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A Review of Adaptive Learning Pathways Using Artificial Intelligence

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Abstract— *This article analyzes adaptive learning methods employing artificial intelligence, aimed at personalizing the educational process. The study aims to examine approaches that facilitate the creation of individualized learning pathways. The paper discusses the elements of adaptive learning, including the customization of educational materials to meet learner needs, the prediction of academic outcomes, and the automatic adjustment of learning strategies. The methodology encompasses an examination of machine learning algorithms, neural networks, knowledge graph models, and recommendation systems. Special attention is given to data processing using predictive modeling and reinforcement learning methods. The results demonstrate that AI-driven platforms enhance engagement, reduce knowledge gaps, and ensure mastery of material. Additionally, challenges such as data privacy, algorithm interpretability, and difficulties in scaling solutions for large educational systems are explored. The practical significance of the study lies in the potential application of its findings for the development of software for educational institutions, pedagogical practice, and professionals in the field of digital technologies. The information provided in this article will be valuable to staff and specialists involved in designing intelligent learning support systems and in the broader context of the digital transformation of educational institutions.*

Keywords— *Adaptive learning, artificial intelligence, machine learning, education personalization, knowledge graph models, neural networks, reinforcement learning algorithms, educational platforms, interactive environments, e-learning.*

I. INTRODUCTION

Modern educational processes are transforming the influence of digital technologies and artificial intelligence. Traditional methodologies based on fixed and linear programs are being replaced by systems capable of adapting to the individual characteristics of learners. The growing diversity of educational needs and differences in information perception styles necessitate the use of methods aimed at personalization, which enhances the effectiveness of the learning process.

Adaptive learning systems, powered by artificial intelligence algorithms, provide tools to address this challenge. These systems analyze student behavior, assess the level of material comprehension, and adjust the content and difficulty of educational materials based on the learner's progress. At the core of such platforms lie analytical tools, including neural networks, knowledge graph models, and reinforcement learning algorithms, enabling the construction of optimal learning trajectories in real time.

The use of these technologies increases student engagement, improves motivation, and helps eliminate knowledge gaps. However, the implementation of adaptive platforms comes with challenges. Among these is the need to improve algorithm transparency, ensure user data privacy, and address scalability issues for educational institutions.

Additionally, there is a need to analyze the impact of these systems on the cognitive development of learners. It is essential to consider not only cognitive aspects but also the influence of emotional and motivational factors, which significantly affect learning effectiveness.

The goal of this study is to examine approaches that enable the creation of individualized learning pathways.

II. MATERIALS AND METHODS

In the study by Deng W., Wang L., and Deng X. [4], algorithms for the dynamic adaptation of educational materials are proposed. These methods enable real-time adjustments to content based on changes in the learning process. The implementation of such algorithms improves academic performance and increases student engagement through personalized approaches.

The work by Pardosi V. B. A. et al. [9] builds upon these ideas, describing an AI-based learning management system. The system automatically adjusts content depending on test results and student preferences, allowing for modifications to educational trajectories during the learning process.

Thuan T., De N., and Toai N. [6] examine the factors that determine the success of integrating personalized educational platforms. Their research analyzes the architecture of such systems, methods for implementing AI, and the needs of educational institutions in the context of digital transformation. Attention is also paid to creating intuitive interfaces that ensure usability and flexibility.

Some studies focus on applying AI to develop adaptive educational platforms, enhancing learning processes. For instance, AL-Fayyadh H. R. D., Ganim Ali S. A., and Abood D. B. [5] describe the use of neural networks in the development of adaptive educational systems. Neural networks process large volumes of data, identify patterns, and predict potential learning difficulties, making them valuable tools for creating intelligent educational systems.

Lin L. and Wang F. [12] propose the use of knowledge graphs to design personalized learning pathways. Knowledge graphs illustrate the relationships between topics and concepts, enabling the system to recommend the next steps based on previously mastered material. This approach is particularly

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effective in subjects with complex structures, such as mathematics and programming.

