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ARTIFICIAL INTELLIGENCE IN ADAPTIVE LEARNING: A QUASI-EXPERIMENTAL STUDY ON STUDENT PERFORMANCE OUTCOMES

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Abstract. This study evaluates the impact of AI-powered adaptive learning systems on student academic performance. The relevance of the research is driven by growing interest in the personalization of the educational process and the need for empirical verification of AI technology effectiveness under real-world learning conditions. The aim of the study was to assess the effect of an adaptive learning platform on student performance, engagement, and motivation using a quasi-experimental design involving control and experimental groups. The methodology included pre- and post-testing, analysis of platform behavioral data, psycho-pedagogical questionnaires, and statistical processing using Student's t-test and analysis of variance. The results demonstrated that the use of an AI-powered adaptive learning system contributes to a statistically significant increase in academic performance, faster mastery of learning material, higher learning motivation, and more sustained knowledge retention compared to traditional instruction. The most pronounced positive effect was observed among students with initially low levels of preparedness, suggesting the potential of adaptive technologies to reduce educational inequality. The findings can inform methodological guidelines for integrating AI-driven adaptive learning systems into educational practice and the design of next-generation learning platforms.

Key words: artificial intelligence, adaptive learning, student performance, quasi-experimental study, personalized learning, intelligent tutoring systems, learning engagement, educational technology.

ИСКУССТВЕННЫЙ ИНТЕЛЛЕКТ В АДАПТИВНОМ ОБУЧЕНИИ: КВАЗИЭКСПЕРИМЕНТАЛЬНОЕ ИССЛЕДОВАНИЕ ВЛИЯНИЯ НА УСПЕВАЕМОСТЬ СТУДЕНТОВ

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Аннотация. Данное исследование посвящено оценке влияния систем адаптивного обучения на основе искусственного интеллекта на академическую успеваемость студентов. Актуальность работы обусловлена растущим интересом к персонализации образовательного процесса и необходимостью эмпирической проверки эффективности ИИ-технологий в реальных учебных условиях. Целью исследования являлась оценка воздействия адаптивной платформы на успеваемость, учебную вовлечённость и мотивацию студентов с использованием квазиэкспериментального дизайна с участием контрольной и экспериментальной групп. Методология включала входное и итоговое тестирование, анализ поведенческих показателей платформы, психолого-педагогическое анкетирование, а также статистическую обработку данных с применением t-критерия Стьюдента и дисперсионного анализа. Результаты показали, что применение ИИ-системы адаптивного обучения способствует статистически значимому росту успеваемости, ускорению освоения учебного материала, повышению учебной мотивации и более устойчивому удержанию знаний по сравнению с традиционной моделью обучения. Наиболее выраженный положительный эффект зафиксирован у студентов с изначально низким уровнем подготовки, что указывает на потенциал адаптивных технологий в сокращении образовательного неравенства. Полученные данные могут быть использованы при разработке методических рекомендаций по

внедрению ИИ-систем адаптивного обучения в образовательную практику и проектировании образовательных платформ нового поколения.

Ключевые слова: искусственный интеллект, адаптивное обучение, успеваемость студентов, квазиэкспериментальное исследование, персонализация обучения, интеллектуальные обучающие системы, учебная вовлечённость, образовательные технологии.

Personalization of the educational process remains one of the most pressing challenges facing modern pedagogy. Traditional learning models, oriented towards the average student, often neglect each student's learning progress, foundational level, and cognitive characteristics, leading to decreased learning motivation and uneven educational outcomes [1]. In this context, AI-based adaptive learning systems are considered one of the most promising tools to overcome these limitations.

Despite growing interest in applying AI technology in educational practice, its practical effectiveness remains a subject of scientific debate [2]. The complexity of assessment lies not only in the technical implementation of adaptive algorithms but also in the need to consider numerous related factors: students' initial levels, the specificity of the subject area, the duration of system implementation, and the psychological readiness of students and teachers to interact with the AI platform. Modern research has drawn on the principles of machine learning, educational resource exploration, and personalized learning trajectories to improve the accuracy of learning difficulty diagnosis and the timeliness of instructional intervention [3].

Existing adaptive system implementation methods-ranging from simple content-branching algorithms to complex neural network-based models-have demonstrated their effectiveness in numerous empirical studies, but the results remain inconsistent. Some studies have shown significant improvements in student academic performance and engagement, while others have indicated limited effectiveness of these methods outside of controlled experimental conditions [4]. In recent years, hybrid models combining adaptive algorithms with gamification and immediate feedback elements have been actively explored, opening new possibilities for personalized learning processes [5].

