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Design of an AI-based system with dynamic difficulty adjustment and real-time feedback for personalized adaptive learning

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ABSTRACT

The paper presents the design and experimental evaluation of an adaptive digital learning system based on artificial intelligence, which involves the integration of personalization algorithms, a recommendation module, and a mechanism for dynamically adjusting the complexity of tasks. The proposed system used user behavioral data and digital interaction analytics to compile individualized learning trajectories in real time. The system architecture includes analytics modules, a recommendation mechanism, and an adaptive complexity adjustment algorithm. The experimental evaluation of the system was conducted in four academic groups (180 users) within the framework of a quasi-experimental design. Statistical modeling methods, Learning Analytics data analysis, and multiple regression were used to analyze the effectiveness. The results showed a statistically significant improvement in learning outcomes in groups working in the adaptive AI mode ($\eta^2 = 0.60$). In addition, a moderate group × time interaction effect was recorded ($\eta^2 = 0.19$). Analysis of behavioral metrics indicated that the integration of AI modules made it possible to increase the intensity of user interaction with the system. The main predictors of learning effectiveness were the intensity of interaction with the system's recommendations and the total time of active work in the platform. The personalized recommendations module had the greatest impact on the results. Therefore, the integration of adaptive algorithms and recommendation mechanisms made it possible to determine the importance of digital learning architecture.

Keywords: Artificial intelligence, Adaptive systems, Dynamic difficulty adjustment, Adaptive algorithms; Digital educational platforms

1. Introduction

Artificial intelligence has become the main technology for developing intelligent digital systems capable of automating data processing, making adaptive decisions, and optimizing user interaction with information environments. In modern information systems, AI is used to build adaptive algorithms, recommendation models, and behavioral data analytics systems [1], [2]. Thus, this technology allows for the creation of software platforms with a high level of individualization of user interaction with digital content.

At the same time, one of the promising areas of application of AI is the development of adaptive educational systems, in which machine learning algorithms are used to analyze user behavioral data, automatically adjust educational content parameters, and create individual scenarios for interaction with the educational platform. Such systems involve the implementation of complex software architectures consisting of data collection and processing modules, recommendation algorithms, mechanisms for dynamically adjusting task complexity, and automated feedback systems [3], [4].

Modern adaptive learning platforms are based on the use of several interconnected technological aspects. These include learning analytics systems, predictive modeling algorithms, recommender systems, dynamic difficulty adjustment mechanisms, and real-time feedback modules that operate based on the analysis of users' behavioral parameters. The use of such technologies allows the system to dynamically change the complexity of tasks, offer personalized educational content, and automatically generate prompts. In the studies of Motorina et al., it is indicated that the integration of AI technologies into digital educational platforms can increase the effectiveness of adapting the learning environment to the individual characteristics of users [5]. In particular, algorithmic data analysis models allow taking into account the frequency of interaction with the platform, the speed of task completion, the number of errors, and other behavioral parameters [6]. However, despite the active development of research in the field of AI-oriented educational systems, a significant part of scientific works is mainly conceptual or even an overview in nature. Many studies describe general models of personalization of learning or potential possibilities for using intelligent algorithms in digital educational environments. Besides, detailed experimental studies aimed at assessing the architecture of AI systems, algorithmic adaptation mechanisms and their impact on user behavior in the system remain limited. In addition, the current scientific literature does not sufficiently present comparative studies that would determine the effectiveness of various architectural solutions for integrating AI modules into digital learning platforms. This situation complicates the process of determining optimal architectural models of adaptive AI systems and limits the possibilities of their practical application. In modern information systems, artificial intelligence algorithms are used to process large data sets, build predictive models and optimize decision-making processes [7], [8]. The works of Endla et al. [9] and Zohuri [10] indicate that the active use of machine learning algorithms can significantly increase the speed of information processing, forecasting accuracy, and management efficiency of complex information systems. Besides, on the field of digital technologies, AI is used to create adaptive learning systems that automatically modify the parameters of the learning environment [11], [12]. Moreover, this technology depends on the behavior of users. Such systems use various algorithmic approaches, including: 1. algorithms for recommender systems to personalize educational content; 2. forecasting models to assess the risks of academic failure; 3. algorithms for dynamic adjustment of task complexity; 4. automated feedback systems; 5. methods for analyzing behavioral data [13], [14]. The study by Mahmoud & Sørensen indicated that the use of such algorithms made it possible to create individualized scenarios of educational interaction and optimize the sequence of task completion [15]. Other authors have focused on the role of generative AI in the development of adaptive learning [16]. These articles highlight several key technological components: large Language Models (LLMs) for generating learning explanations and tasks; intelligent tutoring systems that use conversational AI models; and automated feedback systems that provide instant feedback [16]. Moreover, the authors determined that generative AI allows for expanding personalization capabilities, but requires solving engineering problems related to: accuracy of content generation and quality control [17], [18]. The results of the authors' review indicated that the effectiveness of personalization depends on the quality of profile models [19]. For this, behavioral data, test results, and patterns of interaction with digital platforms are used [20]. The authors concluded that future personalized learning systems should develop in the direction of intelligent learning ecosystems [20]. Besides, Hariyanto et al. analyzed algorithmic techniques used in adaptive education systems [21]. The paper identifies several main groups of technologies: classification algorithms, clustering, neural networks, rule-based systems, educational data mining, learning analytics, and predictive modeling [21]. However, other studies have recognized the need for a detailed analysis of the architecture of AI systems and their algorithmic mechanisms [22]. This is especially true for the integration of modules for adapting the complexity of tasks, automated feedback systems, and modules for analyzing user behavioral data [23], [24]. The study by Lagos-Castillo et al. indicated that the integration of such components into a single software architecture can increase the accuracy of recommendations and even reduce task execution time [25]. At the same time, other authors pointed out several risks of algorithmic biases, uneven access to digital infrastructure, and the problem of personal data protection [26], [27].

