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RESEARCH ARTICLE

Advancing Learning Outcomes in Physics Education through Artificial Intelligence Integration

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ABSTRACT

The integration of artificial intelligence (AI) into Physics education has emerged as a prominent area of innovation in recent years. This study investigates the influence of AI-based tools on student learning outcomes, conceptual comprehension, and academic performance in four different introductory physics courses at the undergraduate level in the University of Bahrain. Through an analysis of engagement metrics, academic performance data, and student feedback collected from AI-enhanced instructional settings, it was evident that AI-supported pedagogical approaches can lead to measurable improvements in conceptual mastery, problem-solving proficiency, and overall learner satisfaction. These results suggest a potential paradigm shift in STEM education methodologies, highlighting the transformative role of AI in modern pedagogical practices.

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1. Introduction

Physics, as one of the foundational pillars of scientific inquiry, is essential for understanding the natural world and underpins many technological and engineering advancements. However, the subject is frequently perceived as intellectually demanding due to its abstract concepts, mathematical rigor, and the integration of theoretical and experimental reasoning. These challenges are particularly pronounced at the introductory level, where students must simultaneously develop conceptual models, quantitative skills, and scientific thinking. As a result, many learners experience cognitive overload and disengagement, contributing to suboptimal learning outcomes and reduced interest in STEM fields.

Traditional pedagogical methods, such as primarily lecture-based instruction, textbook problem sets, and summative assessments, often fail to accommodate the diverse learning preferences and prior knowledge of students. Such approaches may inadequately support the development of conceptual understanding and critical thinking skills, particularly in large classroom settings where personalized feedback is limited (Freeman *et al.*, 2014). These shortcomings underscore the urgent need for innovative instructional strategies that can promote deeper engagement, individualized learning trajectories, and sustained academic success in physics education (Hake, 1998).

Recent advances in artificial intelligence (AI) offer promising avenues for transforming the teaching and learning of physics (Pedró Francesc *et al.*, 2019). AI technologies such as intelligent tutoring systems (ITS), adaptive learning environments, and large language models (LLMs) like ChatGPT are capable of delivering real-time, personalized feedback, simulating interactive learning experiences, and scaffolding student understanding based on individual performance and learning patterns (Zawacki-Richter *et al.*, 2019). These tools are increasingly being integrated into educational settings, with emerging evidence suggesting their potential to augment instruction, enhance motivation, and improve academic achievement.

Several studies have evaluated the role of AI in science education. AI-driven tools like intelligent tutoring systems (ITS) offer real-time feedback, simulate experiments, and adapt to individual learning paths. Research shows that these tools enhance learning efficiency, especially in abstract disciplines like physics (Anderson *et al.*, 1995). Adaptive learning platforms such as Knewton and ALEKS have been deployed in physics classrooms to personalize content delivery. Generative AI, including tools like ChatGPT, has been explored for its capacity to facilitate homework help, conceptual explanations, and programming support for simulations (Boulay, 2022).

This manuscript investigates the impact of AI integration on the teaching and learning of key concepts in introductory physics courses taught at the University of Bahrain for undergraduate students, focusing on core domains, including Newtonian mechanics, thermodynamics, electromagnetism, and wave phenomena. Specifically, the study examines how the incorporation of AI tools influences student learning outcomes, fosters conceptual understanding, and promotes active engagement. The research also explores student perceptions of AI-assisted learning environments, offering insights into the pedagogical affordances and challenges associated with these technologies. Quantitative data, including pre- and post-test scores, problem-solving accuracy, and engagement metrics, are complemented by qualitative feedback obtained through surveys and interviews. AI tools deployed in this study include generative models for answering conceptual questions, adaptive platforms for simulation-based learning, and real-time feedback systems for formative assessment.

2. Methodology

This study was implemented at the University of Bahrain. Data were collected over different academic semesters, such as Spring 2022–2023, Fall 2023–2024, and Spring 2024–2025. A total of 320 undergraduate students enrolled in introductory physics courses participated in the study. These students were systematically divided into control and experimental groups to facilitate a quasi-experimental design.

