July 2025 **Volume 2, Issue 3**
JOURNAL OF EDUCATION STUDIES IN PHYSICS
a quarterly publication to be a source for researchers in physics and science
THIS ARTICLE IS AVAILABLE ONLINE AT
https://physics.cfu.ac.ir/
ORIGINAL RESEARCH PAPER

Physics Education in the Age of Artificial Intelligence

Ghadir Jafari *, [1]
[1]*Department of Physics Education, Farhangian University, Tehran, Iran.*

ABSTRACT

In this article, we argue that the development of artificial intelligence (AI) necessitates a fundamental rethinking of educational content and strategies. To substantiate our claim, we explore the interplay between human and machine learning, underscoring both their similarities and differences, and contend that curricula must be fundamentally redesigned to harness AI as an opportunity rather than merely confront it as a challenge. Emphasizing physics education, we propose that AI can handle repetitive, data-intensive, or algorithmic tasks, freeing students to focus on core conceptual and analytical skills. Key competencies such as computational thinking, critical reasoning, scientific modeling, data analysis, and interdisciplinary problem-solving are identified as central to a modern physics curriculum. Using Newtonian mechanics as a case study, we illustrate how AI-supported teaching can reinforce conceptual understanding, foster independent reasoning, and cultivate authentic physicist skills. By integrating AI thoughtfully, education can transform into a dynamic process that enhances learning outcomes, scientific creativity, and prepares students for the evolving demands of contemporary science.

Keywords:
Education, Artificial Intelligence, Physics Education, Machine Learning,

1 .Corresponding author:
Gh.jafari@cfu.ac.ir

The Journal of Educational Studies in Physics **DOI:** 10.48310/esip.2025.20919.1021

Received: 2025-09-17
Reviewed: 2025-09-23
Accepted: 2025-09-28
Pages: 7 to 20

Citation (APA): Jafari, *Gh, (2026). "Physics Education in the Age of Artificial Intelligence". .Educ. Stud. Phys., 2(3), 7-20.*
.Educ. Stud. Phys., 2(3), 7-20.
: 10.48310/esip.2025.20919.1021

INTRODUCTION

In recent years, the rapid advancement of artificial intelligence (AI) has sparked increasing interest in its applications to education. Most of the current discussions, however, approach AI primarily as a facilitator of existing practices. In this view, AI is understood as a tool to make traditional teaching and learning processes more efficient: instructors use AI to generate lesson plans, exercises, or exam questions, while students employ AI to solve problems or to practice conventional tasks more effectively (Zawacki-Richter et al., 2019; Holmes et al., 2022). In essence, AI is treated as an external support for *unchanged content* and *longstanding methods*.

While such applications may indeed enhance efficiency, they risk obscuring a deeper and more urgent question: *Does the very existence of AI require us to reconsider the content and goals of education itself?* This question is especially pressing in physics education, where traditional curricula—largely unchanged for decades—face long-standing challenges. Students often perceive physics as abstract, disconnected from everyday life, and less engaging compared to the rapidly evolving world of digital technologies and interactive media (Redish, 2003; Meltzer & Thornton, 2012). The growing disinterest and lack of motivation among learners highlight a structural problem in how physics has been taught.

The emergence of AI has added new layers to these challenges. Many educators now express concern that students rely on AI systems to solve problems instead of engaging with them directly, leading to weaker individual problem-solving skills (Luckin, 2018). AI is frequently framed as the "culprit" responsible for diminishing student effort and conceptual grasp. Yet, an alternative interpretation is possible: *what if the problem lies not in AI itself, but in an outdated educational model that has failed to adapt to new realities?*

From this perspective, the arrival of AI should not be seen merely as a threat to teaching practices, but rather as an opportunity to rethink them. If AI can perform many of the routine problem-solving tasks that once structured physics education, then perhaps curricula should shift toward developing deeper conceptual understanding, critical thinking, and creative reasoning—skills that remain uniquely human (Mitchell, 2019; Holmes et al., 2022). In this sense, AI may act as a catalyst, forcing us to reevaluate long-held assumptions about what is essential in physics education and to design content that is more meaningful, engaging, and aligned with the needs of the twenty-first century.