Thus, there is a need in the current scientific literature for research that would be aimed at analyzing the architecture of adaptive systems focused on artificial intelligence. This study will address this gap by developing and empirically testing an integrated adaptive learning system using artificial intelligence that combines dynamic difficulty adjustment (DDA) and a real-time feedback mechanism (RFE). Unlike existing studies that focus mainly on conceptual models or isolated algorithmic solutions, this study provides a comprehensive assessment of both the system architecture and user behavior in real learning environments. At the same time, it offers new insights into the role of adaptive algorithms in shaping the engagement model and their impact on learning outcomes.

2. Research method

2.1 Design

The study used a quasi-experimental design to evaluate the effectiveness of an adaptive AI-based learning system that integrated dynamic difficulty adjustment (DDA) algorithms and a real-time feedback mechanism (RFE). The study focused on analyzing both user interaction patterns within the digital platform and learning outcomes reflected in task performance. Four independent groups of users were formed to assess the impact of the proposed system architecture. Two experimental groups worked in an environment with activated adaptive AI-based modules, while two control groups used the standard version of the platform without personalization and optimization algorithms.

This design allowed for a direct comparison between adaptive and non-adaptive AI-based learning conditions. Importantly, the study was conducted using naturally occurring academic groups, which ensured ecological validity and allowed the experiment to reflect the real conditions of digital learning environments. This approach increases the reliability of the results and supports their applicability in authentic educational settings.

2.2 Users and experimental sample

The experimental evaluation of the system was carried out on a sample of 180 users of the digital learning platform from four universities. All participants had previous experience using electronic educational environments and worked with digital platforms within academic disciplines related to the use of educational technologies, digital tools or ICT components. The users were divided into four groups of 45 people each: Experimental Group 1 (n = 45); Experimental Group 2 (n = 45); Control Group 1 (n = 45); Control Group 2 (n = 45) A total of 90 users worked in AI-Adaptive Mode. However, another 90 users used the platform in Standard Platform Mode. The inclusion criteria for the sample were: studying in related academic programs; working with disciplines of the same type; regular access to the digital learning environment; having previous experience using electronic platforms and consent to participate in the study.

2.3 System architecture and procedure

The experimental part of the study consisted of deploying an AI-oriented adaptive system in a digital learning environment for one academic semester. Within the AI-Adaptive Mode, the following modules were activated in the platform: Adaptive Item Generator (AIG): a module for automatic generation of learning tasks of the appropriate level of complexity; Dynamic Difficulty Adjustment (DDA): an algorithm for dynamic adjustment of complexity according to the accuracy and types of user errors; Real-Time Feedback Engine (RFE): a module for automated generation of prompts and corrective feedback in real time; Early-Alert Predictor (EAP): a module for predicting the risk of failure based on behavioral parameters; Recommendation Module: a system for personalized selection of educational content.