The experimental groups were instructed using a blended approach that integrated artificial intelligence (AI) tools alongside conventional pedagogical methods. The AI-enhanced instructional framework comprised three key components:

(i) ChatGPT was used as a conversational agent for real-time conceptual question-and-answer support. (ii) PhET Simulations were augmented with AI-generated guidance to scaffold exploration of core physics principles through interactive visualization.

(iii) Finally, AI-Based Assessment Feedback System was deployed to provide immediate, personalized feedback on formative and summative assessments.

The control groups received traditional instruction without AI integration, relying solely on lectures, tutorials, lab hours, textbooks, and instructor-led problem-solving sessions. Data collection employed a mixed-methods approach, incorporating both quantitative and qualitative measures. Quantitative data were gathered through pre- and post-instruction tests, with the Force Concept Inventory (FCI) serving as the primary instrument for assessing conceptual understanding. Additional metrics included performance in problem-solving tasks and standardized instructor assessments. Qualitative insights were derived from student surveys, semi-structured interviews, and classroom observations, offering a multidimensional view of learner engagement and satisfaction.

Question Design: Assessment instruments were carefully constructed to evaluate students' conceptual grasp of foundational physics topics, particularly Newtonian mechanics, energy conservation, and field theory. Core items were adapted from the established FCI, supplemented by instructor-developed questions tailored to the course syllabus. These items emphasized qualitative reasoning, diagnostic probing of misconceptions, and clarity of conceptual understanding. Illustrative examples include: "*Why does a ball continue moving after it leaves the hand?*" and "*What happens to the net force on an object in equilibrium?*" Such questions aimed to challenge intuitive misunderstandings and promote a deeper engagement with the underlying physics principles. This methodological framework enabled a robust comparison between AI-assisted and traditional instructional modalities, laying the foundation for subsequent analysis of learning gains, engagement metrics, and student perceptions.

3. Results

3.1. Conceptual Understanding

A comparison of normalized gain scores on the FCI between a control group and an experimental group is presented in Fig. 1. The FCI is a widely used instrument for assessing conceptual understanding of Newtonian mechanics. Normalized gain, calculated using Hake's formula (Hake, 1998), represents the actual gain as a fraction of the maximum possible gain, providing a measure of learning effectiveness that accounts for differences in pre-test scores. The experimental group, which received AI-assisted instruction, demonstrated a substantially higher normalized gain (mean gain = 0.55) compared to the control group (mean gain = 0.35). The superior performance of the experimental group can be attributed to the interactive and adaptive nature of AI-driven learning platforms. These tools provided immediate conceptual feedback and personalized scaffolding, which enabled students to clarify misunderstandings in real time and to receive guidance tailored to their learning trajectories. Students reported increased comprehension, particularly in Newtonian dynamics and energy conservation topics. The continuous, responsive support helped address gaps in prior knowledge and encouraged independent exploration. The error bars, representing standard error, suggest that the difference between the two groups is statistically significant.

These results align with recent research highlighting the potential of AI in education. For example, studies

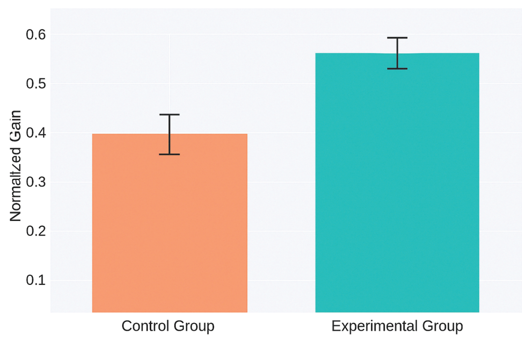

Fig. 1. Comparison of normalized gains in Force Concept Inventory scores between control and experimental groups.

have shown that AI-powered personalized learning systems can adapt to individual student needs, leading to improved learning outcomes (Wayne Holmes & Fadel, 2019). The AI-assisted instruction likely provided students with personalized feedback, adaptive learning pathways, and interactive simulations, which facilitated a deeper and more robust understanding of the fundamental concepts. Furthermore, the use of AI can help address the limitations of traditional instruction by providing scalable solutions for personalized learning (Akinwalere & Ivanov, 2022). Moreover, instructors observed a qualitative shift in classroom dynamics. AI-supported sessions fostered richer discussions, with students demonstrating greater initiative in questioning and reasoning. There was also a discernible decrease in recurring conceptual errors, suggesting deeper cognitive engagement and internalization of fundamental principles. Overall, the integration of AI tools significantly contributed to more effective and meaningful learning experiences.