In this article, we argue that the rise of AI should not be understood merely as a technological enhancement of traditional physics teaching, but as a turning point that necessitates a fundamental reconsideration of educational content. To develop this argument, we first provide a brief overview of how AI works, with a particular emphasis on the role of *machine learning* in contrast to classical algorithmic approaches. From this perspective, since the fundamental concept in AI is "learning" itself, the connection between education and AI goes beyond mere application. This raises a central question: what is the relationship between learning in machines and learning in humans? Therefore, we then compare learning in humans and machines in order to highlight the distinctive skills that human learners must cultivate in the AI era. Building on these foundations, we explore how physics education needs to be restructured, not only in teaching methods but also—more importantly—in curricular content. Finally, we illustrate this perspective with a forward-looking example concerning the teaching of Newton's laws, before concluding with broader implications for the future of physics education.

What is Artificial Intelligence and How Does It Work?

Today, AI has become an integral part of daily life, embedded in smartphones, search engines, recommendation systems, navigation tools, voice assistants, and even advanced medical technologies (Russell & Norvig, 2021). But what does AI actually mean? At its core, AI refers to the ability of machines to perform tasks that would normally require human intelligence, such as language understanding, pattern recognition, decision-making, and problem solving (Nilsson, 2010). But, it could be said that there is two general kind intelligent tasks that are performed by people. To clarify this, consider the following two tasks:

1. *Image recognition.* If a human is shown a picture of a dog, they can immediately recognize it and identify it as a *dog*.
2. *Solving a mathematical problem.* If the same person is given a quadratic equation, they can use a set of logical steps to arrive at the solution, provided they have the relevant mathematical knowledge.

The second case can be described by an explicit sequence of rules, which makes it straightforward to encode in a computer program. Indeed, computers have long been able to perform such algorithmic tasks with high accuracy. The first case, however, involves complex cognitive processes that humans typically explain in vague terms—"I just learned to recognize it." This highlights a fundamental distinction: while some problems can be solved using explicit, predefined rules, others require *learning from experience*. The central achievement of modern AI is precisely this: machines that can *learn* from data, a field known as machine learning (ML) (Goodfellow, Bengio, & Courville, 2016). In machine learning, instead of explicitly programming rules, we provide the system with large amounts of input–output data. The machine then infers underlying patterns that allow it to make predictions or decisions for new, unseen inputs. This approach underpins many widely used AI applications today, including email spam filters, natural language processing, chatbots and large language models, and diagnostic tools in medicine (Jordan & Mitchell, 2015). In all of these cases, the common feature is the reliance on large datasets and algorithms capable of extracting patterns to generate predictions or classifications.

It is therefore important to distinguish between artificial intelligence in general and machine learning in particular:

- **Artificial intelligence** refers to any system capable of performing tasks that require "intelligence," whether through explicitly coded rules or adaptive methods.
- **Machine learning** is a subset of AI in which machines improve their performance on a task by learning patterns from data rather than by following rules explicitly defined by programmers (Chollet, 2021).

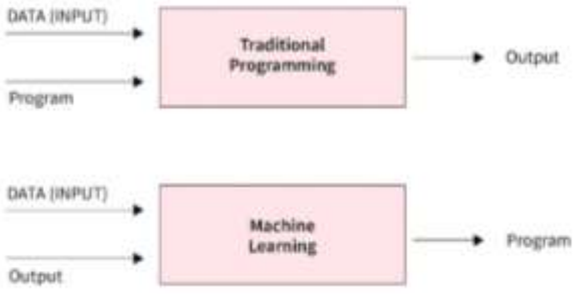

Figure 1 Classical Programming Vs Machine Learning

This contrast can be illustrated by comparing traditional programming with machine learning (see Figure 1). In classical programming, humans design algorithms with precise rules that the computer executes. In machine learning, by contrast, the system is given data and expected outputs; the computer itself adjusts internal parameters to discover the mapping between inputs and outputs.

How Do Machines Learn?

To illustrate how machine learning works, consider a simple case. Suppose we want to model the relationship between two variables, x and y, where the true relationship is given by $y = 3x + 2$. In a classical programming approach, we could encode this exact formula into a program, and the computer would compute y for any given x. No learning occurs; the computer simply executes predefined instructions.

