European International Journal of Pedagogics (ISSN: 2751-000X)

Received: 24 July 2026 | Accepted: 20 August 2026 | Published: 15 September 2026

DOI: 10.55640/eijp-06-09-04

RESEARCH ARTICLE

Development and Evaluation of An Artificial Intelligence-Based Methodology for Improving Physics Laboratory Instruction in Internal Affairs Academic Lyceums

Soliyeva Madina Murodjon qizi

Physics teacher at the Namangan Academic Lyceum of the Ministry of Internal Affairs, Uzbekistan

VOLUME: Vol.06 Issue09 2026

PAGE: 20-29

Abstract

Artificial Intelligence (AI) is increasingly being integrated into educational processes, creating new opportunities for personalized learning, adaptive support, experimental data processing, formative feedback, and competency-based assessment. This study aimed to develop and evaluate an integrated AI-based methodology for improving physics laboratory instruction in Internal Affairs Academic Lyceums. The study employed a comparative pedagogical design involving 148 students from three Internal Affairs Academic Lyceums located in Namangan, Andijan, and Fergana, including 73 students in the experimental group and 75 students in the control group. The proposed methodology integrated AI-supported diagnostic assessment, pre-laboratory preparation, adaptive experimental guidance, experimental data processing, formative feedback, and competency-based assessment while maintaining students' direct engagement with physical experimentation. Students' laboratory learning outcomes were assessed before and after the intervention using three achievement levels: high, medium, and low. The results demonstrated statistically significant changes in achievement distributions within both the experimental group ($\chi^2(2) = 6.53$, $p = .038$) and the control group ($\chi^2(2) = 7.13$, $p = .028$). In the experimental group, the proportion of students at the low achievement level decreased from 39.7% to 20.5%, while the proportion achieving high and medium levels increased from 60.3% to 79.5%. However, the post-intervention comparison between the experimental and control groups did not reveal a statistically significant difference ($\chi^2(2) = 0.142$, $p = .932$). Therefore, the findings do not provide sufficient statistical evidence to establish the superiority of the AI-based methodology over conventional laboratory instruction. Nevertheless, the observed positive changes indicate the pedagogical potential of systematic AI integration in physics laboratory activities. The study suggests that AI is most effective when used as a methodological support mechanism that complements physical experimentation, teacher guidance, students' independent reasoning, and critical evaluation of experimental evidence.

KEYWORDS

Artificial intelligence; physics education; physics laboratory instruction; academic lyceums; AI-supported learning; experimental competence; personalized learning; adaptive learning; experimental data processing; formative assessment; competency-based assessment; science education.

INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most influential technologies shaping contemporary education, scientific research, and technological development. The rapid advancement of generative artificial intelligence, intelligent tutoring systems, adaptive learning technologies, learning analytics, and AI-supported virtual environments has created new opportunities for transforming conventional teaching practices into more personalized, interactive, and data-driven learning processes. In recent years, the integration of AI into education has increasingly shifted from the use of isolated digital tools toward the development of comprehensive pedagogical models capable of supporting learning, assessment, feedback, and individualized instruction. (Zawacki-Richter et al., 2019; Almasri, 2024; Ogunleye et al., 2024).

Physics education represents a particularly important field for the application of AI because effective learning in physics requires the integration of theoretical knowledge, mathematical reasoning, experimentation, measurement, and scientific interpretation. Laboratory instruction plays a central role in this process by enabling students to move beyond the theoretical description of physical phenomena and acquire practical competencies through direct observation and experimentation. Through laboratory activities, students develop skills in experimental planning, measurement, data processing, graphical representation, error analysis, scientific reasoning, and evidence-based conclusion-making. Consequently, improving the quality and effectiveness of physics laboratory instruction is an important pedagogical objective, particularly within specialized educational institutions.

Internal Affairs Academic Lyceums represent a distinctive educational environment in which students receive systematic general academic preparation alongside education oriented toward professional and social competencies. Within such institutions, physics education can contribute not only to the development of students' scientific knowledge but also to the formation of analytical thinking, accuracy, discipline, problem-solving ability, and evidence-based decision-making. These competencies are particularly relevant to educational environments that emphasize responsibility, precision, logical reasoning, and practical application of knowledge.

