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THE ROLE OF ARTIFICIAL INTELLIGENCE (AI) IN PERSONALISED PHYSICS EDUCATION

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ABSTRACT

This study aimed to establish conceptual mechanisms and patterns for applying artificial intelligence (AI) technologies to personalised physics education within the Kazakhstani educational system. Methods. A comprehensive methodology was employed, combining both theoretical and empirical approaches. The theoretical phase involved reviewing regulatory documents in Kazakhstan's education system. The empirical phase consisted of a pedagogical experiment conducted between September and December 2024 across three educational institutions in Taldykorgan, Kazakhstan. The study involved 58 tenth-grade students, divided into experimental and control groups; the experimental group utilised an AI-driven personalised learning system designed to adapt content based on student performance. Data were collected on academic performance, theoretical knowledge, practical skills, and research competencies using pre-tests, interim assessments, and final evaluations. Results. The experimental groups demonstrated a significant improvement in academic performance, with the average score increasing from 4.2 to 4.6. 76% of students in experimental groups successfully solved advanced problems, compared to 52% in control groups. The system fostered improved critical thinking, research competencies, and self-assessment skills, while enhancing students' ability to engage in scientific discourse and apply knowledge in interdisciplinary contexts. Conclusions. The AI-driven model proved highly effective at personalising learning and improving students' academic and cognitive outcomes. It offers a scalable framework for adapting content to individual learning styles, with positive impacts on motivation and problem-solving abilities. The findings contribute to a growing body of research on AI applications in education and provide a foundation for further advancements in personal learning systems.

Keywords: AI in education; personalized learning; physics education; adaptive learning systems; educational technology

INTRODUCTION

The rapid advancement of artificial intelligence (AI) technologies has significantly influenced the evolution of educational processes in the context of personalised learning. Of particular importance is the challenge of effective physics instruction, as this discipline requires a deep understanding of complex concepts and an individualised approach for each learner. Given the rapid digital transformation in education and the growing need for personalised learning approaches, this study addresses the urgent challenge of integrating AI in physics instruction, a discipline critical for developing the scientific literacy of future generations (Trout & Winterbottom, 2025).

The research problem lies in a contradiction between the growing demand for persona-

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lised physics education and the insufficient development of methodological frameworks for AI implementation in Kazakhstan's educational system. Existing approaches to physics teaching do not fully exploit the potential of AI technologies for personalised learning, thereby reducing the effectiveness of the educational process. In the context of global efforts to achieve the SDGs, the integration of AI technologies in physics education is seen as a promising avenue for personalising learning experiences and improving educational outcomes.

A systematic review of scientific literature revealed several key research directions regarding the role of AI in personalised physics education. In the context of digital transformation in education, studies on the integration of modern technologies into physics instruction are of particular interest. Fundamental insights into contemporary educational challenges and transformations are presented in the works of Kazakhstani researchers. For instance, Kossov and Bauyrzhankyzy (2023) highlighted the challenges of integrating AI into Kazakhstan's educational system, noting that adaptive learning technologies have shown promise in improving the understanding of physics concepts, but they have yet to be fully realised in practice. Similarly, Tekesbayeva et al. (2024) addressed the benefits of integrating adaptive learning technologies into the broader educational landscape but acknowledged the limitations in methodology when applying these technologies to natural sciences like physics.

In the field of AI applications for knowledge assessment and personalised learning, significant results have been achieved in studying psychological aspects and educational testology. A comprehensive study by Baizhanov (2024) explores the multifaceted use of AI in assessment systems, emphasising psychological factors in students` interactions with intelligent testing systems. The author identified key factors influencing the effectiveness of AI in knowledge assessment and proposed innovative approaches to developing adaptive testing systems. Concurrently, Mahligawati et al. (2023) conducted a large-scale literature review on AI applications in physics education. Their work systematises existing approaches to AI integration, identifies best practices, and outlines promising directions for intelligent physics learning systems. Of particular value are their recommendations for implementing AI technologies across diverse educational contexts. But these investigations often overlook the specifics of physics education, where content complexity and instructional strategies vary greatly.

Moreover, studies on AI-based assessment systems have explored various aspects of psychological factors in students' interactions with intelligent learning environments (Mahligawati et al., 2023; Baizhanov, 2024), but these investigations often overlook the specifics of physics education, where content complexity and instructional strategies vary greatly. Additionally, while AI's role in personalised learning has been explored through models like those proposed by Laak and Aru (2024) and Hao et al. (2024), their research fails to provide a comprehensive framework that adapts these technologies specifically to physics instruction.

AlShaikh and Hewahi (2021) proposed a dynamic architecture for AI systems in education, but their research primarily focuses on general adaptive learning models rather than the subject-specific application of AI in complex fields like physics. The challenge of tailoring AI systems to the nuances of physics instruction – such as understanding abstract concepts and mathematical modelling – remains underexplored. Additionally, Rane et al. (2023) outlined the conceptual role of AI in personalised education but lacked an in-depth focus on how AI could be integrated into specific pedagogical settings or its practical implications for teachers and students within traditional education systems. Both studies fail to address how AI can be adapted to local education systems with varying levels of technological readiness and resource availability.

The studies by Fang et al. (2023) and Kurni et al. (2023) critique the methodologies of AI in education and they call for better evaluation methods and culturally adapted learning algorithms. Fang et al. (2023) specifically pointed out that current methods to evaluate the effectiveness of AI systems are too general, failing to consider the contextual variables that affect learning outcomes, such as socio-cultural and economic factors. This is a significant limitation in the existing research, as AI's effectiveness can vary greatly depending on the educational context and local needs. For instance, the study by Kurni et al. (2023) emphasises gaps in adapting AI to diverse educational contexts, particularly in non-Western settings, but it does not provide concrete solutions for adapting AI to specific educational systems like Kazakhstan's. This gap is crucial because, without localisation, AI systems may not be effective in addressing the pedagogical challenges unique to Kazakhstan's educational infrastructure.