Now imagine instead that we are given only a set of paired data points (x_i, y_i) without knowing the underlying equation. Our task is to build a model that can predict y for new values of x. A simple model might assume a linear form:

$$y = f(x) = ax + b$$

Here, the parameters a and b are unknown. The process of learning consists of finding the values of a and b that best fit the data. To evaluate the quality of the model, we define a *cost function*:

$$C(a, b) = \sum_{i=1}^{N} \left(y_i - y_i(a, b)\right)^2$$

where y_i is the observed value and $y_i(a, b)$ is the predicted value for the i-th data point. The goal of learning is to minimize this cost function, i.e., to reduce the prediction error as much as possible.

In simple cases, calculus can be used to find the exact minimum. In realistic applications, however, models may have millions or even trillions of parameters, as in modern language models such as GPT, and the optimization problem becomes highly complex. In such contexts, the most widely used approach is *gradient descent*. This algorithm can be understood through an analogy: imagine standing on a mountain in thick fog, unable to see the valley floor. The best strategy to reach the bottom is to take small steps in the steepest downward direction. Similarly, gradient descent updates the model parameters iteratively in the direction that reduces the cost function most rapidly, gradually converging toward an optimal solution (Goodfellow et al., 2016).

Thus, machine learning enables computers not merely to execute explicit rules but to approximate solutions by discovering patterns within vast datasets. This distinction between *rule-based programming* and *data-driven learning* is at the heart of modern AI, and it sets the stage for rethinking how we conceptualize learning itself—an issue that has profound implications for physics education in the AI era.

Lessons from Artificial Intelligence for Education

The process of machine learning resembles human learning in several respects. By examining these parallels—and also the key differences—we can extract valuable lessons for improving educational practices. It should be emphasized, however, that such comparisons are not intended to reduce human learning to a purely mechanical process. Instead, the goal is to use insights from artificial intelligence (AI) as a lens to rethink how teaching and learning can be made more effective in the human context.

Parallels and Lessons

1. **Learning through Experience Rather than Rule Memorization**, In classical programming, computers are given explicit rules and generate outputs based on these rules. In contrast, machine learning systems are provided with datasets of inputs and outputs, from which they extract underlying patterns. This is analogous to experiential learning in humans, where understanding develops through interaction rather than rote memorization. Traditional education often emphasizes the memorization of rules, yet genuine human learning occurs more effectively through engagement and experience. For instance, in language acquisition, children naturally learn grammar through immersion and communication rather than through formal grammar instruction. Rules emerge implicitly in the learner's mind without being explicitly taught (Krashen, 1982).

2. **The Importance of Diversity in Examples**, A major challenge in machine learning is overfitting—when models memorize training data without truly generalizing (Bishop, 2006). A similar issue arises in human education when learners encounter overly repetitive and structurally similar exercises. Research shows that varied, meaningful, and contextually relevant examples promote deeper learning (Ambrose et al., 2010). For example, in physics, presenting Newton's second law only through repetitive, abstract problems like "a 2 kg object is acted upon by a 4 N force" encourages rote memorization rather than conceptual understanding. By contrast, using diverse and concrete contexts—cars, birds, fish, or other real-world systems—encourages learners to connect abstract laws with lived experience.

3. **Testing Knowledge in Novel Contexts**, Machine learning models cannot be evaluated on training data alone; their performance must be tested on new inputs. Similarly, human assessments should go beyond rehearsed problems to probe conceptual transfer. Effective education requires challenges in unfamiliar situations, which better reflect authentic understanding and foster flexible application of knowledge.

4. **The Role of Error and Feedback**, In machine learning, errors are not failures but essential signals for improvement. Models iteratively refine their performance by learning from mistakes. Human learning is similar: errors should be framed as opportunities for growth rather than deficiencies. Constructive feedback loops in education help students move beyond surface learning toward deeper conceptual understanding (Brown et al., 2014).

5. **Continuous Evaluation Instead of Sole Reliance on Final Exams**, Machine learning models are continuously evaluated and optimized during training. Similarly, human learning benefits from ongoing formative assessment rather than relying exclusively on high-stakes final examinations. Periodic quizzes, projects, and peer discussions help track progress and encourage reflection (Wiggins & McTighe, 2005).

6. **The Importance of Data and Instructional Design**, Just as poor-quality or disorganized data hinder machine learning models, weakly structured or poorly presented teaching materials undermine human learning. Effective education requires clear, well-organized content and carefully chosen representations—visuals, real-world analogies, and structured scaffolding—to aid comprehension.