AI modules analyzed behavioral parameters of user interaction with the system and adapted the structure of educational content according to the following indicators: accuracy of task completion; speed of passing test items; frequency of logins to the system; intensity of viewing materials; accuracy and speed of performing educational actions. In Standard Platform Mode, users worked with the standard version of the platform, which allowed access to static materials, regular tests, and basic LMS functions. However, this system did not contain AI-adaptation modules and personalized recommendations (see Figure 1).

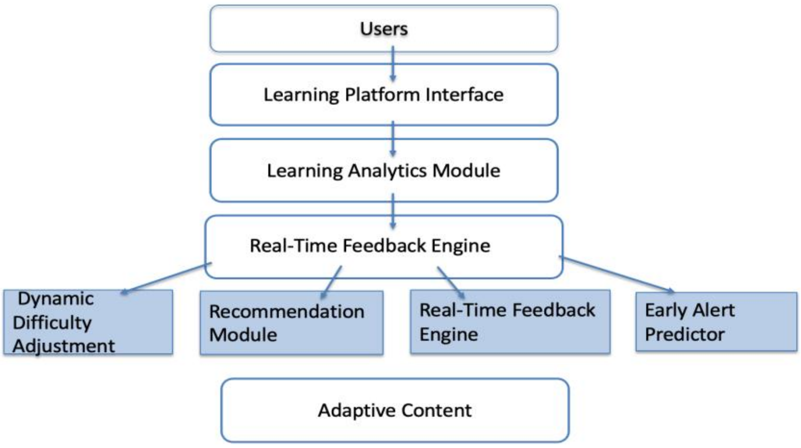

Figure 1. Architecture of the AI-based adaptive learning system

All other parameters of the experimental environment were standardized: the volume of content, the topic of educational material, the number of educational tasks, and the duration of work with the platform were the same in all groups. Moreover, the duration of the experiment was one academic semester (14 weeks) in the second semester of the 2024/2025 academic year.

2.4 Data acquisition and evaluation metric

In order to evaluate the proposed AI-oriented adaptive system, a system of metrics was used, consisting of behavioral parameters of user interaction, task performance, and analysis of individual platform characteristics. The main source of data was the system log files of the digital platform, which automatically recorded user interaction events with the system.

Based on the log data, the following indicators were formed: the number of user logins to the system during the experimental period; the total time of active interaction with the platform; the number of educational materials viewed; the intensity of interaction with recommended content; the timeliness of completing educational tasks; and the number of attempts to pass test modules. These indicators were used as important behavioral indicators in user interaction with the adaptive system.

To evaluate the effectiveness of the implementation of educational tasks, the following indicators were used: pre-test score: the basic level of user knowledge before launching the system; post-test score: results after the end of the period of working with the platform; final course assessment; and normalized learning gain, which allows you to assess the relative increase in results. Pre-test was used as an important control indicator to determine the initial level of knowledge of users, while the post-test allowed you to assess changes in results after using the adaptive system. Subjective characteristics of user interaction with the system were assessed using a standardized questionnaire, which included the following indicators: motivation, perceived personalization, and digital self-efficacy. Each indicator was assessed on the basis of points from 1 to 5. The survey was conducted twice: before the start of the experiment and after the end of the period of working with the system, which allowed you to assess the dynamics of changes in user interaction with the digital platform.

2.5 Reliability and validation of evaluation metrics

To ensure the reliability of the results, a reliability check was carried out on the metrics that were used to assess the effectiveness of the system. The internal consistency of the questionnaire scales was assessed using Cronbach's α, which is a standard approach for testing the reliability of multi-item scales. The reliability of the test instruments (pre-test and post-test) was tested using the Kuder–Richardson coefficient (KR-20). The stability of the digital self-efficacy indicator over time was tested using test–retest analysis on a subsample of users ($n = 25$) with an interval of two weeks before the start of the experiment. The results of testing the reliability of the metrics are presented in Table 1.