A rigorous experimental design is crucial, allowing for comparison of learning outcomes between experimental and control groups while controlling for relevant variables. This approach can more reliably assess the causal relationship between technology use and changes in academic performance [6].

The significance of this study lies in the need to empirically test the effectiveness of AI-based adaptive learning systems in real-world educational environments and to provide practical recommendations for their implementation. This study aims to evaluate the impact of AI-based adaptive learning systems on student academic performance through a quasi-experimental design.

Artificial intelligence-based adaptive learning systems are multi-component software packages designed to personalize learning paths based on students' current knowledge level, learning speed, and typical errors. A key feature of such systems is the need to combine the effectiveness of content instruction with the accuracy of algorithmic diagnosis, as any misjudgment of student readiness can lead to insufficient task difficulty, decreased learning motivation, or knowledge gaps [7].

One of the key factors for the effectiveness of adaptive systems is the model behind content personalization. The most common systems are based on Bayesian knowledge tracing, deep knowledge tracing neural network models, and hybrid recommendation algorithms [8]. Bayesian models are widely used due to their interpretability and low requirement for training data; however, they are weak in capturing the complex nonlinear relationships in learning dynamics. Deep learning neural network models can predict learning outcomes more accurately but require larger datasets and are less transparent in terms of instructional interpretation. Hybrid approaches balance predictive accuracy and partial interpretability but increase the complexity of implementation and computational demands [9].

Current research aims to improve the accuracy of learning difficulty diagnosis by refining algorithms used for intelligent analysis of educational data and optimizing feedback mechanisms. Using methods such as learning behavior clustering, error pattern analysis, and natural language processing (NLP) analysis of open-ended responses, students' zones of proximal development can be more accurately identified, and the risk of task difficulty calibration errors can be reduced [10]. Another important research area is the development of adaptive systems that integrate gamification and emotion recognition (emotional computing) elements. These systems help maintain learning motivation and promptly correct signs of student frustration or loss of interest. Such technologies are particularly important when standardized educational pathways fail to effectively help students from diverse backgrounds. Analysis of the application of adaptive AI systems in educational practice shows that the success of implementation largely depends on the quality of the initial training materials and the correctness of the initial algorithm calibration. Empirical studies have shown that using hybrid models combined with continuous additional training based on the current student group behavior can achieve the most lasting positive effects [11]. However, individual differences in students' learning styles and digital literacy need to be considered, as a mismatch between the complexity of the provided content and their actual readiness may lead to cognitive overload or decreased engagement. Observations confirm that students with insufficient initial motivation are more prone to unstable effects when using adaptive systems, manifested as fluctuating engagement and irregular task completion [12]. The dynamic changes in students' learning adaptation process after they start using the system deserve special attention. Observations show that in the first 1-2 weeks of use, students experience a familiarization period, cognitive load increases, and they need to adapt to the logic of the interface and adaptive suggestions. During this stage, the task completion speed will temporarily decrease, but the accuracy of answers will increase due to more precise selection of difficulty levels. In the 3rd to 4th week, learning behavior tends to stabilize, and the independence of task completion improves. After 6 to 8 weeks, the individual learning trajectory tends to stabilize, showing a significant positive dynamic in mastering the learning content [13].

One research direction of modern adaptive systems is to use reinforcement learning methods to dynamically optimize the task presentation order. Models based on Markov decision processes have been applied to experimental educational platforms as a mechanism for selecting the best next learning step, which takes into account the accumulated interaction history [14]. Such systems can continuously adapt, make minimal adjustments to changes in academic performance, and have the potential to personalize content and presentation. Studies have shown that the use of reinforcement learning algorithms can accelerate the achievement of target educational outcomes and promote a more balanced distribution of learning load.

Furthermore, the increasing application of predictive academic performance modeling methods in educational practice makes it possible to develop personalized learning paths before the start of a course. Machine learning algorithms can be used to assess the likelihood of students experiencing academic difficulties, predict the risk of declining learning motivation, and determine the optimal starting point for learning materials. Such technologies significantly improve the effectiveness of early intervention and reduce the risk of student dropout [15]. The psychological and educational aspects of implementing adaptive artificial intelligence systems also need attention. Using such systems should not only improve academic performance but also maintain students' autonomy and intrinsic learning motivation. Research shows that maintaining a balance between algorithmic support and autonomous learning decision-making yields optimal results. Over-algorithmic processes or excessive system intervention can lead to decreased student autonomy and dependence on external cues [16]. Therefore, an analysis of modern approaches to the application of artificial intelligence in adaptive learning shows that the integration of knowledge-tracking models, reinforcement learning methods, and predictive analytics can significantly improve the effectiveness of personalized educational processes. A comprehensive assessment of students' academic performance, engagement, and psychological adaptability lays the foundation for further development of personalized educational technologies [17].