7. **Hybrid and Multi-Modal Learning**, AI has advanced significantly by integrating multiple learning paradigms, such as supervised, unsupervised, and reinforcement learning. Likewise, effective education should integrate multiple pedagogical strategies: experiential projects, collaborative problem-solving, critical reflection, and guided instruction. Such combinations enhance both engagement and conceptual depth (National Research Council, 2000).

8. **Clear Learning Objectives**, Machine learning models optimize effectively only when clear objectives are defined. The same principle applies in education: teachers and students alike must know the goals of instruction. Explicitly stating what knowledge or skills are expected provides direction and helps align teaching and assessment (Wiggins, 2005).

Taken together, these parallels suggest that adopting principles from machine learning—experiential emphasis, diverse examples, tolerance for error, continuous feedback, and hybrid learning—can make education more adaptive and impactful.

Differences and Further Lessons

Equally important are the fundamental differences between human and machine learning, which themselves highlight key priorities for education:

1. **Transfer Across Domains**, Unlike machines, humans excel at transferring knowledge from one domain to another. Prior learning supports adaptation to new contexts, reducing the need for exhaustive examples. This underscores the importance of interdisciplinary connections in education, where learning in one subject enriches understanding in others (Epstein, 2021).

2. **Learning How to Learn**, Humans possess the meta-cognitive ability to reflect on and refine their own learning strategies—an ability absent in machines, which depend on pre-specified algorithms and hyperparameters. Education should nurture this “art of learning,” giving students autonomy to explore and adopt diverse strategies based on their backgrounds and needs (Carey, 2014).

3. **Multi-Source Learning**, Whereas machine learning is largely restricted to structured data, human learning emerges from a combination of experience, reasoning, observation, and social interaction. Encouraging multi-source and social dimensions of learning strengthens conceptual understanding and applicability (Lave & Wenger, 1991).

4. **Creativity and General Intelligence**, Humans are capable of creative, abstract, and open-ended thinking—capacities that current AI lacks. While machines excel in narrow, domain-specific tasks, human intelligence is general and imaginative. Thus, education must prioritize creativity, problem-solving, and critical thinking rather than repetitive skill acquisition (Nussbaum, 2013).

Education in the Age of Artificial Intelligence

The rise of artificial intelligence compels us to reconsider not only the tools of teaching and learning but also the content and aims of education itself. A central issue is the division of labor between humans and machines in the learning process. Three premises lead to this conclusion. First, the expansion and increasing complexity of scientific knowledge has reached a point where no individual can fully master, or even remain broadly informed about, all disciplines (National Research Council, 2000). Second, as discussed earlier, artificial intelligence systems now exhibit remarkable capacities for pattern recognition, data processing, and adaptive learning (Russell & Norvig, 2021). Third, there remain essential dimensions of human knowledge—particularly creativity, critical judgment, and contextual interpretation—that machines are not capable of replicating (Searle, 1980; Floridi, 2014). Together, these premises suggest a complementary relationship: humans should focus on conceptual understanding and the cultivation of insight, while machines assume tasks involving large-scale data analysis, repetitive processing, or algorithmic learning.

This division of cognitive labor is not historically unprecedented. The trajectory of human civilization shows that as tools evolve, educational expectations shift accordingly. Before the invention of writing, the preservation of knowledge depended on memory; with the emergence of paper and books, humans were freed from memorizing vast bodies of information (Goody, 1986). In the modern era, the advent of digital storage and cloud computing has further reduced the necessity of retaining raw information, as data is instantly accessible (Mayer-Schönberger & Cukier, 2013). A similar transformation occurred with computation: where once humans carried out logical and algorithmic reasoning manually, the invention of mechanical and digital computers allowed machines to take over such tasks, thereby enabling humans to tackle more complex and creative challenges (Denning & Tedre, 2019).

The contemporary expansion of machine learning marks a new stage in this co-evolution of human needs and technological tools. Just as external memory systems relieved the burden of rote memorization, and computational tools relieved the burden of algorithmic calculation, machine learning now promises to relieve the burden of certain forms of learning itself. The scale and complexity of modern knowledge—ranging from genomic data to astrophysical simulations—often exceeds what an individual can meaningfully grasp unaided. Delegating some forms of pattern discovery and adaptive learning to machines is therefore both natural and necessary (Brynjolfsson & McAfee, 2017).

