

# The transformative power of artificial intelligence in science education: a pedagogical perspective

Pearl Iheoma Nweke<sup>1</sup>, Godwin A. Udourioh<sup>2</sup>

<sup>1</sup>Department of Science Education, Faculty of Education, Veritas University, Bwari Area Council, FCT-Abuja, Abuja, Nigeria

<sup>2</sup>Department of Pure and Applied Chemistry, Faculty of Natural and Applied Sciences, Veritas University, Bwari Area Council, FCT-Abuja, Abuja, Nigeria

**Abstract.** The rapid integration of artificial intelligence (AI) into education is reshaping science pedagogy in ways that remain insufficiently explored. While early implementations of AI in teaching show promise – particularly through intelligent tutoring systems, virtual laboratories, and adaptive learning tools – there is a critical gap in understanding how these technologies affect conceptual learning across specific science disciplines. This review identifies underexplored areas, including AI's impact on science epistemology, equity challenges, and educators' professional readiness. Drawing on recent literature, the paper provides discipline-specific analysis across chemistry, physics, and biology, highlighting pedagogical benefits, ethical complexities, and future research needs. To strengthen theoretical contributions, we present an original framework grounded in Vygotsky's sociocultural learning theory and Technological Pedagogical Content Knowledge (TPACK), integrating AI as a mediational tool. This novel analytical perspective allows us to evaluate AI not just as content delivery but as a culturally situated educational artefact. Ultimately, we advocate for a human-centred, critically reflective framework that supports personalised, inquiry-based, and ethical science education.

**Keywords:** artificial intelligence, science pedagogy, chemistry education, AI ethics, TPACK, socio-cultural theory

## 1. Introduction

Artificial intelligence (AI) – including machine learning, natural language processing, and generative models – is becoming increasingly accepted globally in education. Since the advent of powerful tools like ChatGPT (late 2022) and Google's Gemini (2024), millions of students and educators have experimented with generative AI for writing, problem-solving, and more [36]. Rather than banning such tools, experts argue we must help students and instructors learn with AI, understanding its capabilities and limitations [32]. This is especially true in science education, where AI can offer novel ways to teach and learn complex concepts. Recent reviews emphasise that AI integration in undergraduate science (STEM) is still in its infancy, identifying core “pillars” like AI-driven tutoring, virtual/augmented reality, and intelligent data analysis that could reshape pedagogy [60].

In chemistry, physics, and biology, AI-based systems are already being piloted for personalised practice, simulation-based inquiry, and automated assessment [30].

In this paper, we examined how these AI tools are applied across disciplines and why they matter pedagogically. We highlighted the benefits of personalisation and engagement, as well as the implementation challenges and ethical considerations. While this review focuses on chemistry, physics, and biology, the disciplines where AI applications are most empirically studied, we acknowledge that earth sciences and interdisciplinary STEM fields remain underrepresented in the current literature. These omissions are therefore intentional to maintain disciplinary focus, but we highlight them as important directions for future research.

ORCID: 0000-0002-9289-1570 (P.I. Nweke); 0000-0001-8920-6475 (G. A. Udourioh)

Email: nwekep@veritas.edu.ng (P.I. Nweke); udouriohg@veritas.edu.ng (G. A. Udourioh)

URL: [https://www.veritas.edu.ng/staff\\_profile.php?id=70](https://www.veritas.edu.ng/staff_profile.php?id=70) (G. A. Udourioh)

Received	Accepted	Published	Version of record
2025-06-15	2025-09-29	2026-01-25	2026-01-25



Science  
Education  
Quarterly



© Copyright for this article by its authors, published by the Academy of Cognitive and Natural Sciences. This is an Open Access article distributed under the terms of the Creative Commons License Attribution 4.0 International (CC BY 4.0), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

## 2. Methodological and theoretical framework

To ensure transparency and academic rigour, a semi-systematic literature review was conducted, inspired by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, though not formally adopted [43, 49]. Searches were conducted across Scopus, ERIC, Web of Science, and Google Scholar using Boolean operators and combinations such as: “artificial intelligence AND science education”, “AI in chemistry/physics/biology teaching”, “adaptive learning AND STEM”, “virtual labs AND pedagogy”, “educational AI ethics”

The review included peer-reviewed journal articles published from 2015 to 2025, focusing on empirical studies of science pedagogy, with disciplinary diversity, methodological transparency, and availability in English. Studies lacking evidence-based data (e.g., opinion pieces, sponsored whitepapers, or conceptual commentaries) were excluded to maintain credibility [11]. This approach supports narrative synthesis with thematic integration, which is well-suited to exploring emerging interdisciplinary fields such as AI in education [9, 49].

In terms of theoretical framing, this review applies a dual-framework model combining:

1. Vygotsky’s sociocultural theory, which views learning as socially mediated within the zone of proximal development, with AI tools acting as cognitive mediators [20, 57].
2. Technological Pedagogical Content Knowledge (TPACK), which guides the integration of technology with pedagogy and content knowledge [42]. This model helps analyse how AI interventions align – or misalign – with disciplinary science instruction and instructional goals.

Recent scholarship has also begun to explore how generative AI is reshaping science teacher education. Spasopoulos, Sotiropoulos and Kalogiannakis [50] provides a systematic review of AI use in pre-service science teacher education, highlighting both opportunities (e.g., enhanced reflective practice, AI-driven microteaching simulations) and challenges (e.g., ethical preparedness, overreliance on automated feedback). Including such perspectives broadens the theoretical framing of this review by situating AI not only as a tool for student learning but also as a transformative element in preparing the next generation of science educators [50].

To ensure ethical compliance, all cited empirical studies involving human participants (teachers or students) were selected from journals or publishers that explicitly document institutional review board approval, informed consent, and data protection protocols [25, 61]. Guided by this methodological approach, the review was structured around three central questions:

1. How has AI been applied in science pedagogy across chemistry, physics, and biology?
2. What theoretical frameworks (e.g., sociocultural theory, TPACK) best illuminate the pedagogical implications of AI integration?
3. What gaps, limitations, and future opportunities exist for expanding AI in broader STEM education, including earth sciences and interdisciplinary contexts?