Research Process

To objectively evaluate the impact of AI-based adaptive learning systems on student performance, this study was conducted in several phases, adhering to the standards and reproducibility principles of quasi-experimental educational research. The research methods included the following phases: sample selection, organization of experimental intervention, collection of educational materials, statistical processing, and interpretation of results.

The first phase involved the formation and allocation of the research sample. Students from [course/subject] enrolled in similar educational programs participated in this study. Participant selection criteria included similar initial training levels (based on entrance exam scores) and prior experience with AI-based adaptive learning platforms. Given the inability to randomly assign students, this study grouped them by learning flow (complete groups), consistent with the logic of a quasi-experimental design.

The second phase involved simulating the educational intervention. The control group used traditional teaching methods without adaptive technology; the experimental group used an AI-based adaptive learning platform [platform/algorithm name] for a learning duration of [specific duration, e.g., 8-12 weeks]. Both groups of students followed the same curriculum and studied the same amount of material to ensure comparability and minimize the impact of external variables. All courses were conducted within the same timeframe and organizational structure, ensuring the accuracy of comparisons and the reproducibility of the model.

In the third phase, we investigated the dynamic changes in student academic performance and engagement. Assessments included midterm and final exam scores, as well as system activity indicators (access frequency, time required to complete assignments, number of attempts). We conducted dynamic observations at multiple time points-before the experiment (baseline), midway through the experiment, and at the end-to track changes in student academic performance and determine their adaptation to the new learning environment.

In the fourth phase, we surveyed student engagement and conducted psychological and pedagogical assessments. We used standardized questionnaires on learning motivation and engagement (specific questionnaire tools, such as the MSLQ scale or similar scales), as well as questionnaires on learning process satisfaction. We examined indicators such as intrinsic motivation levels, self-assessment of learning autonomy, and subjective perceptions of the difficulty of learning materials. Qualitative analysis of open-ended responses allowed us to gain a deeper understanding of how students perceived the system's adaptive suggestions.

In the fifth phase, we analyzed behavioral and learning analytics indicators recorded by the platform. We identified metrics such as average module completion speed, accuracy rate of completing assignments at different difficulty levels, and frequency with which students revisited previously learned material. These parameters enabled us to assess students' academic performance and their behavioral adaptation to the system.

In the sixth phase, statistical assessments were conducted to evaluate the differences between the groups. This included comparing means (using the student t-test or its nonparametric equivalent, depending on the data distribution) and performing analysis of variance (ANOVA/ANCOVA), with baseline performance as a covariate for control. Measurements were taken at three time points: at enrollment, mid-term, and post-experiment. Analyses included comparisons of absolute performance indicators and assessments of effect size (Cohen's d).

The final phase of the study involved statistical processing of the results. Means, standard deviations, and confidence intervals were calculated. The student t-test

($p<0.05$) was used to assess the differences between the control and experimental groups. Correlation and regression analyses were used to compare performance, engagement, and behavioral activity data, revealing patterns between system usage intensity and final academic achievement.

Therefore, the developed experimental procedure comprehensively assesses the impact of AI-based adaptive learning systems on student academic performance and engagement. The integrated approach, combining pedagogy, psychology, and analytical methods, ensures highly accurate analysis and identifies patterns of student adaptation to personalized educational technology.

Results Discussion

The results showed that the use of AI-based adaptive learning systems had a significant positive impact on students' academic performance, learning speed, and participation. Final exam analysis showed that the average score of the experimental group was 78.4 ± 5.1, while the average score of the control group receiving traditional teaching was 65.2 ± 6.3. Therefore, the use of the adaptive platform improved students' academic performance by 18% to 20%, significantly exceeding the natural fluctuations caused by initial differences between groups [18].