While existing studies have explored AI applications in general education and adaptive learning systems, there is limited focus on their specific implementation in physics education. Key unresolved challenges include the lack of precise methods to evaluate the effectiveness of AI systems in education, the adaptation of intelligent systems to diverse educational contexts, and the need for culturally adapted learning algorithms. Additionally, there is a scarcity of research addressing the integration of AI into existing pedagogical practices and the creation of robust assessment mechanisms for AI-driven, personalised physics education in Kazakhstan. This research contributes to the scientific field by addressing the gap in AI-driven personal physics education in Kazakhstan, offering a novel methodological framework that can be adapted to similar educational contexts globally. This study provides new insights into how AI technologies can be effectively implemented in physics education, contributing to a broader discourse on AI's potential for modernising teaching practices.

This study aims to develop a methodological framework for integrating artificial intelligence into physics education in Kazakhstan, focusing on personalised learning models that cater to individual students' needs and enhance academic performance in the natural sciences.

The following research questions were addressed:

What methodological framework can be developed for the integration of artificial intelligence in physics instruction within the context of Kazakhstan's educational system?

How can the structure and content of personal physics education be defined and effectively implemented using artificial intelligence technologies?

What impact does the integration of artificial intelligence have on individualised physics learning in Kazakh educational institutions?

METHODS

The study used a mixed-methods approach, integrating quantitative analysis to measure academic performance and qualitative insights to evaluate the cognitive, motivational, and practical aspects of personalised learning. The theoretical phase involved an analysis of regulatory documents governing education in the Republic of Kazakhstan, including the Order of the Minister of Education of the Republic of Kazakhstan No. 348 "On Approval of State Compulsory Standards for Preschool Education and Training, Primary, Basic Secondary and General Secondary, Technical and Vocational, Post-Secondary Education" (2022), Law of the Republic of Kazakhstan No. 319-III "On Education" (2007), and the Order of the Acting Minister of Education of the Republic of Kazakhstan No. 500 "On Approval of the Professional Standard "Teacher'" (2022).

The empirical basis consisted of results from a pedagogical experiment assessing the effectiveness of an AI-driven personal physics learning system. The experiment was conducted between September and December 2024 in three educational institutions in Taldykorgan (Republic of Kazakhstan): IT Lyceum School No. 28, Secondary School-Gymnasium No. 12, and Secondary School No. 4. The study involved 58 tenth-grade students divided into experimental (31 students) and control (27 students) groups. The experimental group used the developed personalised learning system, which included adaptive content delivery, intelligent problem-solving support, and individual trajectory adjustments based on performance analysis. The control group followed traditional physics instruction as per the standard curriculum.

Student distribution across schools: IT Lyceum School No. 28 – 19 students (10 experimental, 9 control); Secondary School-Gymnasium No. 12 – 20 students (11 experimental, 9 control); Secondary School No. 4 – 19 students (10 experimental, 9 control). To ensure comparability, participants were selected based on initial physics performance, including high (7-8 students), average (12-13 students), and basic (8-9 students) achievers. At the outset, the experimental group's average physics score was 4.2, compared to 4.1 in the control group (5-point scale), confirming no statistically significant differences. During the experimental phase, quantitative and qualitative indicators of changes in students' academic performance were obtained based on three main parameters: the level of theoretical preparation, the formation of practical skills, and the development of research potential.

Quantitative and qualitative data were collected on three key parameters: theoretical knowledge, practical skills, and research potential. Performance metrics included pre-test, interim, and final assessment results, which were evaluated using standardised tests aligned with national educational standards. Assessment tools included control tasks on Mechanics, Kinematics, and Dynamics, featuring problems of varying complexity, alongside practical and laboratory work.

The quantitative data was analysed using standard statistical methods. For statistical analysis, the Microsoft Excel 7.0 software suite was used, where the Student's t-test was calculated for independent samples. Differences at $p<0.05$ were considered statistically significant. Qualitative data was analysed through a thematic analysis to identify trends in students' cognitive development, problem-solving approaches, and feedback on system usability. Both sets of data were triangulated to provide a comprehensive understanding of the impact of AI integration in personal physics education (Das et al., 2023).

An ANOVA was conducted to compare the performance of the experimental and control groups across multiple time points (pre-test, interim, and final assessments). This allowed for an examination of the within-subject and between-subject effects, providing a clearer understanding of how the personalised learning system influenced students' academic performance over time. Results indicated significant improvements in the experimental group ($p < 0.05$), with students demonstrating greater progress in their problem-solving abilities and theoretical understanding compared to the control group.

To assess the effectiveness of personalised learning, evaluation criteria have been educational outcomes across four main categories: educational efficacy, technological adaptability, pedagogical integration, and cognitive development. Within educational efficacy, metrics included the assimilation of physics concepts through standardised tests, the development of analytical skills via expert assessment of practical work, and problem-solving quality in physics based on control work analysis. Technological adaptability was evaluated through content personalisation accuracy, adaptation speed to student proficiency levels, and difficulty prediction quality using system logs and analytical reports. Pedagogical integration metrics examined compliance with methodological requirements, system configuration flexibility, and usability through teacher surveys and feedback analysis. Students' cognitive development was assessed via critical thinking progression, interdisciplinary competence formation, and self-directed learning skills through comprehensive tasks and project work analysis. During the experiment, regular measurements of these indicators were conducted at varying intervals: weekly monitoring of technological adaptability, monthly evaluation of educational efficacy, quarterly analysis of pedagogical integration, and biannual assessment of cognitive development.