Perera M. [7] explores the integration of various technologies into adaptive educational systems, including neural networks, fuzzy logic, and genetic algorithms. Combining these methods enhances prediction accuracy and improves system flexibility in processing student data.

The study by Gligorea I. et al. [1] demonstrates how AI and machine learning improve the personalization of the learning process in e-learning. The adaptive tools employed analyze student behavior and suggest individualized learning modules based on their preferences and learning pace.

Akavova A., Temirkhanova Z., and Lorsanova Z. [2] emphasize the necessity of analyzing student data to create personalized learning pathways. Their article describes methods for collecting data on test results, task completion times, and student preferences, which form the basis for developing individualized learning strategies.

Pradeep K. R. et al. [8] explore the development of platforms for interactive learning, focusing on two-way interaction between the system and students. These platforms leverage AI to provide real-time feedback and create simulations of educational processes, enhancing student engagement.

Bayly-Castaneda K., Ramirez-Montoya M. S., Morita-Alexander A. [11] examine personalization methods for lifelong learning. Their work highlights the role of adaptive platforms in professional development, where continuous knowledge updates are essential.

Chetyrbok P. V., Shostak M. A., and Alimova L. U. [3] investigate the application of AI in distance learning, emphasizing the potential for growth in this field. The article focuses on challenges such as maintaining student motivation and creating effective communication tools for online environments.

Thimmanna A. et al. [10] analyze the challenges faced by developers of adaptive educational platforms. These include difficulties in data collection, ensuring privacy, and improving the transparency of decision-making algorithms. Nonetheless, the advantages of such systems are noted, including their ability to address individual learning needs and increase student engagement.

Source [13], the information contained in which is from The Business Research Company website has been used to review statistics on the development of the AI market in learning.

Abioye S. O. et al. [14] analyze the current state of technologies in the construction industry, highlighting their role in improving design processes and managing construction projects. Khan M. et al. [17] examine the implementation of intelligent systems in anaerobic co-digestion, demonstrating the use of algorithms to enhance the efficiency of biological resource processing. Del Ser J. et al. [20] describe bio-inspired computational approaches in transportation infrastructure, showcasing the potential of artificial intelligence in regulating traffic flows.

Han S. and Sun X. [15] study the application of genetic algorithms for optimizing product design processes. These methods are also applied in educational platforms to create individualized learning trajectories based on students' performance and preferences. Huang M. H. and Rust R. T. [16] propose a model of human-AI interaction in marketing, which is utilized in educational systems to generate personalized recommendations.

Naseer I. [18] analyzes the use of deep neural networks for enhancing cybersecurity, emphasizing the emerging challenges and opportunities in this field. Xu Y. et al. [19] describe the application of intelligent technologies as a tool for scientific research, demonstrating their role in accelerating knowledge discovery and processing large volumes of data.

A review of current research on adaptive learning using AI demonstrates a wide range of technologies, including neural networks, knowledge graphs, machine learning, and fuzzy logic. Key areas of focus include the creation of personalized learning pathways, optimization of educational materials, and the development of interactive platforms.

However, unresolved issues remain. First, there is no unified methodology for evaluating the effectiveness of adaptive systems, complicating comparative analysis. Second, many studies focus solely on technical aspects, neglecting pedagogical issues such as the impact of technology on student motivation and cognitive development. These areas require detailed analysis to design reliable adaptive platforms capable of addressing personalization challenges in various educational contexts.

The methodology of this study includes an analysis of machine learning algorithms, neural networks, knowledge graphs, and recommendation systems.

III. Results and Discussion

The size of the AI market in education has grown exponentially in recent years. It is projected to increase from $5.47 billion in 2024 to $7.57 billion in 2025, with a compound annual growth rate (CAGR) of 38.4%. Growth during the historical period can be attributed to digital learning platforms, personalized learning initiatives, adaptive learning systems, big data and analytics, and early AI-based learning systems.