## 3. Artificial intelligence in chemistry, physics and biology education

The following sections synthesise findings from the literature search, organised by discipline, while section 2 has already outlined the theoretical framing that underpins this analysis. AI is increasingly transforming education in the sciences – chemistry, physics, and biology – by enhancing how students learn and how educators teach [22]. In chemistry, AI facilitates the modelling of complex molecular structures and reaction mechanisms, aiding in the visualisation and understanding of intricate concepts. Physics education benefits from AI through the development of interactive simulations and virtual laboratories, allowing students to experiment with physical phenomena in a controlled, digital environment [10]. In biology, AI assists in analysing large datasets, such as genetic information, enabling students to engage with real-world biological data and fostering a deeper comprehension of biological systems [41]. Across these disciplines, AI-powered tools such as intelligent tutoring systems and adaptive learning platforms provide personalised learning experiences, catering to individual student needs and promoting active engagement [17].

### 3.1. AI in chemistry education

One major application of AI in chemistry education is the creation of virtual and simulated labs. Platforms like PraxiLabs create interactive 3D experiments (e.g., titrations and molecular simulations) that students can perform on a computer [21]. These AI-enhanced simulations often include intelligent scaffolding: for instance, PraxiLabs virtual labs provide hints, guided walkthroughs, and safety notes to support learning. Such environments let students repeat experiments at no additional cost or risk, deepening conceptual understanding [21, 55]. Comparative trials have shown that Labster users reported a 32% higher engagement score than peers in conventional labs, while PraxiLabs was rated 40% more accessible in low-resource settings due to lower hardware requirements [21, 55]. These findings highlight a trade-off between immersion and inclusivity.

Platforms such as Labster and ChemReaX enable students to manipulate molecules and simulate reactions in real time, thus reducing the cognitive barriers associated with abstract concepts [38]. These tools align with constructivist pedagogy by providing visual scaffolding, yet studies show mixed results regarding knowledge retention when students rely solely on simulations without guided instruction [16].

Moreover, intelligent tutors like Carnegie Learning Chemistry Coach leverage adaptive feedback to customise instruction. While this promotes differentiated learning, concerns persist over algorithmic transparency and the risk of fostering learner dependence [44]. Importantly, foundational frameworks such as TPACK help teachers balance content, pedagogy, and technology for more effective chemistry instruction [42].

Another important use is AI tutoring, and Q&A. Generative chatbots (e.g., ChatGPT) can answer chemistry questions or explain reaction mechanisms on demand [4]. Educators have used ChatGPT to generate practice problems and performance tasks tailored to a curriculum [18]. For example, chemistry instructors report asking ChatGPT to create “performance task” questions on a topic, then using the output (after careful vetting) as novel assignments for student teams. Chatbots can also differentiate instruction: converting an article to a particular reading level or suggesting alternative problem contexts to meet diverse learner needs [17]. AI-driven tutoring systems (domain-specific intelligent tutors) similarly guide students step-by-step through problems (akin to a personal assistant). Together, these tools offer *instant feedback* and can adapt to each student’s misconceptions [17].

Data-driven problem-solving tools are gaining traction too [19]. For instance, computational engines (like Wolfram|Alpha) allow students to explore chemical equations, balance and solve them with natural-language queries. Machine learning models are even being used in advanced labs to predict reaction outcomes or analyse spectra [62]. As one review notes, AI/ML in chemistry education shows promise for personalised learning, adaptive assessment, and data-rich experiments [27]. However, these applications are still emerging. Many require large datasets or careful setup, and educators need training to use them effectively.

### 3.2. AI in physics education

In physics, AI is being used both as a computational aide and a pedagogical partner. A prominent example is the integration of generative AI into labs and homework. Researchers have experimented with asking ChatGPT to simulate a classic physics lab (e.g. mass-spring experiment) and analyse the results in code [12]. In one study, prompting ChatGPT (with a code interpreter plug-in) generated perfect Python analysis code, freeing students from tedious calculations so they could focus on concepts. Similarly, instructors have students brainstorm experiment ideas or lab project plans with ChatGPT: for example, co-designing a two-week projectile-motion lab where the AI suggests equitable role rotations for group members. These uses illustrate AI as a *co-planner* of instruction [12].

On the theory side, AI-driven simulations and problem generation offer new learning modes. Projects at Stanford and elsewhere are leveraging generative models to create physics simulations and virtual labs rapidly. The idea is that an instructor could prompt an AI to “build me an experiment

on wave interference”, and the system would output a runnable simulation. Such approaches aim to provide “complex, personalised content for educational purposes” (akin to a replicator for lab setups) [12]. Makransky, Terkildsen and Mayer [39] reported that immersive VR labs increased students’ presence ratings by 45%. However, post-test conceptual retention declined by 12% compared to desktop simulations, suggesting that higher immersion does not always translate into stronger learning outcomes [39].

As these tools mature, students may engage with dynamic models of electromagnetic fields, quantum wavefunctions, and other advanced phenomena.

Chatbots also support conceptual learning in physics. Physics educators suggest using AI conversation partners to explore topics and foster critical thinking. For instance, students might debate scientific issues with a chatbot set up to take a specific stance, then analyse the AI’s reasoning against evidence. Küchemann et al. [34] notes that rather than banning LLMs, educators should guide students to use them as learning tools. Indeed, current research in physics education is actively examining novel classroom uses of generative AI – from generating problem variants for exams to addressing misinformation [8]. AI applications in physics often involve problem-solving environments, dynamic simulations, and real-time analytics. Tools like PhET Simulations and Newton.ai allow students to model projectile motion, electric circuits, or quantum behaviour interactively. These platforms support inquiry-based learning and align well with Vygotsky’s concept of the zone of proximal development by enabling scaffolded exploration.

However, critical studies indicate that students may exhibit surface-level engagement with such tools if not properly supported by instructional scaffolding or peer collaboration [37]. Furthermore, while adaptive algorithms can enhance learner pacing, they may reduce student autonomy when overregulated [51].