Table 1. Reliability and validation metrics of evaluation instruments

Evaluation metric	Reliability type	Indicator	Value	Interpretation
Digital self-efficacy scale	Internal consistency	Cronbach's α	0.84	Good reliability
Pre-test knowledge assessment	Test reliability	KR-20	0.78	Acceptable reliability
Post-test knowledge assessment	Test reliability	KR-20	0.82	Good reliability
Digital self-efficacy (test–retest, n = 25)	Temporal stability	Pearson's r	0.81***	High stability
Learning analytics metrics	System verification	Log data cross-check	100% match	High data accuracy

Note. ***$p < 0.001$.

2.6 Statistical Analysis

Statistical data analysis was carried out using multivariate data analysis methods.

At the first stage, the equivalence of the experimental and control groups on baseline indicators was tested. For this, t-tests for independent samples were used. The main analysis involved assessing changes in indicators over time using Repeated Measures ANOVA (RM-ANOVA) and Mixed ANOVA (2×2). These methods allowed us to simultaneously take into account the influence of two factors: time and resource on the functioning of the system (AI-Adaptive Mode / Standard Platform Mode). A one-way ANOVA was also used between the four groups, in which the pre-test data were used as a covariate to control for initial differences between the groups. To determine the factors that most influence the user results, multiple regression models were built. In addition, a cluster analysis was conducted, which allowed us to identify typical patterns of user interaction with the digital platform.

Results and discussion

3.1 Baseline system conditions and evaluation

Before using the adaptive system, the equivalence of the experimental conditions was checked. For this, the data from the pre-test were compared, which indicated the baseline level of knowledge of the users before the start of the experiment. The results of one-way ANOVA did not reveal significant differences between the groups: $F(3,176) = 1.12$, $p = .345$. Thus, there was initial homogeneity of the sample. In addition, the mean values of the pre-test results were close between the groups.

After the end of the experimental period, there was a noticeable improvement in the results of the users in all groups, however, in the AI-Adaptive Mode, the increase in indicators was higher. Moreover, the Mixed ANOVA (4 × 2) analysis indicated a significant main effect of time (pre → post): $F(1,176) = 112.4$, $p < 0.001$, $\eta^2 = 0.60$ In addition, a significant interaction of the factors system mode × time was found: $F(3,176) = 5.84$, $p = 0.001$, $\eta^2 = 0.19$. Thus, the dynamics of the change in results depended on the system operating mode (See Table 2).

Table 2. Pre- and Post-Test Performance

Group	Pre-test	Post-test	Gain Score	Normalized Gain
Experimental 1	41.8 ± 7.4	72.3 ± 8.1	+30.5	0.52
Experimental 2	42.6 ± 8.1	70.9 ± 7.8	+28.3	0.49
Control 1	40.9 ± 7.9	61.8 ± 8.7	+20.9	0.34
Control 2	41.1 ± 7.2	60.5 ± 9.1	+19.4	0.32

3.2. Behavior of adaptive algorithms and analytics results

The study also determined the behavior of the adaptation algorithms integrated into the system. In particular, the study determined the effectiveness of the Dynamic Difficulty Adjustment (DDA) algorithm, which automatically changed the level of complexity of training tasks depending on the behavioral parameters of users. Analysis of the system log data indicated that the algorithm adjusted the complexity of tasks on average after 3–5 user interactions with test items. In 68% of cases, after successful completion of tasks, the system increased the level of complexity, respectively, participants moved on to tasks of a higher cognitive level. In contrast, in cases where the accuracy of the user's answers fell below 60%, the system automatically activated the complexity reduction mechanism.

The content of the Recommendation Module, which implemented personalized selection of training content, was specifically analyzed. In general, the algorithms of the recommendation system significantly influenced the structure of user interaction with the platform. Learning Analytics analysis indicated the existence of differences in behavioral indicators of user interaction with the platform. Users who worked in AI-Adaptive Mode had a higher intensity of interaction with the digital environment. In particular, the experimental groups recorded: a greater number of logins to the system; a greater time of active work; a greater number of viewed educational materials and a higher intensity of interaction. One-way ANOVA analysis indicated differences between groups in terms of the time of active work of users in the system: $F(3,176) = 4.91$, $p = 0.003$, $\eta^2 = 0.16$. This indicated a stable effect of using AI algorithms on the intensity of user interaction. In addition, some differences were found for the indicator of the number of educational materials viewed: $F(3,176) = 6.14$, $p < 0.001$, $\eta^2 = 0.19$ The most pronounced effect was recorded for the indicator of interaction with recommended materials: $F(3,176) = 15.7$, $p < 0.001$, $\eta^2 = 0.38$.

