

IRSTI 14.25.09

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AN EXPERIMENTAL EVALUATION OF THE EFFECTIVENESS OF INTEGRATING ELEMENTS OF MEDICAL PHYSICS INTO THE SCHOOL CURRICULUM USING ARTIFICIAL INTELLIGENCE TOOLS

Abstract. This article experimentally assessed the effectiveness of integrating elements of medical physics into school physics using artificial intelligence (AI) tools. The relevance of the study stems from the need to strengthen the role of physics in the career guidance of high school students in Kazakhstan and the lack of systematic introduction of the physical principles of medical devices and diagnostic methods into the subject. The study was conducted using a quasi-experimental design: a control group (without the use of AI, $n=51$) and an experimental group (with the use of AI, $n=52$). The educational intervention was delivered through the "Electromagnetic Field and Elements of Medical Physics" module, consisting of four topics: (i) properties of the electromagnetic field, (ii) physical principles of the magnetic field and MRI, (iii) physical principles of electromagnetic radiation and X-ray/CT, (iv) principles of tomography and ionizing/non-ionizing methods. The results were assessed using a questionnaire consisting of 12 statements on a Likert scale (1–5). According to the main results, the overall index was 4.26 ± 0.23 in the experimental group and 2.54 ± 0.16 in the control group, and the difference between the groups was statistically significant ($p < 0.001$). A consistent advantage was also observed across all sections (all $p < 0.001$), with the largest difference recorded in Section IV. In an internal analysis for grades 10 and 11, the advantage of the experimental group was maintained. In a practical sense, a high index (4–5 points) prevailed in the experimental group, indicating a level of “confident understanding,” and it was proven that the ability of AI to visualize, individually explain, model, and provide immediate feedback on elements of medical physics improves the assimilation of complex concepts.

Keywords: artificial intelligence, school physics, medical physics, MRI, CT, tomography, interdisciplinary integration, elective course, quasi-experiment

Introduction

In recent years, supporting upper-secondary students’ professional self-determination in Kazakhstan’s general education schools has become an important educational and policy priority. National educational development documents emphasize the need to connect curriculum content with real-life and professional contexts, strengthen functional literacy, and demonstrate learning outcomes through applied tasks [1]. Within this agenda, students interested in medicine constitute a particularly relevant group, since many contemporary diagnostic and treatment technologies, including CT, MRI, and tomography, are grounded in core physical principles. In this respect, physics can serve not only as a supporting school subject but also as a conceptual foundation for understanding how medical technologies operate.

Despite this potential, career-oriented learning in the medical direction at school is still largely dominated by chemistry and biology, whereas the contribution of physics is less systematically articulated. Existing guidance materials suggest that career guidance practices often remain event-based and that subject-integrated methodological mechanisms are insufficiently developed [2]. At the same time, the physical principles underlying medical imaging, such as fields, radiation, signal formation, and image reconstruction, are rarely incorporated into school physics in a structured and

pedagogically meaningful way. This creates a notable gap between students' growing interest in medicine and the limited use of physics as a vehicle for medically oriented career learning in secondary education.

A further limitation of the existing practice is that complex medical physics concepts are difficult to present at school level in an accessible and engaging form. In this context, artificial intelligence (AI) tools may offer new instructional possibilities by supporting visualization, adaptive explanation, interactive questioning, and feedback. Kazakhstan's national AI development agenda (2024–2029) explicitly highlights the importance of integrating intelligent technologies across sectors, including education [3]. Internationally, the growing role of AI in medical physics and the need to reflect this development in education and training have also been emphasized in professional and policy-oriented sources [4–6]. However, although the educational potential of AI is increasingly discussed, fewer studies have examined how AI can be used to connect school physics content with medical imaging technologies in a career-oriented secondary school context.

The broader rationale for such integration is consistent with STEM and interdisciplinary approaches, which increasingly conceptualize school subjects as applied and interconnected systems rather than isolated bodies of knowledge [7, 8]. Meta-analytic evidence suggests that integrated STEM instruction may be associated with improved learning outcomes compared with more traditional models [9]. This is particularly relevant in physics education, where learners often perceive concepts such as electromagnetic fields, waves, and radiation as abstract and difficult to visualize. Linking these concepts to authentic medical imaging contexts may therefore strengthen both conceptual understanding and learning motivation [10]. In addition, elective courses provide a flexible format for upper-secondary education, allowing schools to implement targeted, career-oriented modules that can be updated in response to emerging technologies and curriculum priorities [1, 11].