### 3.3. AI in biology education

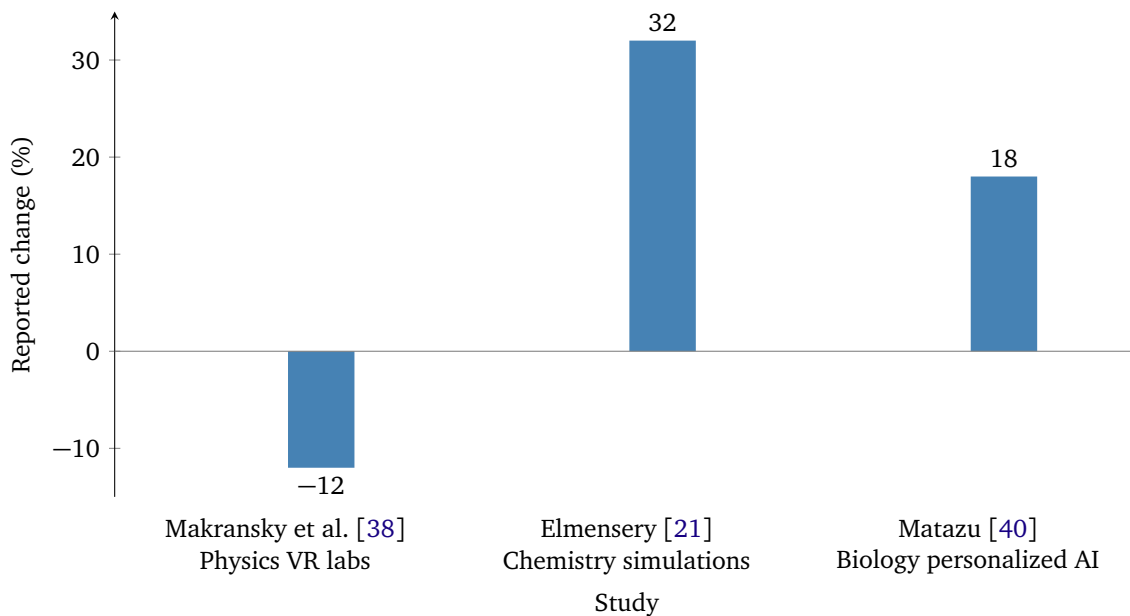
Biology teaching is likewise benefiting from AI in several ways. A key trend is the use of virtual biology labs and simulations [7]. Tools like online ecology and genetics simulators (often leveraging AI) let students safely experiment with parameters in ecosystems or molecular biology. For example, AI-enhanced virtual labs can simulate changes in population biology by allowing students to adjust temperature or habitat factors and instantly observe outcomes [40]. Matazu [40] found that AI-personalised biology instruction improved undergraduate performance in climate change modules by 18% compared with control groups, while also increasing positive learning attitudes by 22%, underscoring AI’s dual cognitive and affective benefits.

As one AI-education guide suggests, students might input a broad concept (“effect of temperature on plant growth”) into an AI chatbot or simulator to receive a range of possible experimental hypotheses [48]. This rapid hypothesis generation jumpstarts scientific inquiry; the student then refines and tests the ideas. AI chatbots can thus act as personal brainstorming partners, proposing experimental designs while students maintain control of interpretation [40, 48].

In cell and genetics courses, AI image analysis is also emerging. For instance, machine-learning tools can classify cells in microscope images or predict protein structures; students can use these to explore real biological data. On the practical side, instructors are piloting adaptive tutoring in biology (e.g. AI-driven quizzes that adapt to student knowledge of cellular processes). Generative AI also aids writing lab reports or research proposals in biology, helping students articulate their methodology and results. Across all science fields, these AI applications can make learning more interactive and conceptually focused [53]. However, biology instructors face similar caveats: AI outputs must be carefully checked for accuracy, and students need guidance on using the tools responsibly. AI innovations in biology span genomics, ecological modelling, and anatomy visualisation. Tools like Visible Body, BioDigital Human, and augmented reality simulators allow deep interaction with complex systems [5]. In ecological education, AI-based simulations enable students to test conservation scenarios or population dynamics. Despite these advances, AI integration in biology remains less structured than in chemistry or physics. Studies suggest limited teacher preparedness in

selecting biologically relevant AI tools, thereby impacting pedagogical consistency [35]. Additionally, ethical dilemmas surrounding the use of genetic data and bioethics simulations are underexplored in the current literature, indicating a research gap.

Figure 1 shows the reported retention and performance impacts of AI-based interventions in science education, based on selected studies. Makransky, Terkildsen and Mayer [39] reported a decrease in conceptual retention despite increased presence in VR labs (−12%), Elmensery [21] documented a 32% higher engagement score in AI-enhanced chemistry simulations, and Matazu [40] found an 18% performance gain in AI-personalised biology instruction.



**Figure 1:** Reported retention and performance impacts of AI in science education.

While AI tools show promise, evidence remains inconsistent, with some studies reporting only marginal learning gains [16]. This suggests that AI integration alone does not guarantee improved outcomes without pedagogical scaffolding.

#### 4. Pedagogical implications of AI in science education

AI's pedagogical utility in science education can be meaningfully interpreted through four inter-related functions: inquiry-based learning, formative assessment, metacognitive development, and teacher facilitation. This thematic organisation enables deeper analytical synthesis across disciplinary boundaries and provides comparative insights into classroom implementation.

##### 4.1. Inquiry-based learning

AI-powered simulations and virtual laboratories are revolutionising how students engage in hypothesis testing and conceptual exploration in physics, chemistry, and biology. Tools like Labster, MEL Science, and PhET Interactive Simulations offer learners immersive environments where scientific variables can be manipulated in real time, fostering authentic scientific inquiry [29, 39]. For instance, in physics education, students can model projectile motion with variable friction; in biology, gene editing and population modelling can be explored in ethical virtual spaces. These environments align with constructivist learning principles by situating learners as active participants in discovery [47]. However, caution is warranted regarding cognitive overload, as some studies report that students without prior conceptual grounding may become disoriented in unguided simulations [39, 51].