From an educational standpoint, this shift implies a profound rethinking of what learning objectives should be. First, rote memorization of data should no longer be regarded as a primary goal, given the abundance and accessibility of external information. Second, even algorithmic reasoning and rule-based problem-solving, once central to training in mathematics and science, must be reframed: students should be taught how to employ computational tools effectively, while also cultivating *computational thinking*—the ability to formulate problems in ways that can be addressed by machines (Wing, 2006). Most importantly, education in the AI era must prioritize capacities that remain distinctively human: critical reflection, ethical reasoning, interdisciplinary integration, and creative imagination.

In physics education specifically, this means designing curricula that both leverage machine intelligence for routine or large-scale analytical tasks and intentionally emphasize the cultivation of conceptual insight, intuition, and the ability to interpret the significance of results within broader scientific frameworks. The challenge is not to replace human learning with machine learning, but to integrate the two in ways that broaden human perspectives, foster general understanding, and prepare learners for collaboration with intelligent systems rather than competition against them.

Physics Education in the Age of Artificial Intelligence

The general arguments outlined in the previous section apply broadly to education, but they acquire special significance in the teaching and learning of physics. Physics has long been regarded as a paradigmatic science for cultivating rigorous reasoning, mathematical modeling, and experimental inquiry. Yet physics education faces persistent challenges: lack of student motivation, the perception of physics as abstract and irrelevant, excessive emphasis on repetitive problem-solving, and insufficient connection to real-world applications (Redish, 2005; Docktor & Mestre, 2014). In the era of artificial intelligence, these challenges are compounded by students' reliance on AI tools to solve standard textbook problems, which can make traditional pedagogical strategies increasingly obsolete.

Far from being a threat, however, AI should be understood as a catalyst for transforming the very goals of physics education. As argued in the recent essay by Kortemeyer (2025), the failure to acknowledge the profound shifts required by AI may amount to the "boiling frog problem" of physics education: educators may adapt too slowly to incremental changes until it is too late to respond effectively. The key is to recognize that the essential role of physics education is no longer to train students in rote memorization of formulas or in solving narrowly defined problems, but rather to cultivate deeper skills that are uniquely human, while simultaneously preparing students to collaborate with AI tools in authentic scientific inquiry.

In this context, physics curricula must evolve toward prioritizing foundational scientific practices and transferable intellectual abilities. Several interrelated skills should become central objectives. Here we first we emphasis on two central skills of *Critical thinking* and *Computational thinking* and then then specifically mention 15 essential skills that should be objective in physics education.

- **Critical thinking.** Critical thinking emphasizes the ability to interrogate assumptions, question definitions, analyze logical structures, and evaluate the scope and limits of theories models, and claims with skepticism, testing their assumptions and applicability (Facione, 2015).
- **Computational thinking.** Formulating problems in ways that can be addressed algorithmically, and using simulations or numerical methods as exploratory tools (Weintrop et al., 2016). Computational thinking should not be misunderstood as "thinking like a computer." Rather, it is the ability to decompose complex problems into well-defined steps that can be delegated to computational tools, including but not limited to modern AI systems (Wing, 2006; Weintrop et al., 2016).

- **Scientific modeling.** Developing and refining models that capture essential features of physical systems, and recognizing the scope and limitations of those models (Hestenes, 1992).
- **Understanding quantities, approximations, and error.** Appreciating the meaning of measurement uncertainty, orders of magnitude, and the role of approximations in building physical understanding.
- **Experimental design and evaluation.** Constructing experiments, selecting appropriate methods of measurement, and critically assessing the reliability and validity of results.
- **Symmetry and invariance.** Grasping the role of symmetries in formulating and constraining physical laws, from conservation principles to modern theoretical frameworks.
- **Intuitive conceptualization.** Cultivating physical intuition and qualitative reasoning before engaging in formal mathematical derivations.
- **Theory–experiment interplay.** Understanding how empirical evidence shapes theory and how theoretical frameworks guide experimental investigation.
- **Theoretical reasoning.** Using logical and mathematical reasoning to extend or challenge existing theories and to generate new hypotheses.