The AI market is expected to continue its exponential growth in the coming years, reaching $30.28 billion by 2029, with a CAGR of 41.4%. Growth during the forecast period can be explained by the expansion of remote and hybrid learning, as well as AI-driven assessment tools (Fig.1).

The data presented above were analyzed to justify the necessity of adopting an adaptive approach in the educational process. The following sections will explore aspects of such systems that enable personalized and targeted learning.

The adaptive approach involves revising educational trajectories based on data collected during the learning process. This data allows the system to adjust the direction of learning according to the achievements or difficulties faced by the student [8,11]. Key aspects of such systems include:

- Diagnostic Profiling: At the initial stage, the system analyzes the student’s knowledge level, identifying individual characteristics to tailor subsequent interactions.
- Modular Flexibility: Educational materials are divided into blocks that adapt to the student’s progress and the complexity of the material.

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- Predictive Adjustment: Prediction algorithms are used to identify potential problems and suggest corrective tasks, thereby minimizing difficulties during the learning process.

Individualized learning, in turn, is based on the creation of student profiles, which include not only the speed of knowledge acquisition but also attention dynamics, preferred perception modes, and overall performance. An important role is also played by implicit characteristics such as emotional state and cognitive load, which are tracked using biometric sensors. This data enables the system to adjust task difficulty and modify instructional methods.

Adaptive educational systems rely on prediction algorithms and active learning methods [4,6,9]. Figure 2 below illustrates the methods used in these algorithms.

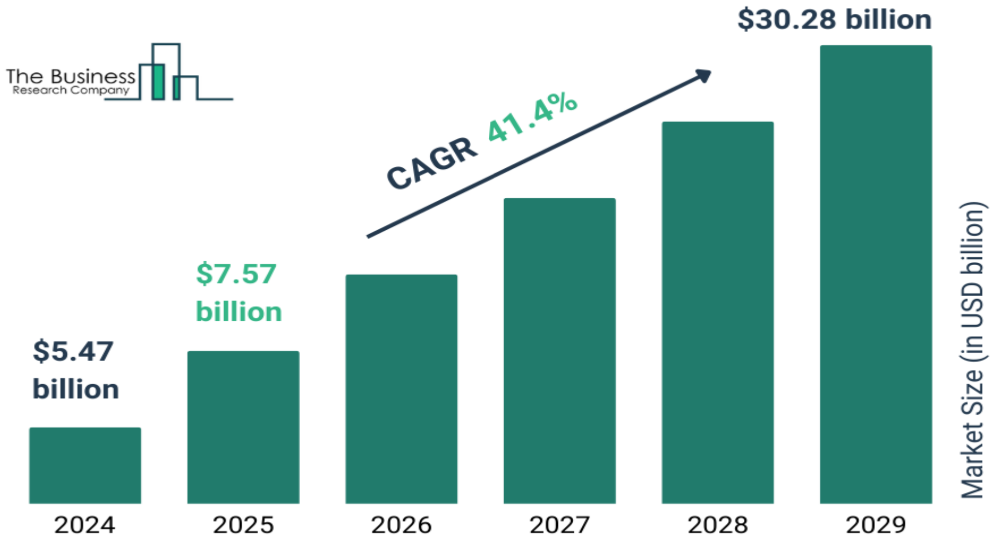

Fig. 1. The size of the AI market in education [13].