To explain the possible educational value of such an approach, the present study draws in part on Social Cognitive Career Theory (SCCT), according to which students' interests and career-related choices are shaped by self-efficacy beliefs, outcome expectations, and environmental supports [12]. Instruction that connects subject content with meaningful professional contexts may therefore enhance students' confidence in their ability to understand the material and, indirectly, support their career orientation. Medical physics is especially suitable for this purpose because it is closely connected with core school physics topics. For example, magnetic fields and resonance principles are foundational for understanding MRI, X-ray attenuation and image formation are relevant to radiography and CT, and nuclear processes provide an entry point to PET-related concepts. Previous studies on medical imaging learning modules for secondary and early tertiary learners suggest that complex technologies can be taught more effectively when they are presented through simplified models and visual explanations [13, 14]. Practical teaching materials likewise show that introductory MRI concepts can be adapted for safe, model-based educational activities [15].

At the same time, the existing literature does not sufficiently address how AI-supported learning activities can be used to integrate medical imaging technologies into school physics in a way that is both pedagogically structured and career-oriented. This study seeks to address that gap. More specifically, it develops and examines an instructional module that links MRI, CT, and tomography concepts with the school physics topics “Electric and Magnetic Fields” and “Electromagnetic Radiation.” The module incorporates AI-supported learning activities, including visualization, interactive explanation, adaptive task scaffolding, and feedback-oriented prompts, which have been identified in the AI-in-education literature as potentially valuable for supporting complex learning [16]. Related evidence from physics education indicates that interactive simulations can improve conceptual understanding, particularly in relation to “invisible” processes such as fields and radiation [17], while learning analytics and data-driven feedback in digital environments may strengthen monitoring and timely instructional support [18, 19]. AI learning tools are also increasingly being documented in K–12 settings [20].

Thus, the present study contributes to the literature in three ways. First, it extends research on AI-supported learning into the specific context of school physics education. Second, it introduces

medical imaging technologies as a career-oriented and conceptually rich context for teaching abstract physics content. Third, it provides empirical evidence from a quasi-experimental school-based intervention implemented under authentic classroom conditions.

The purpose of the study is to evaluate the educational potential of an AI-supported module that integrates medical imaging technologies into school physics. The object of the study is the process of teaching physics at school, and the subject is the methodology of integrating medical physics elements with AI-based didactic support. The research question is as follows: Does the integration of medical imaging technologies into school physics through AI-supported instruction contribute to higher levels of students' perceived understanding of the topic? Based on the instructional design, it was expected that students participating in the AI-supported module would report stronger understanding than students receiving instruction without AI support.

Finally, the study uses a Likert-scale questionnaire as the primary measurement instrument. Likert scales are widely used to capture learners' perceptions, confidence, and satisfaction with learning experiences [21]. At the same time, the ordinal nature of Likert-type data requires careful interpretation, and methodological guidance recommends caution in analysis and inference [22, 23]. Accordingly, the findings of this study are interpreted as reflecting students' perceived understanding rather than objective mastery of the content. Future research may strengthen this line of inquiry by supplementing self-report measures with subject tests, pre-/post-assessments, or performance-based tasks [23].

Methods and materials

This study employed a post-test-only quasi-experimental design involving two independent groups within the same educational setting: a control group, which received instruction without AI tools, and an experimental group, which received instruction with AI-supported didactic assistance. The intervention was implemented through a short instructional module integrating medical imaging technologies into school physics. Both groups followed the same thematic plan, instructional sequence, and lesson duration; the key difference was the inclusion of AI-based support in the experimental group.

The module consisted of four lessons, each devoted to one topic within the section "Electromagnetic Field and Imaging Technologies." The content was aligned with the elective course "Elements of Medical Physics" and focused on one of its thematic units. The structure of the module corresponded to the questionnaire design, which included four sections and 12 statements in total (Table 1). In this way, the module connected core school physics concepts with authentic medical technologies and aimed to reinforce students' perceived understanding of physics in an applied context.