- **Axiomatic and structural thinking.** Building coherent scientific systems by organizing empirical laws under consistent sets of assumptions.
- **The role of mathematics.** Appreciating mathematics not merely as a tool for calculation but as a language shaping physical concepts.
- **Philosophical reflection.** Considering foundational and epistemological questions about the nature of physical laws and scientific explanation (Feyerabend, 2010).
- **Intertheoretic connections.** Relating different domains of physics (e.g., mechanics and thermodynamics) and recognizing unifying principles.
- **Historical and interdisciplinary awareness.** Understanding the evolution of scientific ideas and exploring connections between physics and other disciplines—from chemistry and biology to engineering and even the social sciences.
- **Nonlinear and complex systems analysis.** Developing an appreciation for chaos, emergent behavior, and the challenges of modeling complex phenomena.
- **Data-intensive inquiry.** Acquiring the skills to work with large datasets, using AI-powered image recognition, statistical analysis, and machine learning techniques.
- **Collaborative and communicative competence.** Engaging effectively in team-based projects and communicating scientific ideas clearly to diverse audiences.

In the re-envisioned curriculum, students' use of AI is not a form of "cheating" but a necessary component of scientific practice. For example, a student investigating a physical phenomenon might collect images, preprocess them with AI-based image recognition, extract relevant data, analyze it statistically, construct models, and then critically compare these models with established theories. In such contexts, AI is not merely a convenience but an indispensable partner in inquiry—one that allows students to tackle authentic, open-ended problems that would otherwise be inaccessible in traditional classrooms.

Ultimately, physics education in the age of AI must shift from training students as passive problem-solvers to preparing them as active inquirers, capable of leveraging machines for algorithmic and data-driven tasks while reserving human capacities for creativity, synthesis, and judgment. If educators fail to enact such transformations, the field risks being caught, like Kortemeyer's metaphorical frog, unaware of the depth of change until adaptation is no longer possible.

Let us address a potential objection. One might argue that this vision could impose cognitive overload on students, and that the skills list appears potentially daunting. It should be emphasized, however, that the list presented here is intended as an aspirational framework rather than a prescriptive checklist. Most activities can be adapted to students' prior knowledge, with AI serving as a supportive tool. Moreover, according to the approach proposed in this article, the content of all educational courses—from primary education to graduate studies—should ultimately be reviewed and aligned with these competencies. Consequently, the listed skills are not expected to be fully developed within a single course or program, but rather progressively cultivated and reinforced across the entire educational trajectory. Importantly, this does not imply that these skills should be neglected until a full curriculum redesign is completed; instead, their emphasis can be adjusted across different courses, gradually building students' competencies in scientific modeling, critical reasoning, and philosophical reflection. By framing the list as a flexible and longitudinal guide, we aim to inspire ambitious yet achievable curriculum design without imposing an overwhelming burden on teachers or students.

Example: Teaching Newton’s Laws in AI Age

The previous discussion outlined a general framework for physics education in the era of AI. To illustrate this framework concretely, let us consider how the teaching of Newton’s laws of motion can be re-envisioned. Rather than focusing on repetitive exercises or memorization of formulas, physics education should emphasize the *conceptual and critical foundations* of the laws, while embedding computational and interdisciplinary practices into teaching, assignments, and projects. In the following, we highlight several aspects of teaching Newtonian mechanics in the era of AI, in ways that align with its presence and accord with the principles discussed in the previous sections.

Conceptual and Theoretical Emphasis, Newton’s laws must be taught not merely as problem-solving tools, but as conceptual milestones that demand analytical reflection. For example, students should explore why it took nearly two millennia—from Aristotle’s qualitative framework to Newton’s mathematical formulation—for a coherent theory of motion to emerge. Such analysis encourages students to appreciate both the historical contingency and the logical structure of scientific progress (Cohen, 1994).
The logical interrelations of the laws themselves should also be examined critically. Is Newton’s first law independent, or does it merely define inertial frames? Does the second law define force or mass—or neither? Can a physical law serve as a *definition*, or must it always be a synthetic claim about nature? These questions not only sharpen conceptual understanding but also build the intellectual capacity to evaluate the foundations of science (DiSalle, 2006).

Philosophical and Historical Dimensions, A modern teaching of Newtonian mechanics should not exclude its philosophical backdrop. Newton’s reliance on absolute space and time, for instance, was not an arbitrary assumption but a necessary scaffold for his formulation of mechanics (Koyré, 1957). Revisiting such debates provides opportunities to integrate physics with philosophy and the history of science, cultivating an interdisciplinary sensibility. Students should also be encouraged to question why Aristotelian physics persisted for so long, moving beyond simplistic textbook answers and engaging with sociocultural, methodological, and epistemic explanations.