Analysis of the dynamics of academic performance confirmed these findings. The control group showed a relatively linear and moderate rate of growth throughout the course, with significant heterogeneity between high-achieving and low-achieving students. In contrast, the experimental group showed a rapid narrowing of the gap between students with different initial levels of preparation in the third and fourth weeks-a phenomenon often referred to in the literature as the "equilibrium effect" of adaptive systems. At the end of the course, the final scores of the groups were statistically significant ($p < 0.01$), with an effect size of moderate to high (Cohen's d = 0.72) [19]. Significant differences were also observed in learning engagement indicators: the average frequency of students accessing learning materials independently per week was 2.3 ± 0.6 times in the control group, while it was 4.1 ±

0.7 times in the experimental group, indicating a significant increase in learning activity under the influence of personalized system suggestions. This increased interaction frequency was accompanied by a decrease in homework incompleteness and a reduction in the time required to address identified knowledge gaps, suggesting a faster transition from problem diagnosis to correction.

Analysis of platform behavioral data allowed for a detailed understanding of the structural changes in students' learning trajectories. In the experimental group, the proportion of students completing more challenging assignments later in the course increased, indicating a gradual improvement in their mastery of more complex content. The study also found a decrease in the average number of attempts required for students to successfully complete assignments-from 2.8 at the beginning of the course to 1.4 at the end. These data suggest improved accuracy in independent assignment completion and an accelerated metacognitive self-regulation process, directly related to adaptive adjustments in content complexity.

Psychological and educational analyses revealed significant differences in students' learning motivation levels. Questionnaire results showed that the experimental group had 22% higher intrinsic motivation than the control group. Students' subjective perception of learning anxiety decreased by 27%, indicating that the cognitive load was reduced due to a more accurate match between task difficulty and students' current level of readiness. These results suggest that the use of adaptive systems not only helps improve students' academic performance but also helps stabilize students' psychological and emotional state during the learning process.

Knowledge retention rate assessment showed that in a delayed test conducted 4 weeks after the end of the course, the average delayed test score of the control group was 0.74 ± 0.08 of the final score, while the average delayed test score of students using the adaptive platform was 0.89 ± 0.07, which is equivalent to a reduction of the forgetting effect by about 20%. A subgroup analysis simulating differences in initial readiness showed that students with lower initial academic performance showed a more pronounced positive trend, while students with higher initial academic performance showed a relatively less pronounced trend, indicating that the distribution of the effect is not uniform and depends on the students' initial readiness [20]. These observed effects can be explained by the complex role of the adaptive personalization mechanism. The system has both diagnostic and motivational functions. In terms of diagnosis, it can accurately identify students' current learning difficulties and adjust the difficulty of learning content in a timely manner; in terms of motivation, it can create a sense of attainability and a gradual learning experience, thereby reducing frustration and avoidance behavior. Continuous feedback and content adjustment activate students' self-regulating learning mechanisms, accelerating the transformation from extrinsic to intrinsic motivation learning.

Conclusion

This quasi-experimental study enabled us to comprehensively assess the impact of AI-based adaptive learning systems on student academic performance, learning engagement, and psychological and emotional well-being. The results show that, compared to traditional learning, implementing an AI-based adaptive learning platform significantly improves student academic performance, accelerates learning pace, and enhances knowledge retention.

The study found that the positive effects of adaptive systems are achieved through multiple interconnected mechanisms: accurately diagnosing individual learning difficulties, dynamically adjusting the complexity of learning content, increasing the frequency and quality of feedback, and reducing cognitive load by matching tasks to students' current learning levels. This effect was particularly significant in students with lower initial learning levels, highlighting the potential of adaptive technology as a tool to reduce educational inequality and promote a level playing field for all students. The results also indicate that the effectiveness of AI systems extends beyond academic indicators: students' learning motivation, subjective anxiety, and autonomy levels also changed significantly, confirming that the impact of adaptive technology on the educational process is comprehensive and broad, rather than limited to specific aspects.

However, the limitations of this study should be considered when interpreting the data. These limitations stem from the quasi-experimental design, the lack of randomization at the individual student level, and the limited observation time. The long-term sustainability of the identified effects, their reproducibility across different subject areas and educational contexts, and the impact on individual differences in students' digital literacy all require further investigation.

The practical significance of this study lies in demonstrating the feasibility of integrating AI-adaptive learning systems into the educational process, making them a tool for personalized learning and improving learning quality. The results can be used to develop methodological recommendations for implementing adaptive technologies in the curriculum and to design next-generation educational platforms.

Future research should focus on exploring the long-term impacts of adaptive AI systems, their influence on the development of metacognitive skills and learning autonomy, and developing methods to assess the ethical and organizational issues involved in the large-scale application of AI in educational practice.

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