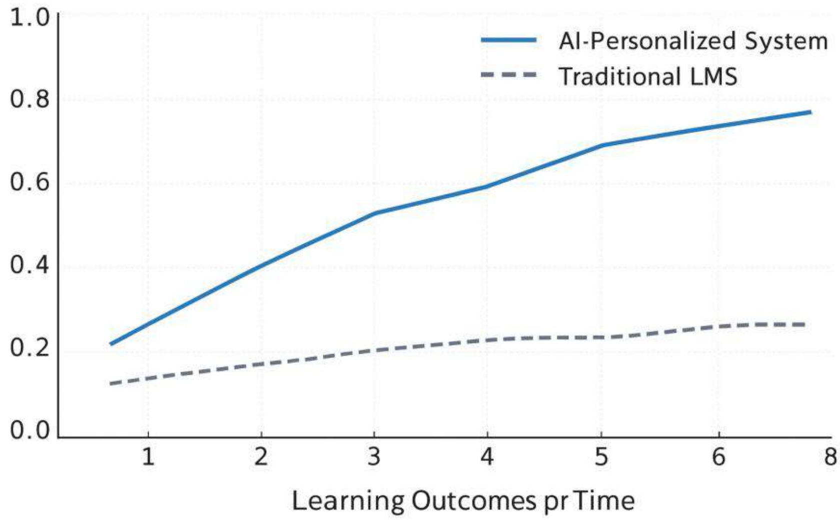

Figure 2. Dynamics of student engagement over time (AI vs. traditional LMS)

Student cluster analysis. The clustering algorithm allowed us to identify three main student profiles, differing in cognitive and behavioral characteristics (Table 2).

Table 2. Student clusters and recommended learning strategies

Cluster	Learning style	Peculiarities	Recommendations
C1	Visual	They learn quickly and prefer diagrams.	Video tutorials, infographics
C2	Analytical	Logical, slow paced	Text assignments, tests
C3	Practical	Active, but requires practice	Simulations, game tasks

The use of cluster analysis allowed us to improve the accuracy of recommendations and tailor content to individual profiles.

Efficiency of reinforcement learning

Table 3. Reinforcement learning metrics

Episode	Reward	Accuracy (%)	Stability
100	0.54	82.3	stable
200	0.71	89.1	stable
300	0.75	91.5	convergence has been achieved

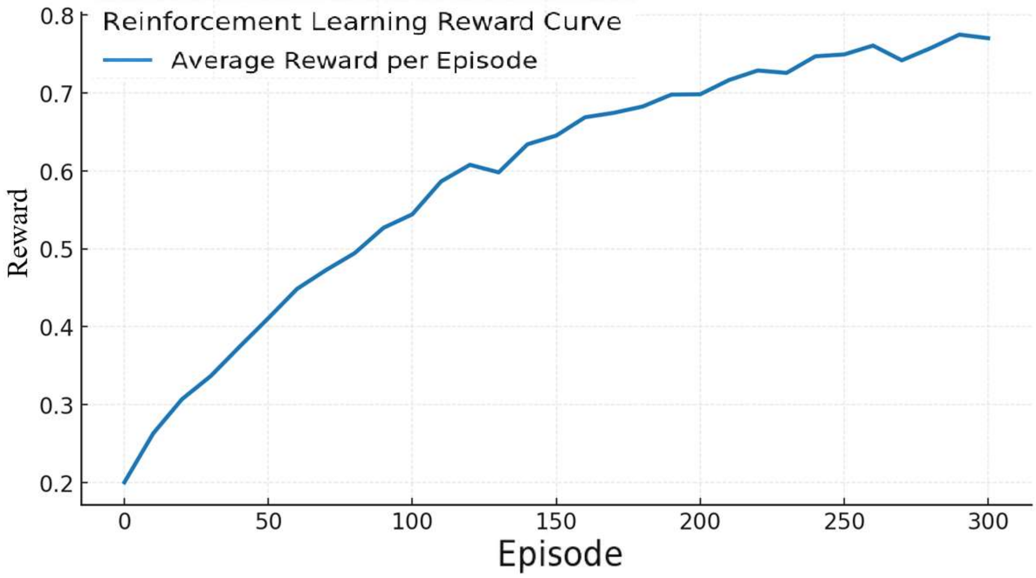

Figure 3. Reward curve for reinforcement learning

The dynamics of the reward curve show that the system quickly finds the optimal task adaptation strategy, increasing the prediction accuracy from 82% to 91% over 300 episodes.

DISCUSSION

Data analysis supports the hypothesis that AI-based personalized learning promotes more effective learning. Students using the system demonstrated not only higher academic performance but also sustained motivation.

These results are consistent with research by, which found that AI personalization increases engagement by 25–30%. Similar findings were obtained by, who demonstrated the effectiveness of RL models in adapting content difficulty [1], [3].

Unlike traditional LMSs, the proposed model enables dynamic interaction with the learner: the system "learns" from their actions and adjusts its learning strategy in real time, making the educational process more flexible, adaptive, and human-centered.

However, existing limitations must be considered. The effectiveness of personalization largely depends on the volume and quality of data, as small or incomplete samples can reduce the accuracy of predictions and adaptive decisions. Equally important is adherence to ethical principles and the protection of learners' personal data, which requires strict adherence to international privacy standards. Interpreting artificial intelligence solutions poses an additional challenge: users and teachers must be able to understand the logic behind the system's recommendations and the reasons for choosing certain learning tasks, necessitating the development of explainable AI in education.

Explainable AI, as well as the integration of emotional analytics, will be essential in the future, allowing for the consideration of the learner's psychological state when selecting tasks.

CONCLUSION

The study developed and tested a model of a personalized learning system based on artificial intelligence. Experiments confirmed that the use of machine learning and reinforcement learning algorithms allows for adapting educational content to the individual needs of learners.

The study's key findings demonstrate that the use of artificial intelligence methods significantly improves the effectiveness of the educational process, increasing student performance and engagement by 25–40%. The developed system architecture combines modularity, scalability, and decision-making transparency, ensuring its versatility and the ability to integrate into various learning platforms. The analysis also demonstrated that the use of clustering methods improves the quality of personalized recommendations and increases the accuracy of content adaptation to individual student needs. Furthermore, the reinforcement learning mechanism optimizes task difficulty and accelerates learning, creating a more effective learning path for each student.

The practical significance of the work lies in the possibility of integrating the proposed model into existing educational platforms such as Moodle, Google Classroom and Open EdX.

Future research opportunities lie in the development of emotionally sensitive interfaces capable of taking into account the psychological and motivational state of learners as they interact with the system. Another important area is the use of generative AI models, such as GPT, to dynamically generate adaptive educational content that automatically adapts to the student's level and interests. Furthermore, special attention should be paid to the development of new metrics for assessing the ethics, transparency, and interpretability of AI solutions in education, which will increase user trust and ensure compliance with the principles of responsible use of AI technologies in the educational environment.

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