Table 1. *The module Electromagnetic Field and Imaging Technologies*

Questionnaire section	Statement numbers	Module focus (Electromagnetic Field and Imaging Technologies)
Section I	1–3	Core physical properties of the electromagnetic field; interrelations between fields
Section II	4–6	Magnetic field and the physical principles of MRI (resonance idea; non-ionizing diagnostics)
Section III	7–9	Electromagnetic radiation and the fundamentals of X-ray/CT (radiation absorption; image formation)
Section IV	10–12	Principles of tomography; differences between technologies; distinguishing ionizing vs. non-ionizing methods

The participants were Grade 10–11 students enrolled in upper-secondary school, with a total sample of $N = 103$: 51 students in the control group and 52 students in the experimental group. The

inclusion criteria were as follows: (1) enrollment in Grade 10 or 11; (2) prior completion of the curriculum units relevant to the module, including electric and magnetic fields and electromagnetic radiation; and (3) regular attendance during the intervention period.

Because a pre-test was not administered, baseline equivalence between the two groups could not be established through direct measurement of prior knowledge. However, to reduce the risk of major imbalance, the groups were compared at the organizational level in terms of grade level distribution and general academic performance. This point should be regarded as a limitation of the design, and the results should therefore be interpreted with appropriate caution.

The module implemented in the study covered four thematic areas: Section I addressed the core physical properties of the electromagnetic field and the interrelations between fields; Section II focused on the magnetic field and the physical principles of MRI, including the idea of resonance and the distinction between ionizing and non-ionizing diagnostics; Section III examined electromagnetic radiation and the fundamentals of X-ray and CT, including radiation absorption and image formation; Section IV addressed the principles of tomography, differences between imaging technologies, and the distinction between ionizing and non-ionizing methods.

In the experimental group, AI tools were used as a teacher-guided instructional support mechanism rather than as an autonomous source of information. Their pedagogical functions included adaptive explanation, visualization, modeling, task personalization, reflective prompting, and immediate feedback. A central function of AI support in this study was the visualization of diagnostic methods during classroom instruction. For this purpose, several AI-enabled digital platforms were used, depending on the instructional task: Canva and Gamma for generating visual explanations and animated presentations, BioDigital and Mozaik Education for 3D visualization of organs and medically relevant structures, Genially and ThingLink for interactive visual materials, and Labster for simulation-based demonstration of medical diagnostic technologies. These tools helped explain, compare, and visually demonstrate the physical principles underlying imaging methods such as X-ray imaging and MRI.

In the control group, the same content was taught without AI support, using conventional explanation, textbook- and worksheet-based tasks, and the teacher's oral feedback. Thus, both groups studied the same subject matter under comparable instructional conditions, while differing in the availability of AI-supported scaffolding.

To assess learning outcomes, a 12-item questionnaire based on a five-point Likert scale was administered after the completion of the module. The instrument was organized into four sections corresponding to the four thematic blocks of the module. The questionnaire was designed to capture students' perceived understanding of the content, including their confidence in understanding key concepts, ability to distinguish between imaging technologies, and perceived clarity of the studied material. For analysis, both an overall index based on items 1–12 and section-level indices based on the four thematic blocks were calculated.

The statistical analysis included descriptive and inferential procedures. For descriptive purposes, mean values (M) and standard deviations (SD) were calculated for the overall index, section indices, and individual items. Because Likert-type responses are ordinal in nature, the Mann–Whitney U test was used as the primary method for between-group comparison. Statistical significance was evaluated at $p < .05$. To complement significance testing, an effect size was also reported. For nonparametric comparisons, the preferred effect size was r , calculated from the standardized test statistic using the formula $r = Z / \sqrt{N}$. If mean-based comparisons are additionally presented for descriptive interpretation, this should be clearly distinguished from the primary nonparametric analysis.

The results should be interpreted in light of the study's methodological limitations. First, the design did not include a pre-test, which restricts the ability to establish initial equivalence between the groups. Second, the questionnaire captured students' self-reported understanding rather than objective subject mastery. Therefore, the findings are more appropriately interpreted as evidence of differences in perceived understanding associated with the instructional format, rather than definitive proof of differences in actual knowledge. Future studies could strengthen the design by incorporating

pre-/post-testing, subject-based achievement measures, or performance tasks alongside self-report instruments.