Interdisciplinary and Comparative Perspectives, Dynamics, as the study of change, transcends mechanics. AI-powered tools make it feasible to compare Newtonian dynamics with dynamical systems in economics, biology, or sociology. Such comparisons illuminate the universality—and the limits—of physical modeling. They also prepare students to apply physics-inspired reasoning in broader scientific and technological contexts (Strogatz, 2015).

Computational and Data-Driven Skills, Assignments and projects should deliberately integrate computational practices:

- Symbolic and numerical problem-solving using computational tools.
- Modeling real-world systems with uncertainty and complexity.
- Using data-driven methods, including machine learning, to identify patterns in physical phenomena. For example, image processing of projectile motion can be combined with Newtonian models to highlight the complementarity of empirical data and theory.

This approach also raises deeper questions: How much detail should be ignored in building useful models? Are Newtonian models still meaningful in chaotic or multi-body systems? What is the proper relation between simplified mechanical models and the massive datasets now available from natural and artificial sensors?

Modeling and Experimental Competence, Students should experience physics as model-building. Galileo's abstraction of motion by neglecting friction can be revisited as an early example of computational thinking: stripping away noise to reveal governing principles. Similarly, modern lab activities can require students to evaluate how to reduce or retain friction, how to estimate errors, and how to select the most appropriate experiment to test a theory—for example, why the pendulum offers a more precise determination of gravitational acceleration than direct free-fall measurements.

Mathematics as a Tool of Physics, The intimate relation between mathematics and physics should be emphasized through the example of Newton's invention of calculus for mechanics. This underscores that mathematics is not merely a toolbox but a constitutive part of physical modeling (Steiner, 1998).

Real-World and Collaborative Projects, Assignments should include real-world contexts that demand interdisciplinary engagement. For instance:

- Why do roads curve with banking angles?
- How can slipping on ice be minimized?
- Why do we not sink into the ground despite gravity?

Such problems, approached with computational and collaborative tools, mirror the way actual scientific and engineering challenges are addressed.

Ultimately, teaching Newton's laws in the age of AI requires a paradigm shift: from rote problem-solving toward *critical, computational, and conceptual engagement with physics as a living discipline*. Failure to adapt risks a "boiling frog" scenario in which physics education slowly loses its relevance until it is too late to recover (Kortemeyer, 2025).

Finally, let us point out that although in this section and the previous one we have discussed the core skills required in the age of AI, and have illustrated through the example of Newtonian mechanics how these skills might be shaped in practice, a full design of curricula or detailed syllabi lies beyond the scope of this article. We hope, however, to address this issue in future publications by presenting sample course designs aligned with AI-based education, developed on the basis of the framework proposed here.

CONCLUSION

The relationship between artificial intelligence (AI) and education is not unidirectional. Rather, the very nature of AI—developed through machine learning processes—has intrinsic connections to the concept of learning and pedagogy. In this context, the parallels and differences between human and machine learning offer crucial insights into how education can be restructured. Recognizing these insights, modern education should emphasize the cultivation of skills such as *critical thinking, computational thinking, modeling, data analysis, and interdisciplinary reasoning*. These skills allow learners to not only understand core concepts but also to navigate complex scientific and real-world problems effectively.

Revising educational content in light of AI transforms its role from a potential challenge into an opportunity and even an imperative. Given the continuous expansion of scientific knowledge, the increasing complexity of problems, and the capabilities of AI relative to human cognitive limits, integrating AI into education will likely become unavoidable. Moreover, this integration can help address longstanding challenges in education, such as lack of motivation, insufficient engagement with complex concepts, and difficulties in connecting abstract principles to real-world applications.

In physics education, we examined which foundational skills are critical for a curriculum aligned with AI integration. Specifically, the teaching of Newtonian mechanics illustrates how essential competencies—such as *scientific modeling, quantitative reasoning, experimental design, understanding of symmetries, dimensional analysis, and theoretical reasoning*—can be reinforced and accelerated with AI support. These are authentic skills that any physicist must possess, and modern AI tools enable students to acquire them more efficiently, freeing cognitive resources from repetitive or procedural tasks that can now be handled by computational models and language-based AI systems.

Ultimately, the synergy between human intellectual strengths and AI's computational power offers a unique opportunity to redefine physics education. By strategically leveraging AI, educators can foster students who not only understand physical principles but also develop the critical, computational, and creative skills required to explore, innovate, and solve complex problems in the 21st century. This transformation is not merely about technological adoption but about cultivating a fundamentally more effective, relevant, and forward-looking approach to teaching and learning.