The study collected and analysed data on error patterns in physics problem-solving, task completion times, autonomous experiment planning capabilities, and project work quality. Results from comprehensive tasks requiring integration of knowledge from various physics domains were examined, along with data on students' scientific communication skills development. Metrics of cognitive engagement and learning motivation were measured through analysis of advanced problem-solving tasks and participation in subject-specific discussions.

Reliability of the assessment instruments was ensured using Cronbach's Alpha. This measure was applied to assess the internal consistency of the standardised tests and task ratings used in the study. For example, the Cronbach's Alpha for the problem-solving tasks and the theoretical tests ranged between 0.85 and 0.90, indicating high internal consistency across the different instruments used to assess students' physics performance and cognitive skills. This result demonstrates that the tests provided reliable and consistent measurements of students' understanding and abilities.

RESULTS AND DISCUSSION

The conceptual framework for AI integration in education is based on the principle of multi-level content adaptation to learners' individual characteristics. A fundamental component of this model is the adaptive learning system, which performs continuous analysis of educational data and dynamic adjustment of learning trajectories (Kurni et al., 2023). The adaptive mechanism operates through automated analysis of multiple parameters: knowledge acquisition rates, preferred information presentation formats, typical problem-solving errors, and physics concept comprehension patterns (Krokhmalnyi et al., 2021; Smagulov et al., 2022). A key advantage of the developed model is its integration of machine learning mechanisms that identify non-obvious patterns in physics learning processes and predict potential difficulties in understanding specific topics (Kumar et al., 2023). Particular attention is given to developing a flexible assessment system that evaluates knowledge acquisition and provides detailed analytics on each learning aspect, enabling timely identification and remediation of knowledge gaps (Heeg & Avraamidou, 2023; Tschisgale et al., 2023). A significant achievement in developing this conceptual model is the algorithm for dynamic difficulty adaptation, which considers both students' current proficiency levels and their potential development within the zone of proximal development. This approach maintains an optimal balance between sustaining learning motivation and gradual task complexity progression, fostering a more profound understanding of physical phenomena and principles.

The localisation mechanism for Kazakhstan's education system incorporates a multi-level content adaptation framework where physics concepts are contextualised through examples from national industry, scientific achievements, and technological developments (Mamadova et al., 2019; Nurgaliyeva et al., 2025). The intelligent system automatically selects relevant examples from a database of Kazakhstani research projects, industrial enterprises, and scientific institutions, significantly enhancing student engagement (Ahmad et al., 2021; Ivanashko et al., 2024). In accordance with the Order of the Minister of Education of the Republic of Kazakhstan No. 348 "On Approval of State Compulsory Standards for Preschool Education and Training, Primary, Basic Secondary and General Secondary, Technical and Vocational, Post-Secondary Education" (2022) and the Law of the Republic of Kazakhstan No. 319-III "On Education" (2007), the technological infrastructure is adapted to varying school equipment levels – from basic computer facilities to fully equipped multimedia classrooms – ensuring AI technology accessibility for educational institutions across all regions. The phased implementation of intelligent technologies occurs through four sequential integration levels, each corresponding to an institution's technical capabilities, fully aligning with digital education principles.

The pedagogical practice analysis algorithm, adapted from the methodology of Laak and Aru (2024), employs a comprehensive approach to assessing individual teaching styles. The system analyses parameters including assignment type frequency, preferred content presentation formats, information delivery pace, and student feedback characteristics. The analysis encompasses both quantitative metrics and qualitative aspects of pedagogical interactions, including student motivation strategies, complex physics concept explanation methods, and group work organisation techniques. An in-depth evaluation of teaching method effectiveness includes assessing its impact on students with different cognitive styles, learning paces, and proficiency levels, enabling precise recommendations for optimising educational processes. The implemented approach integrates mechanisms for teacher experience sharing, allowing the system to accumulate successful methodological solutions tailored to specific educational objectives. The algorithm also accounts for regional educational particularities, adapting methodological recommendations to individual institutions' contexts and facilitating effective dissemination of innovative physics teaching practices.

The integration of this algorithm into the developed AI system significantly expands its capabilities for personalising the educational process. The automatic adjustment of data visualisation parameters, the pace of content delivery, and the types of generated tasks are tailored to each teacher's individual style, in accordance with the requirements of Order of the Acting Minister of Education of the Republic of Kazakhstan No. 500 "On Approval of the Professional Standard "Teacher"" (2022). The system provides teachers with tools for flexible adaptation parameter configuration, preserving their methodological autonomy when using modern educational technologies. The developed interface enables teachers to integrate their own methodological materials and pedagogical techniques into the intelligent system's operation, expanding the educational resource base and adapting it to specific learning objectives. Machine learning algorithms analyse the effectiveness of various methodological approaches in different educational contexts, generating recommendations for the optimal use of pedagogical tools (Galchynsky et al., 2021; Ibatov et al., 2021). The technological platform ensures secure storage and processing of pedagogical data, guaranteeing the confidentiality of information about individual teaching practices and learning outcomes (Sakhipov et al., 2022).

The developed criteria for evaluating the effectiveness of AI in physics teaching form a multi-level system of indicators covering various aspects of the educational process. A key focus is monitoring students' cognitive development through qualitative and quantitative indicators. To ensure an objective assessment of the impact of intelligent systems on the quality of physics education, a comprehensive system of indicators has been developed, accounting for both the technological aspects of AI functioning and its pedagogical effectiveness in the educational process (Table 1).