Table 3. Analytics metrics

Indicator	Exp G1	Exp G2	Ctrl G1	Ctrl G2	F	p

Logins	39.6 ± 8.1	38.2 ± 7.5	30.1 ± 6.9	29.8 ± 7.4	9.12	<0.001
Time spent (min)	812 ± 155	785 ± 163	620 ± 144	598 ± 151	4.91	0.003
Viewed materials	92.4 ± 21.0	88.7 ± 23.3	65.5 ± 20.6	63.9 ± 18.8	6.14	<0.001
Recommended interactions (%)	68	64	22	24	15.7	<0.001
Timely submissions (%)	87	84	69	72	7.44	<0.001

The data show that the experimental groups (experimental group G1 and experimental group G2) consistently outperformed the control groups on all measures. Specifically, users in the experimental conditions demonstrated higher login frequency, more time spent, increased content consumption, and significantly higher engagement with recommended materials. In addition, higher rates of timely completion of tasks were observed, indicating improved academic discipline and engagement. The differences in user interaction patterns across the different system modes are further illustrated in Figure 2, which visualizes key behavioral measures, including login frequency, time spent, content progress, and engagement intensity.

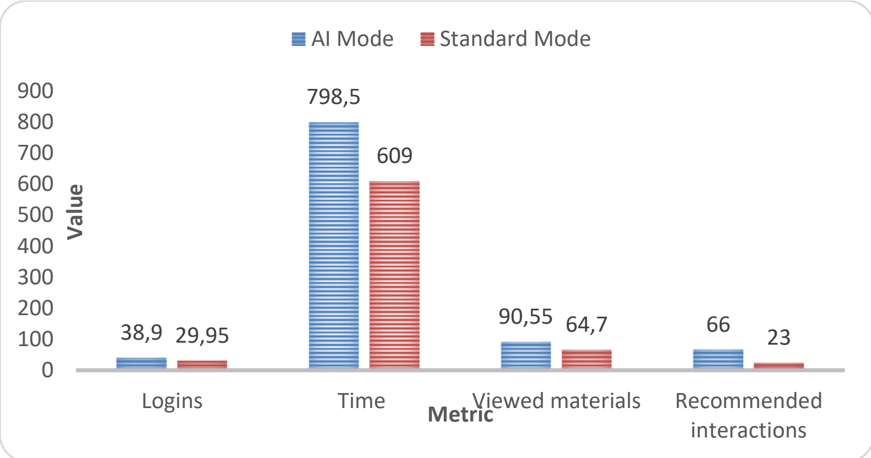

Figure 2. User interaction patterns in the adaptive AI and standard platform modes.

Furthermore, the authors assessed the effectiveness of the proposed adaptive AI system. The analysis of the results showed that the integration of adaptation modules had a positive impact on the results of task performance and behavioral characteristics of user interaction with the system. In the adaptive AI mode, there was an increase in post-test scores compared to the other training conditions. At the same time, higher levels of user engagement were recorded, particularly in terms of platform engagement intensity and content engagement frequency. Learning analytics metrics further demonstrated that personalization algorithms had a measurable impact on user behavior patterns. Effect size analysis revealed a moderate effect on overall user engagement metrics ($\eta^2 \approx 0.16$–0.19), indicating a significant but not dominant contribution to overall engagement. However, the most pronounced effect was found for engagement with recommended content ($\eta^2 = 0.38$), indicating that personalized learning materials play a central role in improving learning outcomes.

To further examine the contribution of behavioral engagement metrics to user performance, a multiple regression analysis was conducted using post-test scores as the dependent variable. The model included three predictors: engagement with recommended content, total time spent on the platform, and motivation to learn after the intervention. The regression data showed that all predictors were statistically significant. In particular, the intensity of engagement with recommended resources and total time spent on the platform demonstrated the strongest relationship with post-test results. Positive β coefficients indicate that users who engaged more with personalized content and spent more time on the platform achieved significantly higher learning outcomes.