Table I presents a comparative analysis of student performance between the control group (traditional instruction) and the experimental group (AI-enhanced instruction) across key topics in introductory physics. The data reveal consistent improvements in the experimental group, with the most notable gains observed in Newtonian mechanics (82% vs. 68%), followed by electromagnetism (80% vs. 64%), waves and optics (79% vs. 66%), and thermodynamics (77% vs. 62%). These results suggest that AI-supported learning methodologies contribute to enhanced conceptual understanding and problem-solving proficiency compared to conventional teaching approaches. The observed performance differentials, ranging from 12 to 15 percentage points across all topics, underscore the potential of AI integration in improving physics education outcomes.

3.2. *Problem-Solving Ability*

The incorporation of AI tools significantly enhanced students' problem-solving competencies by delivering instantaneous feedback and guiding learners through structured, logical steps. As depicted in Fig. 2, the experimental group demonstrated a higher percentage of accurate solutions to multi-step physics problems compared to the control group. In addition to improved solution accuracy, students in the AI-assisted group exhibited noticeable development in metacognitive strategies. These included the ability to select appropriate equations, apply them within context, and evaluate the plausibility of their solutions (Niebert & Gropengiesser, 2014). The AI-supported environment enabled students to actively monitor their thought processes and make adjustments in real time, contributing to more effective problem-solving.

TABLE I: Comparative Percentage Scores Across Physics Subtopics for Control and AI-Assisted Groups

Topic	Control group (%)	Experimental group (%)
Newtonian mechanics	68	82
Thermodynamics	62	77
Electromagnetism	64	80
Waves & Optics	66	79

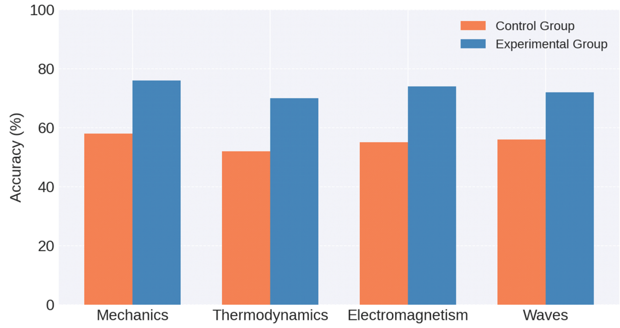

Fig. 2. Percentage of students accurately solving multi-step physics problems in both control and experimental groups.

Future research should prioritize identifying specific intervention components and aligning them with established learning theories, such as constructivism or cognitive load theory (Paas *et al*., 2003). Rigorous control of confounding variables and detailed demographic analysis are also necessary to establish the intervention's generalizability and furthermore, interactive sessions facilitated by AI tools encouraged learners to externalize and articulate their reasoning, a practice closely associated with deeper cognitive engagement and durable learning. Several students reported increased confidence when approaching unfamiliar or complex problems, citing the nonjudgmental, responsive nature of AI tools as instrumental in reducing performance anxiety and supporting iterative exploration (Inoferio *et al*., 2024). This adaptive feedback loop promoted a safe learning space where students could experiment with strategies, reflect on mistakes, and refine their approach without fear of penalization.

3.3. *Student Engagement and Feedback*

A comparative engagement score between a "Control Group" and an "Experimental Group" across four distinct metrics, such as Interest in Lessons, Class Participation, Homework Completion, and Conceptual Questions, is presented in Fig. 3. Engagement scores are quantified on a Likert-type scale ranging from 1 to 5, where higher values indicate greater engagement. A consistent pattern is evident across all four engagement metrics. The Experimental Group exhibits significantly higher engagement scores compared to the Control Group. Specifically, the most notable difference is observed in "Interest in Lessons" and "Conceptual Questions," suggesting that the student engagement within the AI-assisted cohort effectively fostered both intrinsic motivation and deeper cognitive engagement. The differences in "Class Participation" and "Homework Completion," while still significant, are comparatively smaller, indicating a broader impact of the AI-intervention beyond mere task completion.