## 4.2. Formative assessment

The integration of AI into formative assessment enables instructors to monitor student progress in real time and adapt instruction accordingly. Intelligent tutoring systems (e.g., Carnegie Learning), learning analytics dashboards, and NLP-powered feedback engines can diagnose misconceptions and adjust difficulty levels dynamically [31, 33].

From a theoretical standpoint, these tools operationalise Vygotsky's zone of proximal development by providing timely scaffolding. AI enables differentiated instruction at scale, improving responsiveness to diverse learner needs. However, AI-driven assessments may lack transparency into how responses are interpreted, and there remains a risk of over-reliance on surface-level indicators, such as keyword matching, rather than conceptual understanding [16, 25].

## 4.3. Metacognitive development

AI has shown potential to support learners' metacognitive skills, particularly through reflective prompts, automated feedback loops, and dialogic agents such as ChatGPT. In chemistry, AI-generated explanations can stimulate student articulation of reasoning. In biology, chatbots can pose recursive questions that promote self-monitoring of learning strategies [3, 46].

These approaches are underpinned by social constructivism, especially Bruner's concept of scaffolding and dialogic learning [13]. Nevertheless, the extent to which current AI tools genuinely promote deep self-regulation – rather than passive content consumption – remains a contested area requiring further empirical inquiry [37].

## 4.4. Teacher facilitation and efficiency

AI enhances instructional design efficiency by automating routine tasks like grading, quiz generation, and content adaptation. In science education, teachers use platforms like PraxiLabs or Google's Socratic app to curate resources tailored to learners' needs rapidly.

Moreover, TPACK integration is facilitated as teachers learn to balance technological functionality with content accuracy and pedagogical intent [42]. However, scholars caution that AI's automation capabilities could lead to teacher deskilling if professional judgment is sidelined in favour of algorithmic outputs [8, 58].

In summary, AI tools can reinforce pedagogical best practices in science education, but their integration requires critical awareness of contextual limitations, cognitive development trajectories, and teacher agency. Table 1 summarises the key AI tool categories used across chemistry, physics, and biology, along with their educational benefits and limitations.

Building on the classification of AI tools in table 1, table 2 provides a structured summary of representative studies, showing how AI has been applied across science disciplines, the pedagogical outcomes reported, and their theoretical foundations.

Together, these studies illustrate both the diversity of AI applications in science education and the theoretical frames guiding their interpretation, setting the stage for a comparative analysis of tool effectiveness and pedagogical alignment in the next section.

## 5. Comparative effectiveness and pedagogical alignment of AI tools in science education

AI tools deployed in science classrooms vary significantly in their design, functionality, and alignment with cognitive learning outcomes. Comparative analysis reveals distinct affordances and limitations across platforms such as Labster, PraxiLabs, MEL Science VR, Smart Sparrow, and ChatGPT.

### 5.1. Labster

Labster provides gamified, immersive 3D virtual labs across biology, physics, and chemistry. Its storyline-based modules are aligned with inquiry-based learning by enabling hypothesis testing,

experimentation, and variable manipulation. Anchored in constructivism and situated learning, Labster mirrors Bruner's [13] scaffolding concept by providing interactive cues and feedback loops. Research by Elmensery [21] highlights improved student engagement and conceptual understanding, especially in abstract topics like optics and molecular biology. However, studies caution that unguided use may lead to superficial interaction if not paired with instructor-led reflection [39, 59].

## 5.2. PraxiLabs

PraxiLabs incorporates AI-enhanced feedback and embedded assessments into 3D simulations of experiments such as titration, DNA extraction, and Newtonian motion. PraxiLabs aligns with TPACK [42] by enabling teachers to combine content knowledge with pedagogical and technological tools for differentiated instruction. Unlike Labster, it offers direct teacher analytics and is optimised for low-resource settings, making it relevant for inclusive pedagogy [55]. Comparative studies find it effective at improving procedural knowledge, though it is less interactive than Labster in storytelling and game mechanics.

## 5.3. MEL Science VR

MEL Science VR focuses on visualising microscopic and atomic-level processes using virtual reality. Its strength lies in enhancing spatial and structural reasoning – a key component in chemistry and

**Table 1**

Key AI tool categories used across chemistry, physics, and biology.

N <sup>o</sup>	AI tool / category	Educational benefits	Limitations and cautions	References
1	AI chatbots / LLMs (e.g., ChatGPT)	24/7 Q&A tutor; generates practice problems, explanations, and lab scenarios; enables differentiated assignments; supports lab report writing and conceptual discussions	May produce incorrect (“hallucinated”) answers; risks of misinformation, prompt dependence, and plagiarism if unchecked	[4, 18, 26]
2	Virtual lab simulators (e.g., Labster, PraxiLabs)	Simulate real lab environments; support inquiry learning and lab safety training; enable remote practice in biology (e.g., ecology simulators), chemistry (e.g., titration), and physics (e.g., mechanics)	Limited realism compared to physical labs; access costs; may oversimplify experimental complexity	[21, 55]
3	Adaptive / personalised platforms (e.g., ITS, Smart Sparrow)	Customise learning paths based on student data; adjust difficulty and pace; support remedial instruction	Algorithmic bias; costly development; limited transparency in adaptation logic	[27]
4	AR/VR experiences (e.g., MEL Science AR, VR labs)	Enable immersive simulations (e.g., atomic orbitals, electric fields, cell division); foster spatial and kinesthetic learning	Hardware-dependent; may cause cognitive overload or novelty-driven distraction	[10, 52]
5	Automated assessment tools (e.g., Gradescope, CodeEval)	Support rapid grading of equations, code, or quizzes; offer instant feedback for formative assessment	Less effective for creative or open-ended tasks; susceptible to gaming by students	[6, 14]
6	Content creation AI (e.g., quiz generators, note summarisers)	Efficient generation of questions, lab prompts, and lecture outlines; useful for flipped classrooms and differentiated tasks	Needs educator oversight; outputs may contain conceptual errors or outdated information	[18, 28]

**Table 2**

Some reviewed literature on AI in science education (2019–2025).