Results and Discussion

The experimental evaluation was conducted with Grade 10–11 students using two independent groups: a control group (without AI support, $n = 51$) and an experimental group (with AI support, $n = 52$). The assessment instrument was a 12-item questionnaire rated on a 1–5 Likert scale; the items were grouped into four sections (I–IV) according to content. The AI-supported instructional content was linked to interactive lessons (MRI, CT, tomography) in the “Electromagnetic fields and imaging technologies” unit of the elective course *Elements of Medical Physics*.

Across all sections, the experimental group outperformed the control group (Table 1). The largest difference was observed in Section IV (items 10–12), suggesting that AI support particularly strengthened students’ understanding of tomography and their ability to distinguish diagnostic methods by their physical nature.

Table 2. Presents section-level means and between-group differences

Indicator	Control group (M $\pm$ SD)	Experimental group (M $\pm$ SD)	ΔM	p
Overall index (1–12)	2.54 $\pm$ 0.16	4.26 $\pm$ 0.23	1.72	< 0.001
Section I (1–3)	2.35 $\pm$ 0.19	4.13 $\pm$ 0.32	1.78	< 0.001
Section II (4–6)	2.63 $\pm$ 0.25	4.19 $\pm$ 0.40	1.55	< 0.001
Section III (7–9)	2.52 $\pm$ 0.19	4.26 $\pm$ 0.24	1.74	< 0.001
Section IV (10–12)	2.65 $\pm$ 0.30	4.47 $\pm$ 0.29	1.82	< 0.001

At the item level, the experimental group mean exceeded the control group mean for each of the 12 statements (Table 2), and all differences were significant at $p < 0.001$. The greatest gains were found in the following conceptual areas: item 10 (explaining tomography from a physics perspective; $\Delta M = 2.28$, $p < 0.001$) and item 2 (explaining the relationship between electric and magnetic fields; $\Delta M = 2.11$, $p < 0.001$). These results suggest that AI-supported visual/model-based explanations and interactive tasks can transform complex abstract concepts (fields, field interrelations, tomographic image formation) into “visible evidence,” thereby strengthening comprehension.

Table 3. Reports the mean $\pm$ SD for each item, ΔM , and p-values

No.	Statement (short description)	Control (M $\pm$ SD)	Experimental (M $\pm$ SD)	ΔM	p
1	I understand the concept of the electromagnetic (EM) field.	2.10 $\pm$ 0.36	3.77 $\pm$ 0.58	1.67	< 0.001
2	I can explain the relationship between electric and magnetic fields.	2.43 $\pm$ 0.54	4.54 $\pm$ 0.50	2.11	< 0.001
3	The EM field is the basis of medical technologies.	2.51 $\pm$ 0.64	4.08 $\pm$ 0.27	1.57	< 0.001
4	I know the properties of the magnetic field.	2.76 $\pm$ 0.43	4.29 $\pm$ 0.46	1.52	< 0.001

5	I can explain the principles of MRI.	2.69 ± 0.47	4.02 ± 0.70	1.33	< 0.001
6	MRI is a non-ionizing diagnostic method.	2.45 ± 0.50	4.25 ± 0.44	1.80	< 0.001
7	I can distinguish types of EM radiation.	2.47 ± 0.50	4.10 ± 0.49	1.63	< 0.001
8	I understand the difference between X-ray imaging and CT.	2.51 ± 0.50	4.48 ± 0.50	1.97	< 0.001
9	I can explain why bones appear clearly on an X-ray image.	2.57 ± 0.54	4.29 ± 0.54	1.72	< 0.001
10	I can explain the concept of tomography.	2.24 ± 0.43	4.52 ± 0.50	2.28	< 0.001
11	I know that CT, MRI, and PET are based on different physical principles.	3.08 ± 0.48	4.35 ± 0.56	1.27	< 0.001

The pattern remained stable across grade levels: in both grades, the experimental group achieved higher outcomes. In Grade 10, the overall index increased from 2.64 ± 0.09 to 4.07 ± 0.11 ; in Grade 11, it rose from 2.42 ± 0.14 to 4.47 ± 0.10 (both $p < 0.001$). Thus, the effectiveness of the approach was not limited to a single grade but was evident at both levels.