Table 1. Criteria and Indicators for Evaluating the Effectiveness of AI in Physics Teaching

Criterion Category	Indicators	Evaluation Methods	Frequency
Educational effectiveness	Mastery level of physical concepts	Standardised tests	Monthly
	Development of analytical skills	Expert assessment of practical work	
	Quality of physics problem-solving	Analysis of test results	
Technological adaptability	Content personalisation accuracy	System logs	Weekly
	Adaptation speed to the student level	Analytical reports	
	Difficulty prediction quality	Prediction accuracy metrics	
Pedagogical integration	Compliance with methodological requirements	Teacher surveys	Quarterly
	System customisation flexibility	Feedback analysis	
	Usability	Expert evaluation	
Cognitive development	Critical thinking development	Complex tasks	Biannually
	Interdisciplinary competencies	Project work	
	Self-learning skills	Achievement portfolios	

Notes: system logs – records of the AI system's operation, including data on user interactions and its adaptive responses; prediction accuracy metrics – quantitative measures assessing the system's correctness in predicting students' educational needs.

Source: developed by the authors based on Ahmad et al. (2021), Kumar et al. (2023), Heeg and Avraamidou (2023), Allam et al. (2023), Zanca et al. (2021), Dahlkemper et al. (2023).

The developed criteria system enables a comprehensive evaluation of the effectiveness of AI integration in physics teaching. Regular monitoring across all indicator groups ensures timely system parameter adjustments and optimises the educational process. Of particular importance is the balance between quantitative and qualitative evaluation methods, providing a holistic understanding of AI's impact on the quality of physics education within the Kazakhstani educational system.

The personal physics learning system integrates five key components, ensuring the individualisation of the educational process. The core of the system is the educational data intelligence module, which conducts continuous monitoring of student activity and generates a detailed profile of their learning needs. This module represents a comprehensive solution that combines multiple analytical tools for a multifaceted analysis of learning behaviour. It evaluates not only academic performance but also interaction patterns with learning materials, the speed of assimilating different information types, and preferred formats for presenting physical concepts, enabling the creation of a multidimensional model of each student's educational profile (Ezzaim et al., 2022; Yeadon & Hardy, 2024). The second component – the adaptive content generator – produces personalised learning materials tailored to each student's current physics comprehension level and individual information perception preferences. This component uses an extensive database of educational resources and machine learning algorithms to generate optimal learning content. The system automatically adjusts task difficulty, selects the ideal number of practical examples, and regulates the pace of new material delivery based on continuous analysis of topic mastery and individual learning progression.

The interactive physics visualisation module, as the third component, adapts the presentation of complex physical concepts to students' individual perception characteristics, significantly enhancing their assimilation of abstract ideas. The module incorporates diverse visualisation formats, ranging from classic animations and interactive graphs to virtual laboratories and 3D models of physical processes, allowing students to explore phenomena with varying levels of detail. The fourth component implements an intelligent physics problem-solving support mechanism, offering personalised hints and step-by-step explanations tailored to each student's specific difficulties (Alawneh et al., 2024; Vakarou et al., 2024). The system analyses error patterns, identifies gaps in understanding fundamental concepts, and develops an individualised support strategy that combines theoretical clarifications with practical problem-solving guidance. The fifth component – the learning trajectory monitoring and adjustment system – ensures a dynamic adaptation of the educational process based on student progress analysis, enabling timely identification and remediation of knowledge gaps. This system continuously tracks material assimilation quality, curriculum progression pace, and the effectiveness of selected learning strategies, automatically adjusting personalised parameters to optimise educational outcomes.

The functional interactions of the personalised physics learning system components are realised through a multi-tiered educational process adaptation mechanism (Pak et al., 2021; Kozhevnikova & Kozhevnykov, 2024). The AI system continuously collects and analyses over 50 parameters of learning activity, including task completion time, error patterns, preferred information presentation formats, and interaction trends with learning materials. Based on this data analysis, a dynamic learner profile is generated and updated in real time, and it serves as the foundation for content personalisation. Integrated machine learning algorithms identify individual characteristics of physics concept perception and automatically adjust content delivery strategies (Qu et al., 2022; Ezzaim et al., 2023). Particularly significant is the developed predictive mechanism for anticipating potential difficulties in mastering new topics, based on analysis of prior learning experiences and identified patterns in understanding interrelated physical concepts. The system automatically generates additional explanations and practical exercises for aspects of physics theory likely to challenge individual students, thereby preventing knowledge gaps and ensuring deeper subject comprehension.

In a personalised physics education system, an individual learning trajectory is formed through a comprehensive analysis of a student's current achievements and potential capabilities (Bursova & Vashak, 2024; Dudar et al., 2025). Adaptive learning algorithms enable dynamic adjustment of four key parameters of the educational process: the pace of material acquisition, task difficulty level, information presentation format, and intensity of support during problem-solving (Diachuk, 2024; Shevchuk and Hunaza, 2025). During instruction, the system evaluates the effectiveness of the selected strategy through metrics such as success rates for task completion, time spent mastering new concepts, and the quality of developed competencies. For instance, when studying the Mechanics module, the system monitors not only the accuracy of problem solutions but also students' ability to apply Newton's laws across various contexts – from simple rectilinear motion cases to complex problems involving friction and fluid resistance. If a decline in learning efficiency is detected, the system automatically initiates trajectory adjustments, including modifications to material presentation methods, generation of supplementary explanations, and selection of alternative practical tasks (Ezzaim et al., 2022; Sirnoorkar et al., 2024).

For example, if a student struggles to understand centripetal acceleration, the system may provide an interactive visualisation of circular motion, supplemented with step-by-step explanations and real-world examples. A critical component of the system is its feedback mechanism, allowing students to independently request adjustments to specific learning parameters, thereby fostering metacognitive control skills and enhancing engagement. The system also accounts for the distinct nature of different physics domains, adapting instructional strategies to the subject matter while enabling students to select the most effective learning approaches for their needs.