However, physics laboratory instruction in specialized academic lyceums may face a number of methodological and organizational challenges. These include differences in students' prior knowledge, limited opportunities for individualized teacher support, difficulties in organizing repeated experimental activities, insufficient time for detailed analysis of experimental data, challenges associated with measurement errors, and the subjectivity of some forms of laboratory assessment. In addition, conventional laboratory instruction may not always provide sufficient opportunities for students to independently investigate physical phenomena, modify experimental parameters, compare alternative explanations, and receive immediate formative feedback.

The integration of Artificial Intelligence into physics laboratory instruction provides opportunities to address some of these challenges. AI-based educational systems can support the diagnosis of students' prior knowledge, generate differentiated learning materials, provide adaptive guidance during experimental activities, assist with mathematical and statistical processing of experimental data, visualize physical relationships, and provide immediate formative feedback. Generative AI can additionally support students in formulating hypotheses, interpreting experimental results, identifying potential sources of error, and preparing structured laboratory reports. Nevertheless, AI should not replace students' direct engagement with physical experiments. Rather, it should function as a methodological support mechanism that strengthens students' experimental independence, scientific reasoning, and ability to critically evaluate evidence. (Almasri, 2024; Mahligawati et al., 2023; Yeadon & Hardy, 2024).

Recent research has increasingly demonstrated the pedagogical potential of AI in science and physics education. Mahligawati et al. (2023), in their systematic review of AI applications in physics education, identified significant contributions of AI to conceptual visualization, personalized learning, interactive instruction, and assessment. Their findings indicate that AI can enhance students' learning experiences by adapting instructional content to individual needs and supporting more interactive forms of learning. At the same time, the authors identified important implementation challenges, including technological infrastructure, teacher preparedness, ethical considerations, and data privacy.

Yeadon and Hardy (2024) investigated the use of generative AI and large language models in physics education and reported that such systems demonstrate considerable potential for conceptual explanations, scientific writing, and programming-related tasks. However, their performance is less reliable when dealing with advanced mathematical reasoning and complex experimental interpretation. This finding is particularly important for laboratory education, where students must not simply obtain computational results but also evaluate the physical meaning, validity, and reliability of experimental evidence. Therefore, AI-supported laboratory instruction should be designed around guided inquiry, critical evaluation, and human oversight rather than unrestricted generation of answers.

Despite the growing body of research on AI in education and physics learning, an important research gap remains. Existing studies have predominantly examined individual AI applications, such as adaptive learning systems, intelligent tutoring, generative AI assistants, virtual laboratories, or automated assessment. Comparatively limited research has focused on developing and empirically evaluating a comprehensive AI-based methodology specifically designed for physics laboratory instruction in specialized academic lyceums. In particular, insufficient attention has been given to methodological models that integrate AI across the entire laboratory learning cycle—from pre-laboratory preparation and adaptive guidance to experimental data processing, formative feedback, competency-based assessment, and learning analytics.

This research addresses this gap by developing and evaluating an AI-based methodology for improving physics laboratory instruction in Internal Affairs Academic Lyceums. The proposed methodology integrates AI-supported diagnostic assessment, individualized pre-laboratory preparation, adaptive experimental guidance, real and virtual experimentation, AI-assisted data processing, immediate formative feedback, and competency-based assessment into a unified pedagogical framework.

The primary objective of the study is to determine whether systematic integration of AI into physics laboratory instruction can significantly improve students' conceptual understanding, experimental competencies, data-analysis skills, and independent learning compared with conventional laboratory instruction.

Accordingly, the study addresses the following research question:

To what extent does an AI-based methodology improve the physics laboratory competencies of students in Internal Affairs Academic Lyceums compared with conventional laboratory instruction?

The study is based on the hypothesis that students who participate in AI-supported physics laboratory instruction will demonstrate significantly greater improvements in conceptual understanding, experimental competence, data-analysis skills, and independent learning than students who receive conventional laboratory instruction.

The scientific novelty of the study lies in the development of an integrated methodological framework that systematically incorporates Artificial Intelligence into the major stages of physics laboratory instruction within the context of Internal Affairs Academic Lyceums. Unlike approaches that employ AI as an isolated technological tool, the proposed methodology positions AI as a pedagogical support mechanism connecting diagnostic assessment, individualized preparation, experimentation, data processing, formative feedback, and competency-based assessment.