From a practical perspective, the proportion of students reaching a “confident understanding” threshold (overall index ≥ 4.0) was 0.0% in the control group and 100.0% in the experimental group. Moreover, the combined share of ratings 4–5 across all responses was only 2.1% in the control group, compared with 94.2% in the experimental group. This indicates that the AI-supported module systematically shifted students’ understanding from a “moderate/low” level toward a “good/very good” level and demonstrates high applied value for teaching medical imaging technologies within school physics.

Overall, the effectiveness of the AI-supported module integrating medical physics technologies into school physics was evaluated using a quasi-experimental design. The results consistently showed higher performance in the experimental group across all levels of analysis: the overall index was 4.26 ± 0.23 in the experimental group versus 2.54 ± 0.16 in the control group, with a statistically significant difference ($p < 0.001$). Section-level differences were also stable (all Sections I–IV, $p < 0.001$), and the largest gap was observed in Section IV (items 10–12). This section focuses on tomography principles, comparing diagnostic methods, and distinguishing ionizing from non-ionizing technologies—tasks that require comparative reasoning, cause–effect thinking, and integrating multiple concepts into a coherent system. It is therefore plausible that AI’s visualization and personalization capabilities exerted their strongest influence precisely in this cognitively demanding area.

Several interrelated mechanisms may explain the experimental group’s superior outcomes. First, AI-supported visualization helped to concretize abstract concepts: step-by-step representations of “invisible” processes such as electromagnetic fields, radiation, and image formation can enhance conceptual understanding [1]. Second, AI enabled personalized instruction: when students asked follow-up questions or made errors, explanations could be re-presented using alternative examples and at different levels of depth. Such adaptive support may strengthen learners’ self-efficacy and foster psychological readiness to engage with complex content; Social Cognitive Career Theory likewise highlights self-efficacy as a key determinant of interests and choices [10], suggesting that gains in subject understanding may function as an intermediate outcome relevant to career orientation.

Third, the virtual experimentation and modeling component supported “seeing and understanding” causal relationships. For example, ideas such as how attenuation affects image

contrast, how layer-by-layer information accumulates in tomography, or why MRI is non-ionizing may be learned more robustly when presented through short demonstrations or stepwise models. Fourth, the interdisciplinary context—linking physics concepts to medical technologies—may have increased learning motivation: students perceived physics not only as a theoretical subject but also as a tool for explaining the operating principles of professional technologies (MRI, CT, X-ray). The positive role of contextualization and interdisciplinary integration for motivation and understanding is well established in physics and STEM integration research [6, 12, 20].

Item-level results further support this interpretation. The largest gains occurred in item 10 (the concept of tomography) and item 2 (the relationship between electric and magnetic fields). Both content areas require high abstraction and systematic organization of interrelated concepts; accordingly, AI-based visualization (“making it visible”) and personalized explanations appear to have provided the most effective support in these difficult zones. Additionally, the advantage of the experimental group persisted in the Grade 10–11 subgroup analysis (Grade 10: 4.07 ± 0.11 ; Grade 11: 4.47 ± 0.10 ; both $p < 0.001$ compared with the respective controls), indicating that the effect is not grade-specific but observable across levels.

The findings align with broader contemporary research on AI effectiveness in education. Systematic reviews report that AI can positively influence learning outcomes by adapting instruction, strengthening explanations, accelerating feedback, and supporting learning activities through data-informed mechanisms [17]. In the field of learning analytics and educational data mining, enhanced feedback in digital environments is likewise considered a significant factor affecting instructional quality [13]. The present study уточняет these general claims within a concrete applied context of school physics—medical imaging topics. From an interdisciplinary integration perspective, the results are also consistent with meta-analytic evidence showing the impact of STEM integration on academic outcomes [20]. Furthermore, professional discourse on the need to incorporate AI competencies into medical physics education underscores the strategic value of establishing foundational concepts already at the school level [11, 19].

In practical terms, the results suggest concrete ways to introduce medical imaging technologies into school physics. First, an effective format is to implement a four-lesson module within an elective course or to provide brief contextual integration when teaching the core units “electric and magnetic fields” and “electromagnetic radiation” in the main curriculum. Second, lesson scenarios may be structured using the sequence “professional problem, physical explanation, modeling/virtual experiment, leveled tasks, reflection and micro-test.” Third, AI use should follow principles of safety and academic integrity: medical examples should be open and ethically safe; students’ answers should be justified in their own words; and source-citation habits should be cultivated. Fourth, a concise teacher guide (goals, expected outcomes, sample AI prompts, assessment criteria) can support repeated implementation and scaling.