The AI-enhanced personalised physics learning system constitutes a sophisticated, integrated framework where each component fulfils specific functions in individualising the educational process (Järvis et al., 2022; Ahmed, 2024). The study identifies key characteristics of the system's components, their functional interrelations, and adaptation mechanisms to student needs. Particular emphasis is placed on the interaction methods of various system elements to maximise the efficacy of personalised physics instruction (Table 2).

Table 2. Functional Structure of the Personalised Physics Learning System

Structural Element	Functional Characteristics	Adaptation Mechanisms	Personalisation Forms
Analytical core	Processing educational data and student profiling	Dynamic activity analysis	Formation of an individual learning profile
Content module	The organisation and presentation of learning materials	Adaptive content generation	Personalised material formats and complexity levels

Interactive component	Facilitation of interaction with physics concepts	Intelligent visualisation	Adaptation of information representation methods
Feedback system	Monitoring and supporting learning activities	Learning progress analysis	Individualisation of support and counselling

Notes: the analytical core comprises a set of algorithms for processing data on learning activities; the content module encompasses all forms of educational material presentation: textual, visual, and interactive; the interactive component provides various formats for engaging with learning materials based on student preferences.

Source: developed by the authors based on Ezzaim et al. (2023); Alawneh et al. (2024).

The developed structure of the personal physics learning system ensures a comprehensive approach to individualising education. The interplay of all system components creates a unified adaptive environment capable of dynamically responding to each student's educational needs while providing optimal conditions for mastering physical concepts. Of particular significance is the system's dynamic parameter adjustment capability, enabling continuous refinement of the learning process based on accumulated interaction data across diverse student categories. An examination of student performance trends during the experimental implementation of the personalised physics learning system (September – December 2024) revealed consistent positive progress across experimental groups in all three educational institutions. For a comparative analysis of experimental and control groups, academic performance data were systematically compiled (Table 3).

Table 3. Dynamics of Academic Performance in Physics in Experimental and Control Groups (September-December 2024)

Educational Institution	Group	Initial Score	Final Score	Improvement
Secondary School No. 4	Experimental	4.2	4.6	+0.4
	Control	4.2	4.3	+0.1
Secondary School-Gymnasium No. 12	Experimental	4.1	4.5	+0.4
	Control	4.1	4.3	+0.2
IT School-Lyceum No. 28	Experimental	4.3	4.7	+0.4
	Control	4.2	4.3	+0.1

Notes: academic performance was assessed on a 5-point scale; in the experimental group, the highest improvement (+0.7) was observed among students with baseline proficiency.

Source: developed by the authors based on experimental study results.

The findings demonstrate a substantial disparity in performance trends between experimental and control groups. The most notable progress was observed in experimental groups, where the average score increased by 0.4 points, 2-4 times higher than in control groups. The greatest improvement occurred among students with baseline proficiency, indicating the system's effectiveness across diverse learner categories. The stability of positive trends across all three institutions confirms the system's universality and adaptability to varying educational contexts.

A detailed assessment of practical skills revealed significant differences between experimental and control groups in applying theoretical knowledge to physics problems. When solving complex tasks requiring integration of knowledge from multiple physics domains, 68% of experimental group students from Secondary School-Gymnasium No. 12 and IT Lyceum No. 28 demonstrated advanced mathematical proficiency and logical problem-solving strategies. At Secondary School No. 4, this figure was 63%, still markedly exceeding the control group's 41%. Time spent on standard Kinematics and Dynamics tasks decreased by 15% in the experimental group, with the most pronounced improvement among mid-level students.

Error analysis indicated that experimental group students made fewer conceptual errors (34% reduction) and exhibited greater computational accuracy (28% improvement). An analysis of advanced problems revealed enhanced physical modelling skills: 72% of experimental students correctly identified key factors influencing physical processes and justified modelling assumptions, compared to 45% in the control group. In experimental tasks, the experimental group displayed superior understanding of measurement errors and their impact, improving data processing quality by 31%.

Analysis of the development of students' research competencies revealed significant differences in approaches to conducting laboratory and project work between the experimental and control groups. Students from Secondary School No. 4, who utilised a personalised learning system, demonstrated a higher level of autonomy in planning experimental research; 82% of participants in the experimental group successfully developed a methodology for conducting a physics experiment without substantial teacher assistance, whereas this figure stood at 57% in the control group. At IT Lyceum School No. 28, students in the experimental group exhibited improved skills in operating measuring instruments and processing experimental data – the average grade for laboratory work increased from 4.3 to 4.8. Notable progress was observed in their ability to evaluate measurement errors and their impact on the final results. Participants from Secondary Gymnasium School No. 12 demonstrated an enhanced capacity for formulating hypotheses and experimentally testing them: 73% of students in the experimental group independently proposed and substantiated scientific assumptions when completing project work, compared to 48% in the control group. When performing complex research tasks, students in the experimental group displayed more advanced scientific communication skills, reflected in the quality of their research reports and their ability to defend their findings with well-reasoned arguments.

Significant changes were observed in the development of meta-subject skills and cognitive abilities among students in the experimental group. While working with the personalised learning system, students from IT Lyceum School No. 28 showed substantial improvement in self-organisation skills: 79% of participants in the experimental group developed effective strategies for planning academic activities and time management, resulting in the timely completion of 92% of assignments. At Secondary Gymnasium School No. 12, a marked development in critical thinking was observed: students in the experimental group were 34% more likely to employ methods of verifying obtained results and demonstrated a greater ability to identify logical inconsistencies in physics problem statements. Analysis of cognitive engagement at Secondary School No. 4 revealed an increase in academic motivation: 85% of students in the experimental group regularly completed additional high-complexity assignments, compared to 47% in the control group. Of particular note was the development of interdisciplinary knowledge transfer skills: students in the experimental group successfully applied physics concepts to solve problems in related disciplines, demonstrating a profound understanding of the universality of physical laws and their manifestations across various scientific fields.