The practical significance of the research lies in the possibility of applying the proposed methodology to improve the organization and effectiveness of physics laboratory instruction in specialized academic lyceums. The methodological framework may also provide a basis for adapting AI-supported laboratory instruction to other science subjects and specialized secondary educational institutions.

LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into science education has become an increasingly important area of educational research, particularly because AI technologies can support personalized instruction, intelligent feedback, assessment, data analysis, and interactive learning environments. However, the pedagogical value of AI depends not simply on access to AI tools but on how these technologies are incorporated into the instructional process. This distinction is particularly important for physics education, where meaningful learning requires students to combine conceptual knowledge with mathematical reasoning, experimentation, measurement, and interpretation of empirical evidence.

One of the foundational systematic reviews of AI applications in education was conducted by Zawacki-Richter et al. (2019). Their review analyzed 146 studies selected from 2,656 initially identified publications covering the period from 2007 to 2018. The authors identified four major areas of AI application in higher education: profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems. Importantly, the review revealed that much of the research was technology-driven and that the pedagogical role of educators received comparatively limited attention. This finding is relevant to the present study because it suggests that effective AI integration requires a pedagogically structured framework rather than the simple introduction of an AI tool into an existing teaching environment.

More recent research has expanded the analysis of AI from individual technological applications toward its broader impact on science teaching and learning. Almasri (2024), in a systematic review of empirical studies published in Research in Science Education, examined the effects of AI on science education and highlighted its potential to transform instructional practices, assessment, and student learning. The review provides evidence that AI-supported approaches can facilitate individualized learning, automated or intelligent feedback, and data-informed instructional decisions. At the same time, the study emphasizes the need for further empirical research examining how AI can be pedagogically integrated into authentic science learning environments rather than being treated as an independent technological intervention.

Within physics education specifically, Mahligawati et al. (2023) conducted a comprehensive literature review examining the application of AI to physics learning. Their analysis identified several important areas of AI application, including concept introduction and visualization, individualized learning, social interaction, and assessment. The authors concluded that AI can contribute to more interactive and personalized physics learning by adapting instructional content and supporting students in understanding complex physical concepts. However, the review also identified significant barriers, including technological infrastructure, teacher preparedness, ethical issues, and data privacy. These findings demonstrate that the effectiveness of AI in physics education depends on the interaction between technological capabilities and the pedagogical conditions under which AI is implemented.

The potential and limitations of generative AI in physics education were examined in greater detail by Yeadon and Hardy (2024). Their study evaluated the performance of a large language model on 1,337 physics examination questions covering GCSE, A-Level, and introductory university curricula. Using their most effective prompting approach, the model achieved average scores of 83.4% on GCSE questions, 63.8% on A-Level questions, and 37.4% on university-level questions. The authors also reported limitations in mathematical operations and automated marking, with the model's agreement with human markers averaging 50.8%. These findings are particularly important for laboratory education because they demonstrate that generative AI can provide useful conceptual and instructional support, but its outputs cannot be assumed to be scientifically reliable without human verification.

The findings of Yeadon and Hardy (2024) are especially relevant to academic lyceum education. Their results indicate that generative AI performs relatively well on physics content at earlier educational levels, while its reliability decreases as the complexity of mathematical reasoning increases. This suggests that AI may be particularly useful for supporting pre-laboratory preparation, conceptual explanation, question generation, and guided reflection in academic lyceums, provided that students are explicitly taught to verify AI-generated information. Thus, AI should function as a cognitive and methodological support mechanism rather than as a substitute for students' own scientific reasoning.

Research on generative AI more broadly also supports the need for structured pedagogical integration. Ogunleye et al. (2024), in a systematic review of generative AI research indexed in Scopus, initially identified 625 publications and included 355 studies in the final analysis. Their review demonstrated the rapid expansion of research on generative AI in education but also identified a continuing need for interdisciplinary and multidimensional studies examining how generative AI can be incorporated into teaching, learning, and assessment practices. This finding strengthens the argument for moving beyond studies that merely examine students' attitudes toward AI or the accuracy of AI-generated answers and toward empirical research investigating structured instructional methodologies.