This data suggests that AI tools positively influenced student engagement across multiple dimensions. Enhanced engagement, particularly in areas like conceptual understanding and interest, has been shown to correlate with improved learning outcomes and academic achievement (Fredricks *et al*., 2016). The availability of immediate conceptual clarification, interactive simulations, and adaptive feedback mechanisms significantly contributed to an enriched learning experience. Students consistently

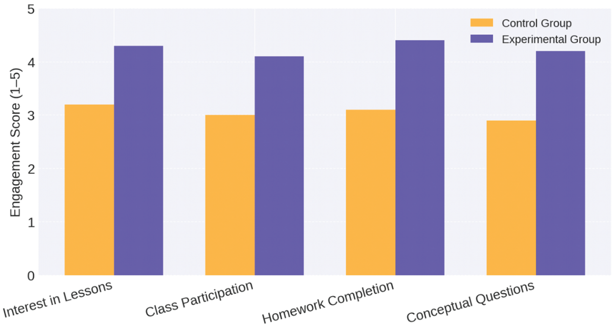

Fig. 3. Student self-reported engagement levels during AI-enhanced vs. traditional instruction, measured using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

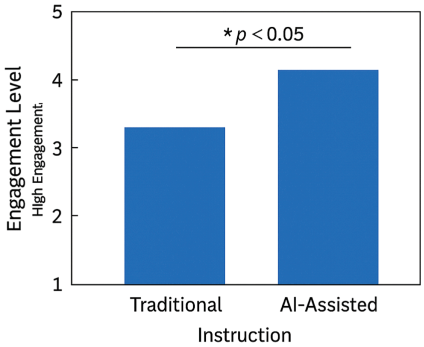

Fig. 4. Student self-reported engagement levels during AI-enhanced vs. traditional instruction, measured using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

expressed appreciation for the responsive and interactive nature of AI-enhanced instruction, which allowed them to address confusion in real time and remain actively involved in their learning process. The consistent improvement across diverse engagement metrics implies that AI intervention's effectiveness is not isolated to a single aspect of student involvement but rather promotes a holistic enhancement of engagement. Further investigations by aligning AI tools with established engagement theories, such as self-determination theory or flow theory, would be beneficial (Ben-Eliyahu *et al.*, 2018).

From a pedagogical standpoint, AI tools added a layer of personalization that is often lacking in traditional lecture-based formats. These systems fostered greater learner agency, enabling students to explore content at their own pace and revisit difficult concepts as needed. The ability to engage with AI interfaces outside scheduled class hours further supported continuous learning and reflection. Notably, instructors observed increased participation among students who were typically passive or disengaged. The anonymity and immediate feedback provided by AI tools appeared to reduce the anxiety often associated with public classroom discourse, thereby encouraging more learners to contribute and collaborate (Inoferio *et al.*, 2024). This aligns with emerging research emphasizing the role of digital tools in fostering inclusive and equitable educational environments.

Complementing this, Fig. 4 reinforces the positive impact of the intervention by depicting a statistically significant increase in overall engagement levels among students exposed to AI-assisted instruction, relative to those receiving traditional instruction. Given that the experimental intervention likely incorporated AI-based instructional strategies, our findings substantiate and extend the domain-specific improvements observed in Fig. 3. This convergence of evidence across different measurement perspectives, both detailed and aggregate, demonstrates the internal consistency and external validity of the results. These findings not only reinforce the credibility of the observed effects but also highlight the potential of AI-assisted instructional methods to meaningfully enhance student engagement (Wayne Holmes & Fadel, 2019; Zawacki-Richter *et al.*, 2019). This synthesis of evidence bolsters the overall validity of the study and affirms the utility of the intervention in educational contexts seeking to leverage technology for pedagogical improvement.

TABLE II: Sample Qualitative Student Feedback Highlighting Perceived Benefits of AI-based Learning Tools

Feedback category	Representative comment
Conceptual clarity	"ChatGPT explained concepts better than the book."
Accessibility	"I could study at my own pace with AI tools."
Motivation	"It made physics more fun and less intimidating."