The implementation of a personalised physics learning system significantly transformed the nature of academic interactions among students. At Secondary Gymnasium School No. 12, a new model of educational communication emerged: students in the experimental group initiated subject-specific discussions 47% more frequently and demonstrated an enhanced ability to substantiate their positions when debating physical phenomena. At IT Lyceum School No. 28, the effectiveness of group work improved: during collaborative projects, 83% of students in the experimental group exhibited skills in productive role allocation and task coordination – a 31% increase compared to the control group. At Secondary School No. 4, students in the experimental group achieved significant improvements in scientific presentation skills: the average grade for public presentations of physics research findings rose from 4.2 to 4.7, with 76% of presentations incorporating elements of interactive audience engagement and detailed responses to questions. Analysis of academic discussion records revealed that students in the experimental group employed more precise physics terminology and demonstrated an increased ability to correctly interpret scientific data during communication.

The three-month pilot implementation of the personalised learning system across three schools in Taldykorgan identified key areas for optimisation to facilitate large-scale adoption in Kazakhstani educational institutions. The experience at Secondary Gymnasium School No. 12 brought attention to the need to expand the database of interactive physics models for the "Electrodynamics" and "Quantum Physics" sections, where students traditionally struggle with visualising processes. At Secondary School No. 4, the necessity for additional refinement of algorithms assessing complex mathematical derivations was established: the system requires improvements in recognising alternative methods for solving high-complexity problems. The application of the system at IT Lyceum School No. 28 confirmed the need to develop supplementary tools to support project-based learning, including modules for experiment planning and statistical data processing. The collective findings underscore the advisability of creating an adaptive module for generating individualised assignments that account not only for students' current proficiency levels but also for their professional interests in physics and related disciplines. A synthesis of the results from the experimental implementation of the personalised physics learning system across three educational institutions in Taldykorgan revealed quantitative and qualitative changes in students' academic performances. To standardise the obtained data and provide a clear representation of the implementation's effectiveness, a comparative analysis of key metrics for the experimental and control groups was developed (Table 4).

Table 4. Comparative Indicators of the Effectiveness of Implementing the Personalised Physics Learning System

Indicator	SS No. 4		SSG No. 12		IT SL No. 28	
	EG	CG	EG	CG	EG	CG
Average physics score (increase)	+0.4	+0.1	+0.4	+0.2	+0.4	+0.1
Solving advanced problems (%)	76	54	71	49	78	53
Independent experiment planning (%)	82	57	78	51	85	59
Quality of project work (avg. score)	4.7	4.2	4.6	4.1	4.8	4.3
Initiation of subject discussions (%)	73	42	68	45	75	47

Notes: SSG No. 12 – Secondary School-Gymnasium No. 12; SS No. 4 – Secondary School No. 4; IT SL No. 28 – IT School-Lyceum No. 28; EG – experimental group; CG – control group; data reflect status as of December 2024.
Source: developed by the authors.

The presented results demonstrate the substantial positive influence of the personalised learning system on the quality of physics education. Statistically significant differences between the experimental and control groups are observed across all key metrics, confirming the efficacy of the developed system and the feasibility of its further implementation in educational institutions across Kazakhstan. Of particular significance is the fact that positive dynamics are observed not only in the assimilation of theoretical material but also in the development of students' practical skills and research competencies.

The experimental implementation of an AI-enhanced personalised physics learning system demonstrated a substantial increase in the effectiveness of the educational process. The study recorded significant improvements in academic performance, development of practical skills, and research competencies among students in the experimental groups. The qualitative changes in learning activities are particularly important as they foster greater independence in experiment planning, enhance complex problem-solving skills, and contribute to the formation of cross-curricular competencies.

The results of this study significantly contribute to the ongoing scientific discourse on adaptive learning systems in educational contexts. While prior research, such as that by Yekollu et al. (2024), emphasises the importance of adapting learning paces for improving educational outcomes, our study extends this understanding by demonstrating a broader influence of personalisation on student performance. Notably, the experimental group showed more substantial improvements, especially in solving advanced-level physics problems, which are more substantial than those reported in Yekollu et al. (2024). This study thus highlights that personalisation through AI not only supports learning speed but also fosters deeper cognitive engagement and problem-solving capabilities.

Similarly, findings from Bessas et al. (2025) align with the present study by noting AI's positive impact on student performance. However, our research demonstrates that the scale of improvement observed in the experimental group substantially exceeds previous reports. Specifically, the experimental group's ability to solve complex, interdisciplinary problems and its enhanced practical skills offer new insights into the transformative potential of AI in physics education, underscoring its capacity to elevate both theoretical understanding and applied knowledge.

Moreover, Pradeep et al. (2024) and Wu et al. (2023) have documented increases in student motivation and engagement with adaptive learning systems, which resonate with the findings of the present study. The current research, however, introduces a more detailed examination of how AI influences not only motivation but also the development of critical thinking and interdisciplinary competencies. The enhanced problem-solving abilities and the students' ability to transfer physics knowledge across disciplines further solidify the role of AI in fostering comprehensive cognitive skills.

While studies such as those by Wu et al. (2023) focused on using AI for engagement via computer vision, the present research takes this a step further by showing how personalised AI systems can transform cognitive, communicative, and practical abilities. The integration of AI into the learning process, as demonstrated here, leads to significant improvements in scientific communication, autonomous research skills, and the development of more sophisticated scientific reasoning, rather than simply increasing engagement or interaction.

A substantial expansion of scientific understanding regarding AI's role in education is presented in Alarbi et al. (2024), emphasising the importance of continuous content adaptation. However, the present study demonstrates the more profound influence of personalisation on developing domain-specific physics skills, as evidenced by qualitative improvements in students' abilities in physical modelling and experimental data interpretation.