A particularly relevant direction for the present study is the integration of AI with virtual and simulation-based laboratory learning. Although virtual laboratories are not synonymous with AI, research on virtual laboratory environments provides important evidence regarding the pedagogical value of technology-supported experimentation. For example, Asiksoy (2023) investigated virtual laboratory experiences among 240 first-year engineering students enrolled in a physics laboratory course. The study found that simulation-based physics experiments positively affected students' learning achievement, while students also reported generally positive perceptions of virtual laboratory activities. The findings suggest that digital experimental environments can complement conventional laboratory instruction, particularly when physical laboratory resources are limited.

Recent research has begun to move from conventional virtual laboratories toward AI-generated simulations. Ben-Zion et al. (2025) explored the use of generative AI for rapidly creating physics simulations and virtual laboratory environments. Their work demonstrates the emerging possibility of using AI not only to provide explanations or feedback but also to support the creation of interactive simulations of physical phenomena. Such developments are particularly relevant to the proposed methodology because they create opportunities for students to manipulate parameters, formulate predictions, compare simulated and experimental results, and investigate physical situations that may be difficult to reproduce using conventional laboratory equipment.

More direct empirical evidence concerning AI-supported physics laboratory learning has also begun to emerge. Ben-Zion et al. (2026) investigated the use of generative AI in simulation-based physics experiments by comparing three laboratory approaches: physical equipment, a prebuilt simulation, and an AI-generated simulation. The study was conducted in a second-semester physics course and focused on an electric-potential laboratory. Significant differences were found among the three groups in conceptual assessment performance, with an effect size of $\eta^2 = 0.359$. Post-hoc analyses showed that students using both AI-generated and prebuilt simulations achieved significantly higher conceptual assessment scores than students using physical equipment alone. Students in the simulation conditions also reported more favorable perceptions of the learning experience. Importantly, the researchers emphasized that the process of designing, refining, and validating AI-generated simulations can itself become an opportunity for developing students' modeling skills.

At the same time, research on generative AI in physics education highlights important limitations in mathematical reasoning, experimental interpretation, and the reliability of AI-generated outputs (Yeadon & Hardy, 2024). These limitations reinforce the necessity of verification procedures, teacher supervision, and carefully designed boundaries for AI use in laboratory instruction.

The literature on virtual and simulation-based laboratories also suggests that technology can complement conventional laboratory instruction. Asiksoy (2023) reported positive effects of virtual laboratory experiences on students' physics learning achievement and perceptions, while Ben-Zion et al. (2025, 2026) demonstrated emerging possibilities for AI-generated simulations. These findings support a blended approach in which digital environments extend, rather than automatically replace, direct physical experimentation.

Taken together, the reviewed literature reveals several important tendencies. First, AI has demonstrated potential for personalized learning, conceptual explanation, feedback, assessment, and data-supported instruction. Second, physics education is a particularly promising field for AI integration because students must simultaneously manage conceptual, mathematical, experimental, and analytical tasks. Third, virtual and AI-generated simulations can extend opportunities for experimentation and conceptual exploration. Fourth, the literature consistently indicates that AI-generated outputs require human verification because inaccuracies and misleading responses remain possible. Finally, much of the existing research examines individual technological applications rather than comprehensive pedagogical methodologies that integrate AI throughout the entire laboratory learning cycle. (Almasri, 2024; Mahligawati et al., 2023; Yeadon & Hardy, 2024; Ogunleye et al., 2024).

Despite the growing number of studies on AI in physics education, a specific research gap remains in relation to specialized secondary and pre-university education, particularly Academic Lyceums. Existing empirical research has predominantly focused on universities, general school education, or isolated technological interventions. Comparatively little empirical evidence is available concerning comprehensive AI-supported physics laboratory methodologies designed specifically for students in specialized academic lyceums. Moreover, there is a lack of studies simultaneously examining the effects of AI-supported laboratory instruction on conceptual understanding, experimental competence, data-analysis skills, and independent learning within a controlled pedagogical experiment.

Therefore, the present study seeks to address this gap by developing an integrated AI-based methodology for physics laboratory instruction in Internal Affairs Academic Lyceums.

The proposed approach differs from isolated uses of generative AI by integrating AI-supported diagnostic assessment, pre-laboratory preparation, adaptive experimental guidance, real and virtual experimentation, experimental data processing, formative feedback, and competency-based assessment into a unified instructional framework. The study consequently extends existing research from the question of whether AI can be useful in physics education toward the more specific question of how a systematically designed AI-based methodology can improve physics laboratory competencies among students in a specialized academic lyceum context.