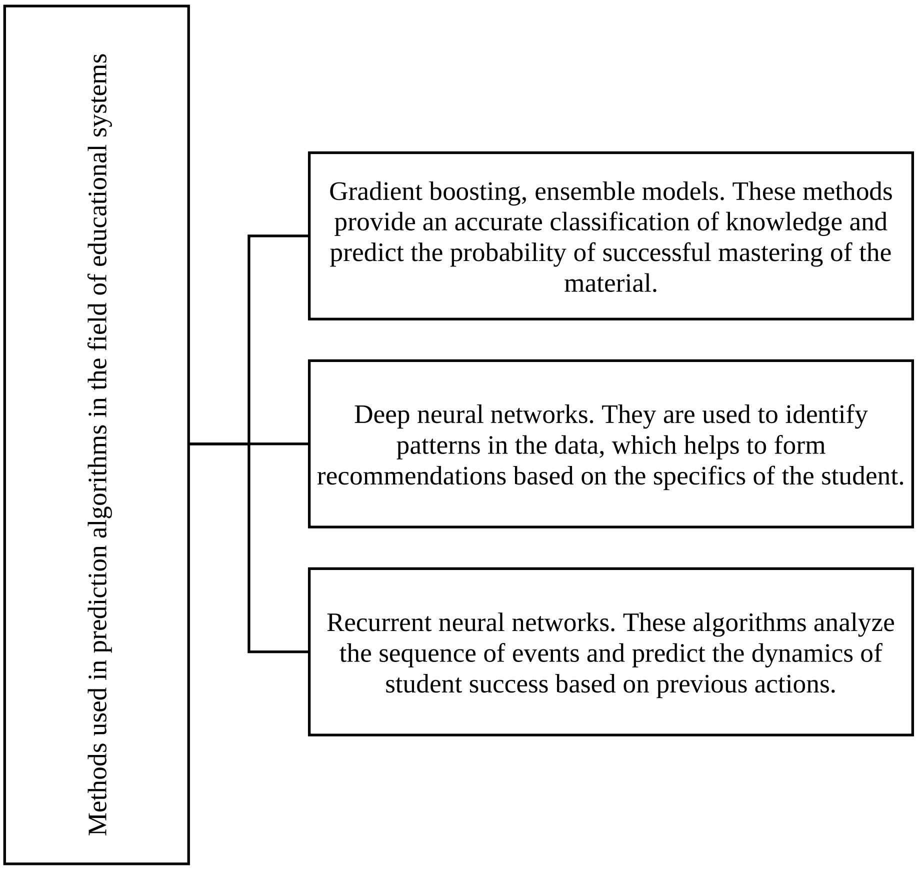

Fig. 2. Methods used in prediction algorithms in the field of educational systems [4,6,9]

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In turn, platforms employ several methods of content personalization, including:

- Collaborative filtering, where the system analyzes the pathways of other users with similar trajectories to recommend suitable materials;
- Content personalization is characterized by algorithms evaluating the relevance of materials and their alignment with current learning stages and the cognitive characteristics of the student.

The integration of adaptive technologies into online education, such as on platforms like Moodle and Smart Sparrow, demonstrates their effectiveness in managing educational processes under scalable conditions. Key features include:

- Individually tailored assignments: The complexity of materials adjusts according to test results, maintaining an optimal workload;
- Behavior analysis: The platform tracks task completion times and error types to identify potential challenges;
- Feedback generation: The system provides recommendations for material improvement based on task performance.

Adaptive educational systems are developed using a modular approach and a multilayered structure, making them flexible, scalable, and resilient to failures. Each layer performs a specific function, interacting with other components of the system to ensure efficiency [7, 5, 12]. The architecture layers are described below in Figure 3.