According to Kortemeyer (2023), analysis of cross-curricular outcomes and cognitive development in the experimental groups revealed substantial changes in self-regulated learning and critical thinking. While the author examines the impact of intelligent assistants on study skills, the findings are limited to general academic performance and engagement metrics. The present study demonstrates deeper cognitive transformations, including enhanced learning planning abilities, development of effective study strategies, and improved self-monitoring skills. The advancement of interdisciplinary thinking is particularly significant, as it enables students to apply physics concepts when solving problems from related disciplines (Nurakenova and Nagymzhanova, 2024; Zarrabi and Mohammadi, 2024). An important aspect of the achieved results is the development of sustained cognitive motivation, reflected in the increased proportion of students regularly completing advanced assignments and showing interest in supplementary learning materials.

Substantial improvements were observed in the development of communication competencies and scientific discussion skills. While Pardamean et al. (2022) analyse adaptive systems' impact on educational communication, but their research primarily focuses on technical aspects of student-system interaction. The current study's results demonstrate significant development in students' capacity for substantive scientific discourse, including argumentation skills, critical analysis of proposed solutions, and constructive discussion of physical concepts. The observed changes encompass both quantitative participation metrics in subject-specific discussions and qualitative communication characteristics. Experimental groups exhibited substantial improvements in scientific terminology usage, clearer formulation of questions and hypotheses, and enhanced research presentation skills. The integration of collaborative work and project-based learning mechanisms played a particularly important role in developing communication competencies by creating natural conditions for scientific dialogue and idea exchange.

Notable results were obtained regarding the formation of practical skills and the ability to apply theoretical knowledge in experimental work. While Pradeep et al. (2024) present an analysis of adaptive learning platforms' effectiveness with emphasis on general knowledge acquisition metrics, the present study demonstrates substantial improvements in experimental group students' ability to apply physics concepts to practical problem-solving. The findings indicate qualitative enhancements in laboratory skills, including independent experiment planning, optimal measurement method selection, and error estimation. The development of integrated theoretical-practical application abilities is crucial, as it improves experimental research quality and helps students formulate evidence-based conclusions from obtained data. These changes reflect the formation of a holistic understanding of physical phenomena that extends beyond the rote memorisation of formulas and definitions.

Regarding metacognitive strategy development and independent learning skills, the results significantly expand understanding of AI's role in physics education. While Ejjami (2024) examines general aspects of AI's influence on learning competencies, noting positive changes in self-directed learning, the present study reveals more profound transformations in metacognitive control and self-regulation. Experimental groups developed effective learning planning strategies, self-assessment skills, and conscious selection of optimal physics problem-solving methods. Particularly significant is the development of reflective skills, which enable students to analyse their own cognitive processes and adjust their learning strategies. An important outcome is the establishment of intrinsic motivation to study physics, manifested through increased cognitive engagement and pursuit of advanced subject knowledge.

Of substantial interest are the results concerning systemic physics reasoning development and interdisciplinary knowledge transfer abilities. While Désy (2023) discusses the general aspects of adaptive learning with a focus on educational system implementation technologies, the present study demonstrates the deeper cognitive impacts of personalised approaches. Observed changes include enhanced analysis of complex physical systems, identification of cause-and-effect relationships between physical phenomena, and construction of sophisticated physical models. Experimental group students' improved ability to transfer physics concepts to novel contexts plays a crucial role in solving interdisciplinary problems and analysing natural phenomena. These results indicate the development of a profound understanding of physical laws and their fundamental role in describing the natural world.

An analysis of the effectiveness of personalised support for complex physics problem-solving reveals the developed system's significant potential. While Das et al. (2023) examine general personalisation effects on learning outcomes, noting positive dynamics in core material mastery, the present study substantially expands our understanding of effective learning support mechanisms. Experimental groups exhibited qualitative changes in approaching complex physics problems, including the development of multi-step solution strategies, improved physical condition analysis skills, and enhanced identification of key patterns. Students' increased ability to independently overcome cognitive obstacles is particularly important, as it substantially reduces reliance on direct instructor assistance when solving non-standard problems (Usanova et al., 2024; Rudenko, 2025). These changes indicate the formation of sustainable, independent learning skills and the improved utilisation of available educational resources.

In the context of the long-term impact of personalised learning on educational outcomes, a comparative analysis with the study by Sushama et al. (2022) is of considerable interest. Their work examines the prospects of AI-driven distance learning, with a primary focus on the technical aspects of implementing educational platforms. The present study demonstrates more profound transformations in the educational process, affecting fundamental aspects of developing physical reasoning. In the experimental groups, sustained development is observed in the ability to independently master new physical concepts, cultivate critical analysis skills for scientific information, and refine the application of acquired knowledge in diverse contexts. The development of students' capacity to construct individual learning trajectories, accounting for their cognitive interests and professional orientations, plays a crucial role (Bokshyts & Kamenska, 2024; Vakulyk, 2025).

A comprehensive analysis of changes in students' educational activities reveals the substantial advantages of the personalised learning system developed. Gharahighehi et al. (2024) explore general principles of adaptive learning in their research, noting potential benefits of continuous adjustments to the educational process. The results of this study demonstrate the practical implementation of these principles in the context of physics education, revealing significant qualitative changes in learning activities. In the experimental groups, the formation of an integrated system of physical knowledge is observed, which is characterised by a deep understanding of interconnections between various branches of physics, the ability to apply theoretical concepts in practical tasks, and the development of scientific reasoning skills. Of particular importance is the observed advancement of meta-subject competencies, including the ability to work effectively with information, critical thinking skills, and the capacity for interdisciplinary knowledge transfer.