Author(s)	Discipline / Context	AI application	Key findings / contribution	Theoretical link
Elmensery [21]	Science	PraxiLabs virtual simulations (3D labs)	Enhanced student engagement and procedural knowledge; low-cost safe experimentation	TPACK, constructivism
Udourioh, Ikegwu and Nweke [55]	Chemistry	AI-driven innovations in teaching	Demonstrated potential of AI in personalizing chemistry instruction and assessment	TPACK
Tan et al. [51]	General STEM	AI-enabled adaptive learning platforms	Adaptive systems regulate pacing effectively but risk reducing autonomy	Cognitive constructivism
López-Simó and Rezende Jr. [36]	Physics	Generative AI in physics Q and A	Showed promise in generating diverse problem types, but accuracy varied	AI literacy, constructivism
Mercan and Selçuk [41]	Biology	AI in genetics and systems biology	Enabled student interaction with real biological datasets, improving comprehension	Inquiry learning, ethics
Aripin et al. [7]	Biology	Literature review of AI in biology education	Identified limited teacher preparedness as a major barrier to structured integration	Pedagogical readiness
Matazu [40]	Biology / Climate change	AI-personalized learning in biology	Improved student performance and attitudes in climate change education	TPACK, constructivism
Aravantinos et al. [5]	Cross-disciplinary	AR/VR biology/chemistry platforms	Highlighted potential of AI-based simulations but stressed digital divide challenges	Equity inclusive pedagogy
Bruneau et al. [12]	Physics	ChatGPT for lab simulations and coding	AI-generated code supported analysis, freeing cognitive resources for conceptual focus	Sociocultural theory (AI as mediator)
Bogusevski, Muntean and Muntean [10]	Physics	3D VR and virtual labs in secondary schools	Students achieved deeper conceptual understanding in mechanics and electricity	Inquiry-based learning
Makransky, Terkildsen and Mayer [39]	Chemistry / Physics	Immersive VR simulations	VR labs increased presence but risked lower conceptual learning without scaffolding	Cognitive load theory

physics. Rooted in dual coding theory and experiential learning, it supports cognitive development by combining visual-spatial inputs with kinesthetic interaction. Studies report significant gains in learner motivation and conceptual clarity, especially among visual learners [39].

#### 5.4. Smart Sparrow

Smart Sparrow provides adaptive learning paths in science by tracking learners' decisions in real time. Smart Sparrow, grounded in cognitive constructivism and metacognitive regulation, supports self-regulated learning. It is particularly effective in formative assessment, allowing students to receive tailored feedback and remediate misconceptions. A key advantage is its alignment with cognitive load theory – by regulating task complexity and pacing based on learner response patterns [3, 31].

## 5.5. ChatGPT and emerging AI capabilities

While ChatGPT supports reflective dialogue, scientific explanation, and problem-solving, it presents limitations, including AI hallucinations (the generation of plausible but incorrect content). As Timmons et al. [54] noted, this demands new science literacy skills, including validating AI output through cross-referencing and reasoning. Emerging AI capabilities, such as multimodal reasoning – used in tools like Gemini and Claude – can process visual data (e.g., diagrams and equations), which aligns well with graphical literacy and STEM competence. However, empirical research on their effectiveness in classroom settings remains limited [58].

This comparative synthesis underscores that no single AI tool suffices across all dimensions of science learning. The most pedagogically robust implementations combine tools such as Smart Sparrow for adaptive assessment, MEL Science for spatial learning, and Labster for inquiry-based engagement. Teachers must consider the alignment of AI tools with curricular goals, student readiness, and instructional context. Future research should explore the integration of multimodal AI in science assessment, the long-term impact of gamified environments on critical thinking, and strategies for AI literacy that encompass both affordances and limitations.

Across these studies, quantifiable impacts remain mixed, with effect sizes ranging from marginal to moderate depending on discipline and tool. This underscores the need for more longitudinal, comparative, and multi-contextual research to establish AI's generalisable impact in science education.

## 6. Ethical and practical considerations

Implementing AI in science courses brings ethical and logistical challenges [15]. Among the ethical and logistical concerns are:

1. *Equity and bias*: AI algorithms may perpetuate bias if trained on inequitable data and can inadvertently disadvantage minority or low-income students. For example, automated grading algorithms have been shown to reflect societal biases if not carefully designed [1]. However, only a handful of studies (e.g., [2]) evaluate mitigation frameworks. Future research must examine inclusive dataset design and audit methods [23].
2. *Privacy and surveillance*: Many AI tools require student data to function, raising questions about consent and surveillance. Student data are central to adaptive AI. However, there is insufficient research into safeguarding privacy in classroom use. Guidelines from Hermansyah et al. [24] and U.S. Department of Education, Office of Educational Technology [56] highlight the need for stricter consent protocols. Teachers and institutions must ensure that student information is protected and that AI use complies with policies [24].
3. *AI literacy*: While students increasingly use AI tools, few curricula exist to cultivate AI literacy. Hanna et al. [23] call for integration of critical AI understanding into teacher preparation. Tan et al. [51] report a lack of studies addressing professional development in AI integration. This area requires urgent attention to avoid misapplication or underutilisation of AI in pedagogy. On the positive side, integrating AI into pedagogy offers an opportunity to teach students about its risks and ethical considerations. Educators should cultivate AI literacy and critical thinking.
4. *Academic integrity*: With easy access to AI-generated answers, learners are liable to generate highly plagiarised content. Instructors need strategies to detect misuse (e.g. AI plagiarism) and to create assessments that promote original thinking. Educators should discuss with students how AI works and how to evaluate its outputs without violating ethical principles [44].
5. *Sustainability*: The environmental cost of large AI models remains underexplored in educational contexts [23]. Researchers must investigate greener implementation practices.