METHODOLOGY

The present study employed a comparative pedagogical research design to examine the effectiveness of an Artificial Intelligence (AI)-based methodology for improving physics laboratory instruction in Internal Affairs Academic Lyceums. The study compared the learning outcomes of students who participated in AI-supported laboratory instruction with those of students who received conventional laboratory instruction.

The research was organized around a pre-intervention and post-intervention comparison. At the initial stage, students' performance in physics laboratory activities was assessed and classified into three levels: high, medium, and low. Following the instructional intervention, the same classification was applied to evaluate changes in students' laboratory learning outcomes.

The methodological framework was designed to integrate AI into different stages of laboratory instruction rather than use it as an isolated technological tool. This approach corresponds to the central objective of the study, namely, to examine whether systematic AI integration can improve students' conceptual understanding, experimental competence, data-analysis skills, and independent learning. The study was conducted in three Internal Affairs Academic Lyceums located in Namangan, Andijan, and Fergana. A total of 148 students participated in the study. Of these, 73 students were assigned to the experimental group and 75 students to the control group.

The distribution of participants was as follows: the Namangan Academic Lyceum included 22 students in the experimental group and 26 students in the control group; the Andijan Academic Lyceum included 25 and 24 students, respectively; and the Fergana Academic Lyceum included 26 students in the experimental group and 25 students in the control group. The experimental group received physics laboratory instruction based on the proposed AI-supported methodology, whereas the control group continued to study laboratory topics using conventional instructional approaches. The inclusion of students from three different academic lyceums made it possible to examine the applicability of the methodology across several educational settings.

The proposed methodology was developed as an integrated pedagogical framework in which Artificial Intelligence served as a methodological support mechanism throughout the laboratory learning cycle. The methodology was not intended to replace students' direct interaction with laboratory equipment or their independent scientific reasoning. Instead, AI was used to support preparation, experimentation, data analysis, feedback, and reflection.

The AI-supported laboratory learning process consisted of several interconnected stages.

Stage 1. Diagnostic preparation. Before laboratory activities, students' initial level of knowledge and preparedness was identified. The diagnostic stage provided a basis for determining students' learning needs and for organizing differentiated instructional support.

Stage 2. Pre-laboratory preparation. Students were provided with theoretical and methodological preparation for the laboratory activity. AI-supported resources were used to clarify theoretical concepts, explain physical relationships, generate guiding questions, and support students in preparing for the experimental task.

Stage 3. Experimental activity. Students performed laboratory experiments and worked directly with physical phenomena, measurements, and experimental equipment. AI was used as a supporting mechanism for interpreting instructions, clarifying experimental procedures, considering possible hypotheses, and guiding students toward independent investigation. The physical experiment remained the central component of the learning process.

Stage 4. Experimental data processing. Students processed the measurement results obtained during laboratory activities. AI-supported tools were used to assist with mathematical calculations, organization and interpretation of experimental data, graphical representation, and identification of possible measurement errors. Students were required to examine and verify the generated results rather than accept AI-generated outputs without evaluation.

Stage 5. Formative feedback and reflection. During and after the laboratory activity, AI-supported feedback was used to identify difficulties, provide explanations, and encourage students to reconsider their experimental procedures and conclusions. Particular attention was given to the physical interpretation of results and the relationship between theoretical expectations and experimental evidence.

Stage 6. Competency-based assessment. At the final stage, students' laboratory performance was evaluated according to the established achievement levels. The assessment focused on the extent to which students were able to understand the physical concept, perform the experimental procedure, process and interpret experimental data, and formulate evidence-based conclusions.

Thus, the proposed methodology combined technological support with direct experimentation, teacher supervision, and students' independent analytical activity. This structure was designed to ensure that AI functioned as a pedagogical support mechanism rather than as a substitute for experimental learning.

The pedagogical experiment was conducted in two principal phases: pre-intervention assessment and post-intervention assessment. During the pre-intervention phase, students' performance in physics laboratory activities was assessed and classified into three achievement levels. Students who demonstrated a strong mastery of the laboratory activity were classified as having a high level of achievement; students with satisfactory or intermediate mastery were classified as having a medium level and students who demonstrated insufficient mastery were classified as having a low level. Before the intervention, the experimental group consisted of 18 students at the high level, 26 at the medium level, and 29 at the low level. In the control group, 15 students were classified at the high level, 33 at the medium level, and 27 at the low level.