Several limitations must be noted. Because the primary instrument was a Likert-scale self-assessment, it captures perceived “confident understanding” but may not fully reflect objective knowledge [15]. Moreover, in a quasi-experimental design, baseline differences between groups may not be completely eliminated and should be considered as potential confounding factors. Finally, restricting the sample to a single school or region may limit generalizability.

Accordingly, several directions for future research are proposed. First, to уточнить the effect, objective pre/post testing should be added and self-assessment should be complemented with subject tasks (problem solving, short quizzes, project work). Second, assessing longer-term retention (e.g., several months later) would clarify the module’s potential for durable learning. Third, content expansion is promising: additional modules on ultrasound (waves), radiation safety, dosimetry, and the basics of radiotherapy could systematize medical physics elements into a full career-oriented elective. Fourth, because implementation success depends on teachers’ preparedness in AI pedagogy, investigating teacher training and methodological support systems constitutes an important research direction in its own right.

Conclusion

The aim of the study was to experimentally evaluate the effectiveness of an instructional module that integrates medical physics technologies into school physics through the use of artificial intelligence (AI) tools. The quasi-experimental results demonstrated that the AI-supported approach produced a clear improvement in students' understanding of medical physics: on the overall index, the experimental group scored substantially higher than the control group (4.26 ± 0.23 vs. 2.54 ± 0.16 , $p < 0.001$). Across all four sections (I–IV), the experimental group achieved higher outcomes, and the between-group differences were statistically significant ($p < 0.001$). These findings provide practical evidence that AI-enabled didactic affordances—such as visualization, personalized explanation, and modeling/virtual experimentation—can strengthen students' mastery of complex concepts.

As an applied outcome of the study, a model suitable for implementation in school practice was developed. It recommends systematically introducing a four-lesson module titled “Electromagnetic Field and Imaging Technologies” within the elective course Elements of Medical Physics, or providing a short contextual integration when teaching the corresponding units in the core curriculum. In addition, a ready-to-use methodological package can be offered for schools, including lesson plans and teaching scripts, a set of leveled tasks, assessment tools, as well as pedagogical principles for AI use (visualization, personalization, feedback) alongside safety and academic integrity guidelines. This module can reduce teachers' workload, support consistent implementation, and facilitate adaptation and dissemination to other schools.

Acknowledgements

During the preparation of this manuscript, AI-assisted tools were used solely for language editing and improving clarity of expression. No AI tool was used for data collection, data analysis, interpretation of findings, or drawing conclusions. All scientific decisions and the final version of the manuscript remain the responsibility of the authors.

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ЖАСАНДЫ ИНТЕЛЛЕКТ ҚҰРАЛДАРЫ АРҚЫЛЫ МЕДИЦИНАЛЫҚ ФИЗИКА ЭЛЕМЕНТТЕРІН МЕКТЕП БАҒДАРЛАМАСЫНА КІРІКТІРУДІҢ ТИІМДІЛІГІН ЭКСПЕРИМЕНТТІК БАҒАЛАУ