Practical considerations include teacher training and resource allocation. Studies note that faculty need professional development to use AI tools effectively [45]. Classrooms must be equipped with sufficient technology (computers, VR gear) and technical support. Instructors should start with

pilot programs, measure educational outcomes, and iteratively refine AI integration [23]. Ongoing research also highlights the environmental impact of large AI models (energy consumption) and the need for sustainable practices. While AI's promise is significant, its adoption must be critically evaluated in light of equity and inclusion. Research reveals that AI systems often reinforce digital divides, particularly where access to devices, high-speed internet, or teacher training is limited [5]. For low-resource science classrooms – especially in rural or underserved regions – the benefits of AI may remain aspirational unless accompanied by institutional and infrastructural support. Inclusive pedagogy in the age of AI must therefore include universal design principles, multilingual interfaces, and open-access platforms to reduce participation barriers.

## 7. Conclusion

AI holds significant promise for transforming science education across kindergarten, secondary and tertiary levels by enabling more personalised, engaging, and effective learning experiences. As we have shown, AI tools – from smart chatbots to virtual labs – can support inquiry-based learning, streamline assessment, and provide adaptive feedback that conventional methods cannot easily offer. However, realising this potential requires careful pedagogical design. Teachers must integrate AI in ways that complement active learning principles and maintain academic rigour. They must also navigate ethical pitfalls (bias, privacy, equity) and ensure that AI augments rather than replaces human guidance. By approaching AI as a powerful new “colleague” in the classroom – one to be critically evaluated and thoughtfully used – science educators can enrich STEM curricula for today's students. It is important to note that our review intentionally focused on chemistry, physics, and biology, given the relatively richer empirical literature in these areas. However, earth sciences and broader interdisciplinary STEM contexts represent significant gaps that merit deeper exploration. Future research should examine how AI can enhance geoscience education, such as climate modelling, environmental monitoring, and sustainability education, as well as cross-disciplinary STEM learning environments where boundaries between science domains are increasingly blurred. Addressing these areas will broaden the scope of AI-enabled pedagogy and support a more holistic integration across the sciences.

Ultimately, the goal is a balanced synergy between technological innovation and sound pedagogy, preparing students to both harness and critically assess AI in their scientific careers. This review advances the conversation on AI in science education by proposing a novel analytical framework that integrates sociocultural learning theory with the TPACK model. Through this dual lens, we conceptualise AI not merely as a technological adjunct but as a transformative agent in reshaping pedagogy, curriculum design, and learner cognition. Our semi-systematic methodology, coupled with discipline-specific insights and a critical ethical stance, enhances both the theoretical depth and practical relevance of the study. Future research should further interrogate how AI tools mediate scientific meaning-making and how teacher education programs can embed these frameworks into practice.

## References

- [1] Adams, C., Pente, P., Lemermeyer, G., Turville, J. and Rockwell, G., 2022. Artificial intelligence and teachers' new ethical obligations. *The International Review of Information Ethics*, 31(1). Available from: <https://doi.org/10.29173/irie483>.
- [2] Akgun, S. and Greenhow, C., 2022. Artificial intelligence in education: Addressing ethical challenges in K-12 settings. *AI and Ethics*, 2(3), pp.431–440. Available from: <https://doi.org/10.1007/s43681-021-00096-7>.
- [3] Alevin, V., Roll, I., McLaren, B.M. and Koedinger, K.R., 2016. Help helps, but only so much: Research on help seeking with intelligent tutoring systems. *International Journal of Artifi-*

- cial Intelligence in Education*, 26(1), pp.205–223. Available from: <https://doi.org/10.1007/s40593-015-0089-1>.
- [4] Araújo, J.L. and Saúde, I., 2024. Can ChatGPT enhance chemistry laboratory teaching? Using prompt engineering to enable AI in generating laboratory activities. *Journal of Chemical Education*, 101(5), pp.1858–1864. Available from: <https://doi.org/10.1021/acs.jchemed.3c00745>.
- [5] Aravantinos, S., Lavidas, K., Voulgari, I., Papadakis, S., Karalis, T. and Komis, V., 2024. Educational Approaches with AI in Primary School Settings: A Systematic Review of the Literature Available in Scopus. *Education Sciences*, 14(7), p.744. Available from: <https://doi.org/10.3390/educsci14070744>.
- [6] Ariely, M., Nazaretsky, T. and Alexandron, G., 2024. Causal-mechanical explanations in biology: Applying automated assessment for personalized learning in the science classroom. *Journal of Research in Science Teaching*, 61(8), pp.1858–1889. Available from: <https://doi.org/10.1002/tea.21929>.
- [7] Aripin, I., Gaffar, A.A., Jabar, M.B.A. and Yulianti, D., 2024. Artificial intelligence in biology and learning biology: A literature review. *Jurnal Mangifera Edu*, 8(2), pp.41–48. Available from: <https://doi.org/10.31943/mangiferaedu.v8i2.185>.
- [8] Arun Kumar, U., Mahendran, G. and Gobhinath, S., 2023. A Review on Artificial Intelligence Based E-Learning System. In: G. Ranganathan, R. Bestak and X. Fernando, eds. *Pervasive Computing and Social Networking, Lecture notes in networks and systems*, vol. 475. Singapore: Springer Nature Singapore, pp.659–671. Available from: [https://doi.org/10.1007/978-981-19-2840-6\\_50](https://doi.org/10.1007/978-981-19-2840-6_50).
- [9] Bano, M. and Zowghi, D., 2013. Users' involvement in requirements engineering and system success. *2013 3rd International Workshop on Empirical Requirements Engineering (EmpiRE)*. IEEE, pp.24–31. Available from: <https://doi.org/10.1109/EmpiRE.2013.6615212>.
- [10] Bogusevski, D., Muntean, C. and Muntean, G.M., 2020. Teaching and learning physics using 3D virtual learning environment: A case study of combined virtual reality and virtual laboratory in secondary school. *Journal of Computers in Mathematics and Science Teaching*, 39(1), pp.5–18. Available from: <https://eric.ed.gov/?id=EJ1248093>.
- [11] Booth, A., Martyn-St James, M., Clowes, M. and Sutton, A., 2021. *Systematic approaches to a successful literature review*. 3rd ed. London: Sage Publications. Available from: <https://uk.sagepub.com/en-gb/eur/systematic-approaches-to-a-successful-literature-review/book270933>.
- [12] Bruneau, P., Wang, J., Cao, L. and Truong, H., 2023. The potential of ChatGPT to enhance physics education in Vietnamese high schools. Preprint. Available from: <https://doi.org/10.35542/osf.io/36qw9>.
- [13] Bruner, J., 1981. Vygotski: Una perspectiva histórica y conceptual. *Journal for the Study of Education and Development*, 4(14), pp.3–17. Available from: <https://doi.org/10.1080/02103702.1981.10821841>.
- [14] Casal-Otero, L., Catala, A., Fernandez-Morante, C., Taboada, M., Cebreiro, B. and Barro, S., 2023. AI literacy in K-12: A systematic literature review. *International Journal of STEM education*, 10, p.29. Available from: <https://doi.org/10.1186/s40594-023-00418-7>.
- [15] Cathrin, S. and Wikandaru, R., 2023. The future of character education in the era of artificial intelligence. *Humanika: Kajian Ilmiah Mata Kuliah Umum*, 23(1), pp.91–100. Available from: <https://doi.org/10.21831/hum.v23i1.59741>.
- [16] Chiu, T.K., Xia, Q., Zhou, X., Chai, C.S. and Cheng, M., 2023. Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 4, p.100118. Available from: <https://doi.org/10.1016/j.caeai.2022.100118>.
- [17] Clark, T.M., 2023. Investigating the use of an artificial intelligence chatbot with general chemistry exam questions. *Journal of Chemical Education*, 100(5), pp.1905–1916. Available from: <https://doi.org/10.1021/acs.jchemed.3c00027>.
- [18] Cooper, G., 2023. Examining Science Education in ChatGPT: An exploratory study of generative