Table 4. Regression model predicting post-test performance

Predictor	β	t	p
Interaction with recommended content	0.36	4.92	<0.001
Active time on platform	0.29	3.88	<0.001
Learning motivation	0.21	2.94	0.004

Overall, the regression model indicated 32% of the variance in post-test performance ($R^2 = 0.32$). This indicated the contribution of interaction parameters to the effectiveness of the system (see Figure 3). The active time spent on the platform also had a significant impact. This indicated that continuous interaction with the system had a positive impact on learning outcomes. In contrast, motivation to learn had a smaller, but still significant, contribution to the regression model. Besides, these data from the Figure indicated that behavioral engagement metrics derived from learning analytics played an important role in explaining user performance.

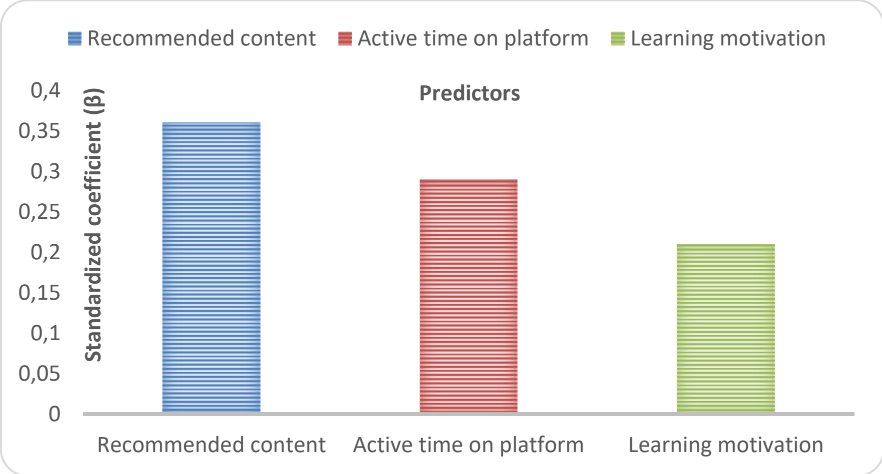

Figure 3. Importance of predictor features in the regression model

The relationship between the intensity of interaction with the platform and user productivity is illustrated in Figure 4. Thus, the Figure shows a positive relationship between the amount of time users spent actively interacting with the platform and their performance after testing. Therefore, users who had higher levels of engagement with the system generally achieved better learning outcomes. This trend highlighted the importance of sustained engagement with adaptive digital environments.

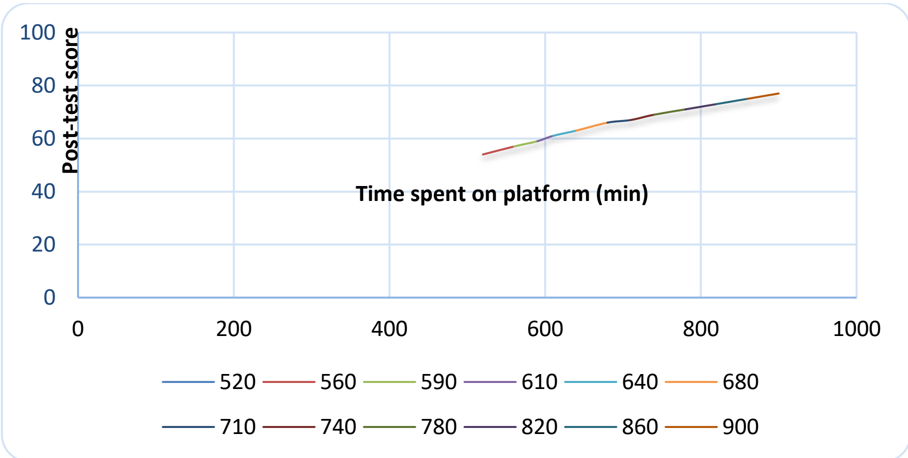

Figure 4. Predictive relationship between user interaction time and effectiveness

Thus, the obtained data indicated the effectiveness of the proposed AI adaptive learning system. The process of integrating adaptive algorithms and dynamic mechanisms led to improved user performance and changed the system of interaction with the digital platform. The results of the experiment indicated that the use of adaptive algorithms made it possible to truly optimize the trajectory of educational activity.