Аңдатпа. Мақалада жасанды интеллект (ЖИ) құралдарын қолдану арқылы медициналық физика элементтерін мектеп физикасына кіріктірудің тиімділігі эксперименттік тұрғыда бағаланды. Зерттеудің өзектілігі Қазақстандағы жоғары сынып оқушыларына кәсіби бағдар беруде физиканың рөлін күшейту қажеттілігімен және медициналық құрылғылар мен диагностикалық әдістердің физикалық негіздерін пән мазмұнына жүйелі енгізудің жеткіліксіздігімен анықталады. Зерттеу квази-эксперименттік дизайнда жүргізілді: бақылау тобы (ЖИ қолданусыз, $n=51$) және эксперимент тобы (ЖИ қолданумен, $n=52$). Оқыту интервенциясы «Электромагниттік өріс және медициналық физика элементтері» атты 4 тақырыптан тұратын модуль арқылы іске асырылды: (I) электромагниттік өріс қасиеттері, (II) магнит өрісі және МРТ-ның физикалық негіздері, (III) электромагниттік сәуле және рентген/КТ-ның физикалық негіздері, (IV) томография қағидалары және иондаушы/иондамайтын әдістер. Нәтижелер Лайкерт шкаласындағы (1–5) 12 тұжырымнан тұратын сауалнама бойынша бағаланды. Негізгі нәтиже бойынша жалпы индекс эксперимент тобында 4.26 ± 0.23 , бақылау тобында 2.54 ± 0.16 болып, топаралық айырма статистикалық мәнді екені анықталды ($p < 0.001$). Бөлімдер бойынша да тұрақты артықшылық байқалды (барлығында $p < 0.001$), ең жоғары айырма IV бөлімде тіркелді. 10 және 11 сынып бойынша ішкі талдауда да эксперимент тобының басымдығы сақталды. Практикалық мағынада «сенімді түсіну» деңгейін көрсететін жоғары көрсеткіш (4–5 балл) эксперимент тобында басым болып, ЖИ-дың медициналық физика элементтерін көрнекілендіру, жекелендіріп түсіндіру, модельдеу және жедел кері байланыс беру мүмкіндіктері күрделі ұғымдарды меңгеруді күшейтетіні дәлелденді. Зерттеу нәтижелері негізінде мектеп тәжірибесіне енгізуге дайын модульдік модель және әдістемелік құрал (сабақ жоспары, тапсырмалар, ЖИ қолдану ережелері) ұсынуға болады.

Түйін сөздер: жасанды интеллект, мектеп физикасы, медициналық физика, МРТ, КТ, томография, пәнаралық интеграция, электив курс, квази-эксперимент

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ЭКСПЕРИМЕНТАЛЬНАЯ ОЦЕНКА ЭФФЕКТИВНОСТИ ИНТЕГРАЦИИ ЭЛЕМЕНТОВ ФИЗИКИ В ШКОЛЬНУЮ ПРОГРАММУ С ИСПОЛЬЗОВАНИЕМ ИНСТРУМЕНТОВ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА

Аннотация. В статье экспериментально оценивалась эффективность интеграции элементов медицинской физики в школьную физику с использованием инструментов искусственного интеллекта (ИИ). Актуальность исследования обусловлена необходимостью усиления роли физики в профессиональной ориентации старшеклассников в Казахстане и отсутствием систематического введения физических основ медицинских приборов и методов диагностики в содержание предмета. Исследование проводилось в квазиэкспериментальном дизайне: контрольная группа (без использования ИИ, $n=51$) и экспериментальная группа (с использованием ИИ, $n=52$). Образовательное вмешательство осуществлялось посредством модуля «Электромагнитное поле и элементы медицинской физики», состоящего из 4 тем: (I) свойства электромагнитного поля, (II) физические основы магнитного поля и МРТ, (III) физические основы электромагнитного излучения и рентгеновской/КТ, (IV) принципы томографии и ионизирующие/неионизирующие методы. Результаты оценивались с помощью анкеты, состоящей из 12 утверждений по шкале Ликерта (1–5). Согласно основным результатам, общий индекс составил $4,26 \pm 0,23$ в экспериментальной группе и $2,54 \pm 0,16$ в контрольной группе, а разница между группами была статистически значимой ($p < 0,001$). Устойчивое преимущество наблюдалось также во всех разделах (все $p < 0,001$), при этом наибольшая разница зафиксирована в разделе IV. При внутреннем анализе для 10 и 11 классов преимущество экспериментальной группы сохранилось. В практическом смысле в экспериментальной группе преобладал высокий индекс (4–5 баллов), указывающий на уровень «уверенного понимания», и было доказано, что возможности ИИ визуализировать, индивидуально объяснять, моделировать и предоставлять немедленную обратную связь по элементам медицинской физики повышают усвоение сложных понятий. На основе результатов исследования можно предложить модульную модель и методический пакет (план урока, задания, правила использования ИИ), готовый к внедрению в школьную практику.

Ключевые слова: искусственный интеллект, школьная физика, медицинская физика, МРТ, КТ, томография, междисциплинарная интеграция, элективный курс, квазиэксперимент

Received 13 March 2026