Acknowledgments

This research is supported by the Farhangian University of Tehran, Iran.

References

[1] Holmes, W., Bialik, M., & Fadel, C. (2019). Artificial intelligence in education: Promises and implications for teaching and learning. Center for Curriculum Redesign..

[2] Luckin, R. (2018). Machine learning and human intelligence: The future of education for the 21st century. UCL Institute of Education Press.

[3] Meltzer, D. E., & Thornton, R. K. (2012). Resource letter ALIP–1: Active-learning instruction in physics. American Journal of Physics, 80(6), 478–496.

[4] Mitchell, M. (2019). Artificial intelligence: A guide for thinking humans. Farrar, Straus and Giroux.

[5] Redish, E. F. (2003). Teaching physics with the physics suite. John Wiley & Sons.

[6] 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).

[7] Chollet, F. (2021). *Deep learning with Python* (2nd ed.). Manning.

[8] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning.* MIT Press.

[9] Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science, 349*(6245), 255–260

[10] Nilsson, N. J. (2010). *The quest for artificial intelligence: A history of ideas and achievements.* Cambridge University Press.

[11] Russell, S., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (4th ed.). Pearson.

[12] Ambrose, S. A., Bridges, M. W., DiPietro, M., Lovett, M. C., & Norman, M. K. (2010). *How learning works: Seven research-based principles for smart teaching*. San Francisco, CA: Jossey-Bass.

[13] Bishop, C. M. (2006). *Pattern recognition and machine learning*. New York, NY: Springer.

[14] Brown, P. C., Roediger III, H. L., & McDaniel, M. A. (2014). *Make it stick: The science of successful learning*. Cambridge, MA: Harvard University Press.

[15] Carey, B. (2014). *How we learn: The surprising truth about when, where, and why it happens*. New York, NY: Random House.

[16] Epstein, D. (2021). *Range: Why generalists triumph in a specialized world*. New York, NY: Penguin.

[17] Krashen, S. D. (1982). *Principles and practice in second language acquisition*. Oxford: Pergamon Press.

[18] Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge: Cambridge University Press.

[19] National Research Council. (2000). *How people learn: Brain, mind, experience, and school* (Expanded ed.). Washington, DC: National Academies Press.

[20] Nussbaum, M. C. (2013). *Creating capabilities: The human development approach*. Cambridge, MA: Harvard University Press.

[21] Wiggins, G., & McTighe, J. (2005). *Understanding by design* (2nd ed.). Alexandria, VA: ASCD.

[22] Docktor, J. L., & Mestre, J. P. (2014). Synthesis of discipline-based education research in physics. *Physical Review Special Topics - Physics Education Research, 10*(2), 020119.

[23] Feyerabend, P. (2010). *Against method* (4th ed.). London: Verso.

[24] Hestenes, D. (1992). Modeling games in the Newtonian world. *American Journal of Physics, 60*(8), 732–748.

[25] Kortemeyer, G. (2025). The boiling-frog problem of physics education. *arXiv preprint*. https://arxiv.org/abs/2508.08842.

[26] Redish, E. F. (2005). Problem solving and the use of math in physics courses. *Proceedings of the World View on Physics Education 2005 Conference*.

[27] Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. *Journal of Science Education and Technology, 25*(1), 127–147.

[28] Janiak, A., & Schliesser, E. (Eds.). (2012). *Interpreting Newton: Critical Essays*. Cambridge University Press.

[29] DiSalle, R. (2006). *Understanding Space-Time: The Philosophical Development of Physics from Newton to Einstein*. Cambridge University Press.

[30] Facione, P. A. (2015). *Critical Thinking: What It Is and Why It Counts*. Insight Assessment.

[31] Koyré, A. (1957). *From the Closed World to the Infinite Universe*, Baltimore: Johns Hopkins Press.

[32] Steiner, M. (1998). *The Applicability of Mathematics as a Philosophical Problem*. Harvard University Press

[33] Strogatz, S. (2015). *Nonlinear Dynamics and Chaos*. Westview Press.

[34] Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Computational Thinking in Science, Technology, Engineering, and Mathematics. *Journal of Science Education and Technology, 25*(1), 127–147.

[35] Wing, J. M. (2006). Computational Thinking. *Communications of the ACM, 49*(3), 33–35.