In particular, the data analysis indicated an increase in post-test scores in groups working in AI-Adaptive Mode. The main effect of time was significant ($\eta^2 = 0.60$), at the same time, the interaction effect of "group × time" had a moderate magnitude ($\eta^2 = 0.19$). Such data indicated that the use of adaptive mechanisms of the system had an impact on the dynamics of user results [28]. Similar results are consistent with studies that identified artificial intelligence systems as an important tool for optimizing digital educational environments [29], [30]. Some researchers emphasized the possibilities of personalizing the educational process [31], [32].

In addition, the analysis of data from learning analytics also indicated differences in behavioral indicators of user interaction with the platform. Users working in the adaptive mode of the system had a higher intensity of interaction with the digital environment. This indicator was determined by a greater number of entries into the system, a longer time of active work and active use of educational materials. In addition, a noticeable effect was recorded for the indicator of interaction with recommended content ($\eta^2 = 0.38$). Such data indicated the important role of recommendation algorithms in the formation of individualized trajectories of user interaction with the system [15], [33]. The results obtained were also consistent with previous studies [34], [35]. In particular, the authors emphasized the role of adaptive recommendations and personalization systems in digital educational environments [36], [37]. As part of this study, it was also shown that recommendation algorithms changed the interaction system and stimulated more regular work with educational content [38].

Additional analysis showed that behavioral parameters of user interaction with the system began to play the role of important predictors of their productivity. The formed regression model indicated that the intensity of interaction with the recommended content, the total time of active work in the system, and the level of user motivation significantly influenced the post-test results. In general, the model explained 32% of the variation in the results ($R^2 = 0.32$). This indicator indicated an important influence of behavioral indicators of interaction on the efficiency of the system [39]. Similar results also agreed with studies that indicated the importance of analyzing user behavioral data for assessing the efficiency of digital educational systems [40], [41]. Therefore, the obtained results of the study are consistent with modern works devoted to algorithmic solutions and the use of digital technologies [29], [42]. In particular, the results confirm the conclusions of the authors, who indicated that the use of innovative technologies allows for increased student activity and improved learning of the material [43], [44]. The obtained results are also correlated with studies that describe modern alternative approaches to the organization of practical training of students [45].

In general, the results of the study indicated that the integration of AI algorithms into the digital educational platform made it possible to change the structure of user interaction with the digital environment. In particular, adaptive recommendations began to play the role of an important mechanism for forming personalized trajectories of work in the system. In addition, as other scientists have proven, algorithms for dynamically adjusting the complexity of tasks can provide an optimal level of cognitive load [39], [46]. Thus, the proposed system architecture indicated the potential for use in scalable digital educational environments [47].

However, the methodology in the study has certain limitations that should be considered. In particular, the formation of groups was carried out naturally within existing academic groups. Although this increased the ecological validity of the study, it limits the possibility of establishing strict cause-and-effect relationships. In addition, all participants worked within the same digital environment. This factor may affect the generalizability of the results to other platforms. In further studies, it is worth testing the system in different types of digital educational systems.

4. Conclusions

Thus, the article presents the design and experimental evaluation of an adaptive digital learning system based on artificial intelligence. The formed system architecture made it possible to dynamically adapt the complexity of learning tasks and form individual educational trajectories of users based on behavioral data.

The results of the study indicated that the use of the AI-adaptive mode made it possible to increase user performance compared to the standard mode of operation of the platform. Statistical analysis showed a significant effect of time ($\eta^2 = 0.60$) and the interaction effect of "group × time" ($\eta^2 = 0.19$). These data confirmed the influence of adaptive algorithms on the dynamics of learning outcomes.

Analysis of data from Learning Analytics determined that the integration of AI modules affected the change in behavioral patterns of user interaction with the system. Participants who worked in the adaptive mode had a higher intensity of interaction with the platform and more often used recommended educational content. The most pronounced effect was recorded for interaction with personalized recommendations. The main predictors of learning effectiveness were the intensity of interaction with recommended content, the total time of active work in the system. Thus, the study indicated the importance of the proposed AI-oriented adaptive architecture for supporting personalized digital learning.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The contribution to the paper is as follows: Oleksandr Muliarevych, Kuanysh Yeskendirov: study conception and design; Oksana Huda, Valentina Motorina: data collection; Oleksandr Muliarevych, Andrii Khyzhniak: analysis and interpretation of results; Kuanysh Yeskendirov: draft preparation. All authors approved the final version of the manuscript.

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