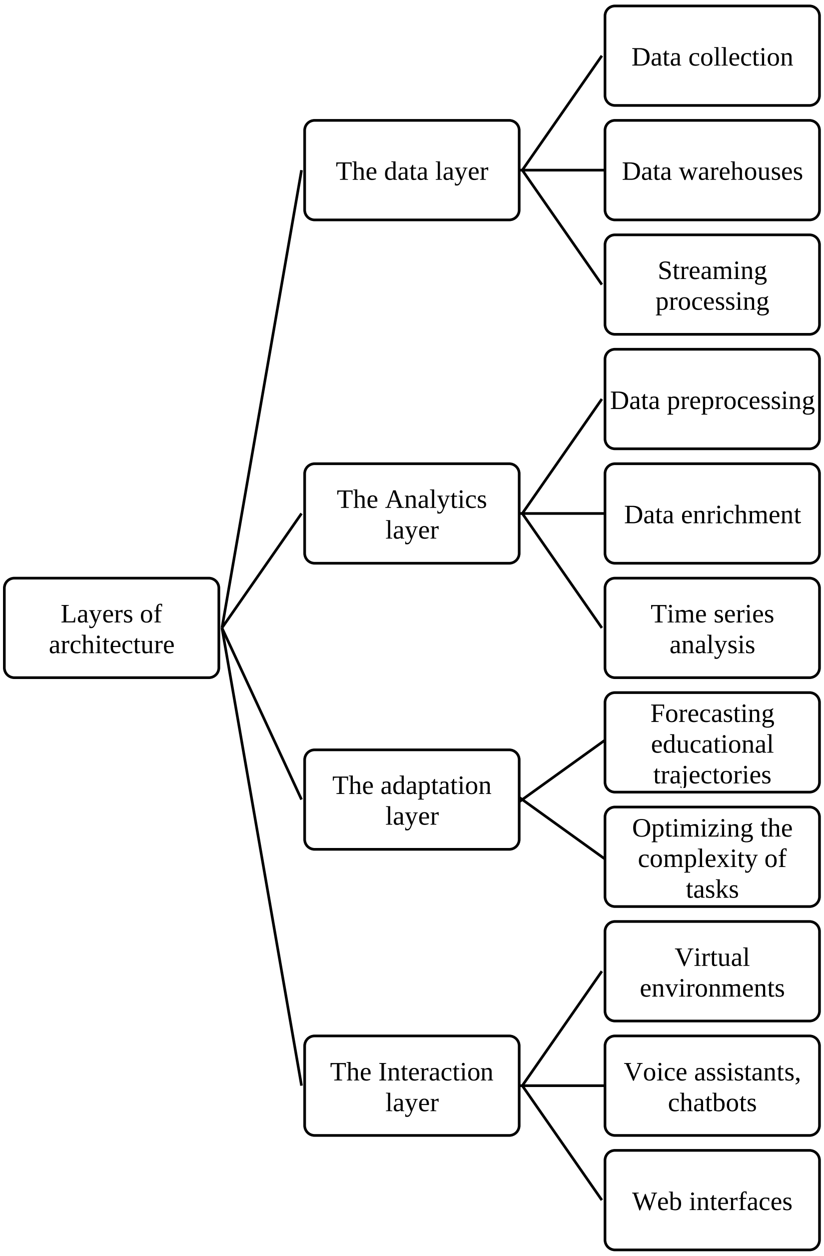

Fig. 3. Layers of architecture [7,5,12]

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To predict student success and assess progress, a variety of approaches are utilized, including:

- Regression models and ensembles are used to predict the likelihood of mastering material. Techniques like Random Forests and Gradient Boosting ensure accuracy in processing diverse datasets.
- Deep Neural Networks (DNNs), enable the analysis of multidimensional data to uncover hidden patterns.
- Reinforcement learning, incorporating methods like Q-Learning, Deep Q-Network, and Proximal Policy Optimization. These techniques allow for real-time adjustment of learning scenarios based on results from previous tasks [3,10].

In analyzing educational materials, text processing tools such as BERT and GPT enable the automation of essay evaluation and the generation of tailored assignments. Sequence-to-sequence models help translate texts and create complexity-specific explanations. Vector representation methods like Word2Vec, FastText, and GloVe are applied to detect similarities between terms, facilitating contextual understanding. Additionally, graph knowledge models based on ontologies like OWL and RDF improve learning by linking disciplines and concepts.

Virtual simulators designed with engines like Unity and Unreal Engine facilitate immersive learning experiences and simulate real-life scenarios. These simulators, when integrated with neurointerfaces, track cognitive activity, offering a precise representation of student progress. Augmented and virtual reality technologies further enhance applied learning, especially in fields like engineering and medicine, by providing adaptive and error-tolerant environments.