During the intervention, students in the experimental group participated in laboratory instruction according to the proposed AI-supported methodology. The methodology incorporated AI-supported preparation, experimental guidance, data processing, feedback, and assessment while maintaining students' direct participation in physical experimentation.

Students in the control group studied the corresponding laboratory material using conventional instructional procedures without systematic integration of the proposed AI-based methodological framework.

At the end of the intervention, students in both groups were assessed using the same three-level classification. The post-intervention results were then compared with the initial results in order to identify changes in laboratory learning performance.

For the purposes of the study, students' laboratory learning outcomes were represented using three achievement categories: high, medium, and low. This classification provided an integrated assessment of students' performance in laboratory activities and allowed the researchers to compare the distribution of achievement levels before and after the intervention.

The primary analytical procedure involved comparing the number and proportion of students in each achievement category within the experimental and control groups. Changes in the distribution of students across the three achievement levels were examined separately for each group and across the three participating academic lyceums.

The pre- and post-intervention results were subsequently prepared for statistical comparison. In particular, the analysis focused on whether the changes observed in the experimental group were greater than those observed in the control group. This approach made it possible to evaluate the effectiveness of the AI-supported methodology while accounting for the initial distribution of student achievement levels.

The methodological design therefore established a direct relationship between the research hypothesis and the empirical assessment: if systematic AI-supported laboratory instruction was effective, the experimental group should demonstrate a more favorable shift toward higher achievement levels than the control group.

RESULTS

The empirical results obtained from the three Internal Affairs Academic Lyceums demonstrate changes in the distribution of students across the three achievement levels following the implementation of the proposed AI-based methodology. A total of 148 students participated in the study, including 73 students in the experimental group and 75 students in the control group. The experimental group consisted of 22 students from Namangan, 25 from Andijan, and 26 from Fergana, while the control group included 26, 24, and 25 students, respectively.

Before the intervention, the experimental group included 18 students (24.7%) at the high level, 26 students (35.6%) at the medium level, and 29 students (39.7%) at the low level. In the control group, 15 students (20.0%) demonstrated a high level, 33 students (44.0%) a medium level, and 27 students (36.0%) a low level.

Following the intervention, the distribution of achievement levels in the experimental group changed considerably. The number of students demonstrating a high level increased from 18 to 26, corresponding to an increase from 24.7% to 35.6%. The number of students at the medium level increased from 26 to 32, or from 35.6% to 43.8%. At the same time, the number of students at the low level decreased from 29 to 15, representing a reduction from 39.7% to 20.5%.

The control group also demonstrated some positive changes. The number of students at the high level increased from 15 to 26, representing an increase from 20.0% to 34.7%. The number of students at the medium level increased slightly from 33 to 35, or from 44.0% to 46.7%. The number of students at the low level decreased from 27 to 14, corresponding to a reduction from 36.0% to 18.7%. The comparison of pre- and post-intervention results indicates that both groups demonstrated improvement in laboratory learning outcomes. However, the pattern of change differed between the groups. In the experimental group, the proportion of students at the high achievement level increased by 10.9 percentage points, while the proportion at the low level decreased by 19.2 percentage points. The medium-level category increased by 8.2 percentage points. In the control group, the proportion of high-level students increased by 14.7 percentage points, while the low-level category decreased by 17.3 percentage points. The proportion of students at the medium level increased by 2.7 percentage points.

These results indicate that the intervention was accompanied by a substantial redistribution of students from the low achievement category toward the medium and high categories in both groups. In the experimental group, the combined proportion of students at the high and medium levels increased from 60.3% before the intervention to 79.5% after the intervention, representing a 19.2 percentage-point improvement. In the control group, the corresponding proportion increased from 64.0% to 81.3%, representing a 17.3 percentage-point improvement.

The difference between the two groups should therefore be interpreted carefully. The descriptive results alone do not demonstrate that the AI-based methodology produced a statistically significant advantage over conventional instruction. Rather, they demonstrate that both instructional conditions were associated with improved laboratory learning outcomes, while the experimental group showed a particularly notable reduction in the proportion of students classified at the low achievement level.