The results of the study make a significant contribution to the development of personalised physics education using artificial intelligence, especially in comparison with previous research in this area. The main innovation of this study lies in the comprehensive approach to personalising the educational process, where AI adapts content to individual student characteristics and significantly improves their cognitive, practical, and research competencies. Unlike many studies that focus solely on the impact of AI on knowledge acquisition, this research demonstrated noticeable improvements in students' ability to apply theoretical concepts to complex interdisciplinary problems, develop critical thinking, and engage in scientific reasoning.

One of the most significant achievements is the creation of an intelligent system that dynamically adjusts content delivery, task difficulty, and support mechanisms based on real-time analysis of student performance. This adaptive approach contributes to a deeper understanding of physical phenomena, enhances problem-solving skills, and significantly improves students' ability to conduct independent scientific research. Additionally, the study indicated that the integration of AI in physics education fosters the development of metacognitive skills, such as self-regulation and learning strategy development, which are crucial for cultivating lifelong learning skills and academic independence. In contrast to previous studies, which often focus on a limited range of educational contexts, this research highlights the universality of the model used, which produces positive results across different educational institutions.

A significant contribution of the study is also the integration of Kazakhstani scientific achievements and examples from national industries into the learning process, which increases student engagement and makes the study of physics more relevant. This aspect is new in the context of using AI in education, as many earlier works do not take into account the specifics of local educational and cultural contexts.

This research provides important perspectives on the potential of AI in physics education, and its practical application offers several benefits for teachers, curriculum designers, and policymakers. Teachers can integrate AI tools into daily physics lessons by utilising the developed system to tailor content to the individual needs of students. This personalisation enables differentiated instruction, allowing teachers to dynamically adjust task difficulties and monitor student progress in real time. By leveraging the system's adaptive learning algorithms, teachers can ensure that each student receives the targeted support they need. Additionally, the feedback mechanism built into the system allows teachers to identify areas where students are struggling and provide personalised interventions, further enhancing the learning experience. AI can also support teachers by automating administrative tasks, which permits them more time to focus on instructional quality and addressing students' individual learning needs.

For curriculum designers, this study suggests the incorporation of AI-based adaptive learning systems into the educational framework in Kazakhstan and potentially in other similar contexts. By aligning AI tools with national curriculum goals, such as the development of critical thinking and scientific reasoning, designers can create a more personalised and engaging learning environment. Additionally, integrating examples from national scientific achievements and industry into the content, as demonstrated in this study, not only increases the relevance of the material but also fosters greater student engagement. This alignment can help ensure that students connect the theoretical knowledge they acquire with real-world applications, further enhancing their learning experience.

Policymakers play a crucial role in ensuring the successful implementation of AI technologies in schools. They must prioritise investments in reliable digital infrastructure and provide ongoing teacher training to facilitate the effective use of AI tools in classrooms. The study emphasises the value of adapting AI systems to the specific needs of Kazakhstan's educational context, ensuring accessibility across regions with varying levels of technological readiness. Policymakers should consider developing policies that incentivise the adoption of AI in schools, promote digital literacy, and support research on AI's potential to transform educational practices.

Overall, the study's results confirm that the integration of AI in personalised physics education not only improves academic outcomes and contributes to the development of a wide range of cognitive, practical, and interdisciplinary skills. These findings significantly expand the scientific understanding of AI's role in education, giving rise to novel ideas for the design and implementation of adaptive learning systems in the field of natural sciences.

The key novelty of this study lies in its comprehensive approach to personalising the educational process, where AI adapts content to individual learning needs and enhances students' cognitive, practical, and research competencies. Unlike previous studies, which primarily focus on the impact of AI on knowledge acquisition, this study reveals substantial improvements in students' abilities to apply theoretical concepts to complex, interdisciplinary problems, develop critical thinking, and engage in scientific reasoning.

While this study provides important contributions to the understanding of AI's role in personalised physics education, several limitations must be acknowledged. One of the key limitations is the sample size: the study involved only 58 students across three educational institutions. This relatively small sample size limits the generalisability of the findings, and future research should aim to include a larger, more diverse sample to provide a more comprehensive understanding of the system's effectiveness across various student demographics. Additionally, the research was conducted in a specific region of Kazakhstan, which may limit the applicability of the findings to other regions or countries with different educational systems. Finally, the short duration of the study, lasting only three months, may not have been sufficient to assess the long-term effects of AI integration on students' academic performance, skills development, and cognitive growth. As such, future research should extend the duration of the study to provide a more thorough examination of the long-term impacts of AI-driven personalised learning. Additionally, this extended research period could help identify any lasting changes in students' problem-solving abilities, critical thinking, and interdisciplinary competencies. Conducting longitudinal studies will contribute to a deeper understanding of the sustained impact of AI in education.

CONCLUSION

This study on the integration of artificial intelligence in personalised physics education has developed a comprehensive theoretical framework tailored to the specific needs of Kazakhstan's educational system. By focusing on multi-level content adaptation and incorporating examples from national industry and science, the proposed model addresses the contextual realities of Kazakhstan's diverse educational landscape. The experimental implementation, conducted across three schools with 58 tenth-grade students, demonstrated the effectiveness of the AI-driven personalised learning system, with significant improvements observed in the students' academic performance, problem-solving skills, and research competencies. The experimental group exhibited notable progress, including a marked increase in the ability to solve advanced-level physics problems, as well as greater autonomy in conducting experiments and formulating scientific hypotheses. The study's results support the scientific field by offering fresh ideas about how AI can be effectively integrated into physics education to enhance student learning outcomes. The research highlights the impact of AI on cognitive development, including advancements in critical thinking, interdisciplinary knowledge application, and self-regulation. Furthermore, the study emphasised the development of communication competencies and scientific discourse skills, demonstrating the potential of AI to foster deeper engagement and motivation among students.

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