The concept of lifelong learning encourages the design of systems adaptable to dynamic professional demands, continuously updating users' knowledge in real time [1,2,8]. Below, Table 1 presents the summarized benefits and challenges of adaptive AI-based learning methods.

TABLE 1. Advantages, Disadvantages, and development trends and their impact on Adaptive Learning Paths Using Artificial Intelligence [1,2,8].

Advantages	Disadvantages	Development Trends	Impact
Adaptive systems can tailor learning paths to individual student characteristics, enabling effective material mastery.	Learning quality depends on the accuracy and completeness of data, leading to errors when data is insufficient or inaccurate.	Development of systems offering personalized learning methods.	Increased motivation for the educational process, effective time management, and a conscious approach to self-education.
AI can analyze student errors and provide feedback, accelerating the learning process.	AI often fails to account for the emotional and social aspects necessary for holistic learning.	Development of virtual mentors and chatbots to assist in the learning process.	Reduced workload for teachers, increased accessibility of education.
Systems optimize the learning process by focusing on student weaknesses, reducing time spent on already mastered topics.	Not all students have access to the required devices or internet to fully utilize adaptive systems.	Emotion recognition through cameras and sensors to adjust the pace and format of material delivery.	Increased learning comfort, reduced stress, improved concentration.
Adaptive systems can accommodate various learning styles (visual, auditory, etc.), improving outcomes for individual students.	AI may inadvertently reinforce stereotypes, overlooking unique student characteristics.	Integration of gamification elements considering individual student traits.	Increased engagement and interest in learning.
Progress tracking allows timely adjustments to the educational process.	Some students may feel discomfort learning with AI instead of a teacher, which can hinder knowledge acquisition.	Combination of traditional and digital learning with course adaptation.	Improved education quality, the possibility of learning in any format.
AI integrates diverse information sources and multimedia materials, enriching topic comprehension.	Developing, implementing, and maintaining such systems require significant financial and time investments.	Analysis of the learning process to identify effective teaching methods.	Optimization of teaching methods.

Adaptive educational platforms offer significant opportunities for personalized learning by tailoring teaching approaches to individual student needs. Additionally, it is essential to incorporate mechanisms for intervention in the adaptation process to account for individual characteristics that algorithms may not recognize.

One of the key components of the proposed Adaptive Learning Path Optimization Algorithm (hereinafter referred to as ALPOA) is the creation of learner profiles through systematic data collection and analysis. This approach considers not only static indicators but also evolving parameters such as engagement levels, content-type preferences, and individual learning speeds. As a result, the system can adjust the learning process in real time, as confirmed by several studies on AI applications in education [15, 17, 18].

At the initial stage of the ALPOA algorithm, multidimensional data are collected in the following areas:

1. Learner Performance: This parameter is characterized by test scores, assessment results, and module completion dynamics. To evaluate performance, the Performance Score (PS) metric is introduced, calculated using the following formula:
$$PS = \frac{Number\ of\ correct\ answers}{Total\ number\ of\ questions} \times 100$$
This metric provides a quantitative assessment of a learner's knowledge level [15].
2. Engagement in the Learning Process: Engagement is determined by analyzing the time spent on assignments, frequency of interaction with educational content, and participation in interactive platform elements. The Engagement Score (ES) metric is calculated as follows:
$$ES = \frac{T_{active}}{T_{total}} \times 100$$

where:

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T_{active} — time actively spent on learning tasks;
T_{total} — total allocated learning time.
This approach to engagement measurement is justified by research [15] and supported by practical data presented in recent studies on adaptive educational systems [14].

To evaluate the effectiveness of the proposed hybrid algorithm for optimizing adaptive learning paths, a platform integrating dynamic learner profile analysis, a genetic algorithm, and a particle swarm optimization algorithm was used. Experiments were conducted on a sample of 1,500 learners covering various subject areas, including mathematics, programming, and language learning, demonstrating the universality of the approach across different educational contexts [15, 16].