- artificial intelligence. *Journal of Science Education and Technology*, 32, pp.444–452. Available from: <https://doi.org/10.1007/s10956-023-10039-y>.
- [19] Daher, W., Diab, H. and Rayan, A., 2023. Artificial intelligence generative tools and conceptual knowledge in problem solving in chemistry. *Information*, 14(7), p.409. Available from: <https://doi.org/10.3390/info14070409>.
- [20] Daniels, H., 2001. *Vygotsky and Pedagogy*. London, United Kingdom: Routledge. Available from: <https://doi.org/10.4324/9780203469576>.
- [21] Elmensery, M., 2025. A partnership between Ain Shams University Faculty of Science and PraxiLabs: A Milestone in Practical Education. Available from: <https://praxilabs.com/en/blog/2025/05/21/ainshams-university-and-praxilabs/>.
- [22] Erduran, S. and Levrini, O., 2024. The impact of artificial intelligence on scientific practices: an emergent area of research for science education. *International Journal of Science Education*, 46(18), pp.1982–1989. Available from: <https://doi.org/10.1080/09500693.2024.2306604>.
- [23] Hanna, M.G., Pantanowitz, L., Jackson, B., Palmer, O., Visweswaran, S., Pantanowitz, J. and Rashidi, H.H., 2025. Ethical and bias considerations in artificial intelligence/machine learning. *Modern Pathology*, 38(3), p.100686. Available from: <https://doi.org/10.1016/j.modpat.2024.100686>.
- [24] Hermansyah, M., Najib, A., Farida, A., Sacipto, R. and Rintyarna, B.S., 2023. Artificial intelligence and ethics: Building an artificial intelligence system that ensures privacy and social justice. *International Journal of Science and Society*, 5(1), pp.154–168. Available from: <https://doi.org/10.54783/ijssoc.v5i1.644>.
- [25] Holmes, W., Bialik, M. and Fadel, C., 2019. *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Boston, MA: The Center for Curriculum Redesign. Available from: <https://www.researchgate.net/publication/332180327>.
- [26] Iyamuremye, A. and Ndiokubwayo, K., 2024. Exploring secondary school students' interest and mastery of atomic structure and chemical bonding through ChatGPT. *Educational Journal of Artificial Intelligence and Machine Learning*, 1(1), pp.1–13. Available from: <https://doi.org/10.58197/prbl/9hk37296>.
- [27] Iyamuremye, A., Niyonzima, F. and Mukiza, J.a.a., 2024. Utilization of Artificial Intelligence and Machine Learning in chemistry education: A critical review. *Discover Education*, 3(95). Available from: <https://doi.org/10.1007/s44217-024-00197-5>.
- [28] Iyer, A. and Zavacki, C., 2024. Reflecting on ChatGPT in our Chemistry Classroom. AACT Periodical, May 2024 issue. Available from: <https://teachchemistry.org/periodical/issues/may-2024/reflecting-on-chatgpt-in-our-chemistry-classroom>.
- [29] Jensen, L.S. and Konradsen, F., 2018. A review of the use of virtual reality head-mounted displays in education and training. *Education and Information Technologies*, 23, pp.1515–1529. Available from: <https://doi.org/10.1007/s10639-017-9676-0>.
- [30] Jia, F., Sun, D. and Looi, C., 2024. Artificial Intelligence in Science Education (2013-2023): Research trends in ten years. *Journal of Science Education and Technology*, 33(1), pp.94–117. Available from: <https://doi.org/10.1007/s10956-023-10077-6>.
- [31] Koedinger, K.R., Booth, J.L. and Klahr, D., 2013. Instructional complexity and the science to constrain it. *Science*, 342(6161), pp.935–937. Available from: <https://doi.org/10.1126/science.1238056>.
- [32] Kotsis, K.T., 2024. ChatGPT in teaching physics hands-on experiments in primary school. *European Journal of Education Studies*, 11(10), pp.126–143. Available from: <https://doi.org/10.46827/ejes.v11i10.5549>.
- [33] Kovanović, V., Joksimović, S., Gašević, D. and Siemens, G., 2017. Piecing the learning analytics puzzle: a consolidated model of a field of research and practice. *Learning: Research and Practice*, 3(1), pp.63–78. Available from: <https://doi.org/10.1080/23735082.2017.1286142>.
- [34] Küchemann, S., Steinert, S., Revenga, N., Schweinberger, M., Dinc, Y., Avila, K.E. and Kuhn, J., 2023. Can ChatGPT support prospective teachers in physics task development? *Physical Review Physics Education Research*, 19(2), p.020128. Available from: <https://doi.org/10.1103/>