Table II summarizes qualitative feedback from experimental group participants regarding the AI-integrated learning intervention, revealing three key categories: Conceptual Clarity, exemplified by "ChatGPT explained concepts better than the book," indicating enhanced understanding through AI explanations; Accessibility, highlighted by "I could study at my own pace with AI tools," showcasing the intervention's flexibility; and Motivation, as shown by "It made physics more fun and less intimidating," suggesting a positive affective shift. These representative comments, derived from thematic analysis, underscore the AI intervention's perceived benefits in clarifying concepts, providing personalized learning, and improving student motivation, complementing quantitative findings by offering a nuanced understanding of its impact.

4. Discussion

While the integration of AI tools presents opportunities to enhance learning, several challenges warrant careful consideration. A potential over-reliance on AI for problem-solving is a concern, potentially hindering the development of students' metacognitive skills (Azevedo *et al.*, 2013). The risk of encountering misinformation generated by these tools is also a significant challenge, demanding robust fact-checking and source evaluation strategies. The digital divide, which affects equitable access to technology, also poses a substantial challenge, potentially exacerbating existing inequalities (Drljić *et al.*, 2025). Educators must, therefore, strive to maintain a balance between leveraging AI support and fostering the development of students' critical thinking skills, ensuring that AI serves as a supplement rather than a replacement for human cognition. Furthermore, it is crucial to provide instructors with adequate training to effectively integrate AI into their pedagogical practices, including strategies for addressing the aforementioned challenges. To ensure the quality and reliability of AI-supported learning, ongoing auditing of AI-generated content and alignment with curriculum standards are also necessary. The ethical dimensions of AI integration in education also demand attention. Issues such as academic integrity, data privacy, and the potential for algorithmic bias must be critically addressed (Miao Fengchun *et al.*, 2021). Students may become overly dependent on AI-generated solutions, potentially hindering the development of deep conceptual understanding. Educational institutions must ensure that AI tools do not inadvertently perpetuate existing biases or exacerbate inequalities. Establishing clear guidelines for the responsible use of AI and promoting digital literacy among both students and educators are essential strategies for mitigating these risks.

5. Conclusion

AI presents transformative potential in physics education. When strategically implemented, AI tools enhance conceptual learning, problem-solving, and engagement. The evidence from this study supports broader adoption of AI in STEM education, with proper guardrails and pedagogical design. The findings of this study align with constructivist and socio-cultural theories of learning, which emphasize active engagement, scaffolding, and the role of feedback in knowledge construction. AI tools provide timely support and personalized learning pathways that echo Vygotsky's concept of the Zone of Proximal Development. Moreover, instant feedback and adaptive problem-solving emulate principles from formative assessment and metacognitive development, reinforcing learner autonomy.

5.1. Limitations and Future Directions

Although this study provides compelling evidence for the positive impact of AI integration in introductory physics education, several limitations should be considered. First, the study's scope was limited to a few introductory courses, which may constrain the generalizability of the findings to diverse educational contexts and cultural settings. Variability in instructor proficiency with AI tools may have also influenced the observed outcomes, highlighting the need for standardized training protocols. Second, the assessment focused on short-term gains in conceptual understanding and problem-solving. The long-term retention and transferability of knowledge were not measured. Future longitudinal research should investigate the sustained impact of AI-assisted learning on academic performance and the development of higher-order scientific reasoning skills. Additionally, the reliance on tools such as ChatGPT introduces the risk of overdependence, where students may prioritize convenience over the development of critical thinking abilities. As generative AI technologies continue to evolve, ensuring the accuracy and relevance of their outputs is paramount. This necessitates future research into the development of AI validation protocols and mechanisms for real-time content auditing (Jürgen Rudolph & Tan, 2023). Future research directions include the development of hybrid pedagogical models that effectively blend AI-assisted instruction with active learning strategies, such as peer instruction and flipped classrooms. Investigating the role of AI in formative assessment, collaborative learning, and differentiated instruction could further elucidate its pedagogical value. Moreover, interdisciplinary studies examining the role of AI in enhancing equity, accessibility, and learner motivation will be crucial for promoting informed and inclusive implementation strategies.

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