During ALPOA implementation, attention was given to the following key aspects: At the first stage, the algorithm generates a diverse set of potential learning paths through initialization, selection, crossover, and mutation operations. The particle swarm optimization algorithm then fine-tunes these solutions by incorporating collective and individual learning experiences, ensuring rapid convergence to a global optimum [15, 17].

Subsequently, the system continuously collects data on performance (Performance Score, PS), engagement (Engagement Score, ES), and content preferences. These indicators are updated in real time, allowing the learning trajectories to adapt dynamically based on changes in learner behavior [18, 19].

To evaluate the effectiveness of ALPOA, the following indicators were identified:

- Learning Efficiency: Measured by the reduction in the average time required to complete modules. The experiment showed a 25% reduction in completion time compared to traditional static systems.
- Engagement Score (ES): Defined as the ratio of active learning time to the total allocated time. Experimental results indicated an increase in ES to 87% with ALPOA, compared to 70% for the static system.
- Knowledge Retention: Assessed through testing one week after course completion. The knowledge retention rate for ALPOA was 85%, which is 15% higher than traditional methods [15, 16].

For a comparative illustration of the results, Table 2 is presented.

TABLE 2. Comparative analysis of the effectiveness of training systems [15, 16].

Metric	Static System	GA	PSO	ALPOA	Improvement (%)
Average completion time (h)	10.5	8.2	7.8	7.2	25% reduction
Engagement Score (ES)	70	78	81	87	30% increase
Knowledge Retention Rate (%)	70%	79%	81%	85%	15% increase

Analysis of Table 2 leads to the following conclusions:

- A 25% reduction in the average time required to complete modules indicates that dynamic content adaptation through ALPOA helps reduce cognitive load and optimize the sequencing of instructional material. This contributes to more efficient knowledge acquisition [15].
- The increase in Engagement Score from 70% to 87% suggests that personalized learning paths generated by the hybrid algorithm enhance learner motivation and activity. Engagement is a key factor in successful learning, as confirmed by prior studies [19, 20].
- The improvement in knowledge retention from 70% to 85% demonstrates that optimized distribution of educational material facilitates better memory retention and information structuring. This effect is achieved through the systematic reinforcement of key concepts via adaptive content modification [16].

For the successful implementation of adaptive learning pathways, it is also crucial to integrate mechanisms that enhance learner motivation. It is recommended to incorporate gamification elements, reward systems, personalized recommendations for additional materials, and interactive testing formats. AI should not only analyze academic performance but also consider emotional states and engagement levels, offering varied formats for content delivery. This approach will create an environment where learning becomes not only effective but also engaging, fostering long-term interest in the subject matter.

IV. CONCLUSION

The approaches proposed in this article for developing adaptive educational systems using artificial intelligence pave the way for the individualization of the learning process. An analysis of current technologies reveals that components of intelligent platforms include neural networks, knowledge graph models, and reinforcement learning algorithms, which enable the system to flexibly adapt to the unique needs of students. These methods allow for the adjustment of educational trajectories, the resolution of difficulties, and the provision of personalized recommendations in real-time.

The implementation of such solutions facilitates the creation of mechanisms that adapt the learning process based on student data, thereby reducing the time required to address knowledge gaps. Integrating these technologies with interactive educational platforms, such as e-learning systems and virtual simulators, enhances the quality of the educational process.

Hybrid algorithms and the ability to process large volumes of data ensure the accuracy and stability of adaptive models. These approaches lay the foundation for developing systems capable of accurately predicting educational needs and tailoring the learning process to the individual characteristics of students.

At the same time, the deployment of such platforms involves several challenges. Key issues include data protection, increasing algorithm transparency, and the scalability of solutions. These aspects require special attention to ensure effective application in large educational institutions.

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