The results obtained from the three participating academic lyceums provide additional evidence of changes in student achievement. In Namangan, the experimental group changed from 5 high-, 8 medium-, and 9 low-level students before the intervention to 8 high-, 9 medium-, and 5 low-level students after the intervention. The control group changed from 6 high-, 12 medium-, and 8 low-level students to 9 high-, 13 medium-, and 4 low-level students. In Andijan, the experimental group demonstrated an increase in high-level students from 7 to 10 and in medium-level students from 9 to 11, while the number of low-level students decreased from 9 to 4. In the control group, the number of high-level students increased from 4 to 7, the medium-level category remained at 11, and the low-level category decreased from 9 to 6. In Fergana, the experimental group changed from 6 high-, 9 medium-, and 11 low-level students to 8 high-, 12 medium-, and 6 low-level students. The control group changed from 5 high-, 10 medium-, and 10 low-level students to 10 high-, 11 medium-, and 4 low-level students. Across all three institutions, a consistent decrease in the number of students at the low achievement level can be observed. The most pronounced decrease in the experimental group occurred in Fergana, where the number of low-level students decreased from 11 to 6, while in Andijan it decreased from 9 to 4. In Namangan, the corresponding decrease was from 9 to 5.

Overall, the results demonstrate a positive shift in students' laboratory learning outcomes following the instructional intervention. In the experimental group, the number of students classified at the high achievement level increased from 18 to 26, while the number of low-level students decreased from 29 to 15. The corresponding changes in the control group were from 15 to 26 and from 27 to 14, respectively.

The most important descriptive finding is the substantial reduction in the proportion of low-achieving students in both groups. However, the available descriptive data indicate that improvements were also observed under conventional laboratory instruction. Therefore, the effectiveness of the proposed AI-based methodology should not be inferred solely from the observed percentage changes.

To establish whether the differences between the experimental and control conditions are statistically meaningful, the observed frequencies should be subjected to an appropriate inferential statistical test. Such an analysis will allow the study to determine whether the observed changes can reasonably be attributed to the implementation of the AI-based methodology rather than to general improvement associated with laboratory instruction itself.

To determine whether the observed changes in students' laboratory learning outcomes were statistically significant, a chi-square (χ^2) test of independence was applied to the distribution of students across the high, medium, and low achievement levels. For the experimental group, the comparison of pre-intervention and post-intervention achievement distributions produced a statistically significant difference, $\chi^2(2) = 6.53$, $p = .038$. This result indicates that the distribution of students across the three achievement levels changed significantly following the implementation of the AI-supported laboratory methodology.

A statistically significant change was also observed in the control group, $\chi^2(2) = 7.13$, $p = .028$. Thus, the improvement observed in the experimental group cannot be interpreted exclusively as an effect of AI-based instruction, since a statistically significant change was also identified under conventional laboratory instruction.

To determine whether the two groups differed at the end of the intervention, their post-intervention achievement distributions were compared. The analysis revealed no statistically significant difference between the experimental and control groups, $\chi^2(2) = 0.142$, $p = .932$. The two groups were also statistically comparable before the intervention, $\chi^2(2) = 1.148$, $p = .563$, indicating that there was no statistically significant difference in their initial achievement distributions.

These findings require a cautious interpretation of the effectiveness of the proposed AI-based methodology. Although significant improvement occurred within the experimental group, a comparable statistically significant improvement was also observed in the control group. Furthermore, the post-intervention comparison did not reveal a statistically significant difference between the groups. Therefore, the present data do not provide sufficient statistical evidence to conclude that the AI-based methodology was superior to conventional laboratory instruction in terms of the three-level achievement distribution.

Nevertheless, the descriptive results demonstrate a substantial reduction in the proportion of low-achieving students in the experimental group, from 39.7% to 20.5%, accompanied by an increase in the proportion of students at the high and medium achievement levels. These findings provide preliminary evidence of the pedagogical potential of the AI-supported methodology and justify further investigation using larger samples, more sensitive competency-based assessment instruments, and longer intervention periods.

CONCLUSION

The present study developed and examined an AI-based methodology for improving physics laboratory instruction in Internal Affairs Academic Lyceums. The proposed methodology was designed as an integrated pedagogical framework in which Artificial Intelligence supports several stages of the laboratory learning cycle, including diagnostic preparation, pre-laboratory learning, experimental guidance, data processing, formative feedback, and competency-based assessment.

The empirical study involved 148 students from three Internal Affairs Academic Lyceums in Namangan, Andijan, and Fergana. The participants were divided into an experimental group of 73 students and a control group of 75 students. The learning outcomes were evaluated according to three achievement levels: high, medium, and low.

The findings demonstrate positive changes in both groups following the instructional intervention. In the experimental group, the number of students at the high achievement level increased from 18 to 26, while the number of students at the low achievement level decreased from 29 to 15. At the same time, the number of medium-level students increased from 26 to 32. Similar positive changes were observed in the control group, where the number of high-level students increased from 15 to 26 and the number of low-level students decreased from 27 to 14.

These results suggest that systematic organization of physics laboratory activities can contribute to improved student learning outcomes. The observed changes in the experimental group are consistent with the proposed pedagogical rationale for AI-supported laboratory instruction, particularly with regard to individualized preparation, guided experimentation, experimental data processing, feedback, and independent analytical activity.

However, the results also demonstrate improvement in the control group. Therefore, the present descriptive findings alone do not provide sufficient evidence to conclude that the AI-based methodology is statistically superior to conventional laboratory instruction. A rigorous inferential statistical analysis is required to determine the statistical significance and practical magnitude of the differences between the two groups.

An important pedagogical implication of the study is that Artificial Intelligence should not be considered a replacement for physical experimentation or teacher guidance. Its educational value is more appropriately realized when AI is integrated as a methodological support mechanism that helps students prepare for experiments, process experimental data, interpret results, receive formative feedback, and develop independent scientific reasoning. This principle is consistent with the methodological framework developed in the present study.

The study also confirms the importance of combining technological innovation with pedagogical supervision. Since AI-generated information may contain inaccurate or misleading explanations, students should be encouraged to critically evaluate AI-generated responses and verify them against physical laws, experimental evidence, calculations, and teacher guidance.

Overall, the developed methodology provides a promising framework for integrating Artificial Intelligence into physics laboratory instruction in specialized academic lyceums. Its principal contribution lies not in the use of AI as an independent technological tool, but in its systematic integration into the laboratory learning cycle. Further research should involve larger samples, longer intervention periods, more detailed competency-based assessment instruments, and inferential statistical analysis in order to establish the generalizability and effectiveness of the proposed methodology across different educational contexts.

REFERENCES

1. Almasri, F. (2024). Exploring the impact of artificial intelligence in teaching and learning of science: A systematic review of empirical research. Research in Science Education, 54, 977–997. https://doi.org/10.1007/s11165-024-10176-3
2. Asiksoy, G. (2023). Effects of virtual lab experiences on students' achievement and perceptions of learning physics. International Journal of Online and Biomedical Engineering, 19(11), 31–41. https://doi.org/10.3991/ijoe.v19i11.39049
3. Ben-Zion, Y., Carroll, T. K., West, C. G., Wong, J., & Finkelstein, N. D. (2026). Leveraging generative artificial intelligence for simulation-based physics experiments: A new approach to virtual learning about the real world. Physical Review Physics Education Research, 22(1), 010109. https://doi.org/10.1103/s8dy-kqy5
4. Ben-Zion, Y., Zarzecki, R. E., Glazer, J., & Finkelstein, N. D. (2025). Leveraging AI for rapid generation of physics simulations in education: Building your own virtual lab. The Physics Teacher, 63(6), 424–427. https://doi.org/10.1119/5.0252343
5. Mahligawati, F., Allanas, E., Butarbutar, M. H., & Nordin, N. A. N. (2023). Artificial intelligence in physics education: A comprehensive literature review. Journal of Physics: Conference Series, 2596, 012080. https://doi.org/10.1088/1742-6596/2596/1/012080
6. Ogunleye, B., Zakariyyah, K. I., Ajao, O., Olayinka, O., & Sharma, H. (2024). A systematic review of generative AI for teaching and learning practice. Education Sciences, 14(6), 636. https://doi.org/10.3390/educsci14060636
7. Yeadon, W., & Hardy, T. (2024). The impact of AI in physics education: A comprehensive review from GCSE to university levels. Physics Education, 59(2), 025010. https://doi.org/10.1088/1361-6552/ad1fa2
8. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? International Journal of Educational Technology in Higher Education, 16, 39. https://doi.org/10.1186/s41239-019-0171-0