- PhysRevPhysEducRes.19.020128.
- [35] Lavidas, K., Voulgari, I., Papadakis, S., Athanassopoulos, S., Anastasiou, A., Filippidi, A., Komis, V. and Karacapilidis, N., 2024. Determinants of humanities and social sciences students' intentions to use artificial intelligence applications for academic purposes. *Information*, 15(6), p.314. Available from: <https://doi.org/10.3390/info15060314>.
- [36] López-Simó, V. and Rezende Jr., M.F., 2024. Challenging ChatGPT with different types of physics education questions. *The Physics Teacher*, 62(4), pp.290–294. Available from: <https://doi.org/10.1119/5.0160160>.
- [37] Luckin, R., Holmes, W., Griffiths, M. and Forcier, L.B., 2016. *Intelligence unleashed: An argument for AI in education*. Pearson / UCL Knowledge Lab. Available from: <https://static.googleusercontent.com/media/edu.google.com/en//pdfs/Intelligence-Unleashed-Publication.pdf>.
- [38] Makransky, G., Andreasen, N.K., Baceviciute, S. and Mayer, R.E., 2021. Immersive virtual reality increases liking but not learning with a science simulation and generative learning strategies promote learning in immersive virtual reality. *Journal of Educational Psychology*, 113(4), p.719–735. Available from: <https://doi.org/10.1037/edu0000473>.
- [39] Makransky, G., Terkildsen, T.S. and Mayer, R.E., 2019. Adding immersive virtual reality to a science lab simulation causes more presence but less learning. *Learning and Instruction*, 60, pp.225–236. Available from: <https://doi.org/10.1016/j.learninstruc.2017.12.007>.
- [40] Matazu, S.S., 2024. Impact of AI-Blended Learning and AI-Personalized Learning on undergraduate biology students' attitude and performance in climate change education. *Anchor University Journal of Science and Technology*, 5(1), pp.83–95. Available from: <https://doi.org/10.4314/aujst.v5i1.8>.
- [41] Mercan, G. and Selçuk, Z.V., 2024. Revolutionizing biology education through Artificial Intelligence: pedagogical strategies, innovations, and ethical frameworks. In: A.A. Khan and O.T. Ozturk, eds. *Studies on Social and Education Sciences 2024*. Monument, CO, USA: ISTES Organization, pp.112–131. Available from: <https://www.researchgate.net/publication/387742934>.
- [42] Mishra, P. and Koehler, M.J., 2006. Technological Pedagogical Content Knowledge: A Framework for Teacher Knowledge. *Teachers College Record*, 108(6), pp.1017–1054. Available from: <https://doi.org/10.1111/j.1467-9620.2006.00684.x>.
- [43] Moher, D., Liberati, A., Tetzlaff, J. and Altman, D.G., 2009. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *PLoS Medicine*, 6(7), p.e1000097. Available from: <https://doi.org/10.1371/journal.pmed.1000097>.
- [44] Nguyen, A., Ngo, H.N., Hong, Y., Dang, B. and Nguyen, B.P.T., 2023. Ethical principles for artificial intelligence in education. *Education and Information Technologies*, 28(4), pp.4221–4241. Available from: <https://doi.org/10.1007/s10639-022-11316-w>.
- [45] Nja, C.O., Idiege, K.J., Uwe, U.E., Meremikwu, A.N., Ekon, E.E., Erim, C.M., Ukah, J.U., Eyo, E.O., Anari, M.I. and Umalili, B., 2023. Adoption of artificial intelligence in science teaching: From the vantage point of the African science teachers. *Smart Learning Environments*, 10(1), p.42. Available from: <https://doi.org/10.1186/s40561-023-00261-x>.
- [46] Roll, I., Aleven, V., McLaren, B.M. and Koedinger, K.R., 2011. Metacognitive Practice Makes Perfect: Improving Students' Self-Assessment Skills with an Intelligent Tutoring System. *Artificial Intelligence in Education – AIED 2011, Lecture notes in computer science*, vol. 6738. Springer, Berlin, Heidelberg, pp.288–295. Available from: [https://doi.org/10.1007/978-3-642-21869-9\\_38](https://doi.org/10.1007/978-3-642-21869-9_38).
- [47] Schunk, D.H., 2012. *Learning theories: An educational perspective*. 6th ed. Boston, MA: Pearson Education. Available from: <https://books.google.com.ua/books?id=FZq4cQAACAAJ>.
- [48] Selvam, A.A.A., 2024. Exploring the impact of artificial intelligence on transforming physics, chemistry, and biology education. *Journal of Science with Impact*, 2. Available from: <https://doi.org/10.21428/a70c814c.747297aa>.
- [49] Snyder, H., 2019. Literature review as a research methodology: An overview and guidelines. *Journal of Business Research*, 104, pp.333–339. Available from: <https://doi.org/10.1016/j.jbr.2019.05.011>.

- jbusres.2019.07.039.
- [50] Spasopoulos, T., Sotiropoulos, D. and Kalogiannakis, M., 2025. Generative AI in Pre-Service Science Teacher Education: A Systematic Review. *Advances in Mobile Learning Educational Research*, 5(2), pp.1501–1523. Available from: <https://doi.org/10.25082/AMLER.2025.02.007>.
- [51] Tan, L.Y., Hu, S., Yeo, D.J. and Cheong, K.H., 2025. Artificial Intelligence-Enabled Adaptive Learning Platforms: A Review. *Computers and Education: Artificial Intelligence*, 9, p.100429. Available from: <https://doi.org/10.1016/j.caeai.2025.100429>.
- [52] Tang, K.S. and Cooper, G., 2025. The role of materiality in an era of generative artificial intelligence. *Science & Education*, 34(2), pp.731–746. Available from: <https://doi.org/10.1007/s11191-024-00508-0>.
- [53] Tang, K.S. and Cooper, G., 2025. The Role of Materiality in an Era of Generative Artificial Intelligence. *Science & Education*, 34(2), Apr, pp.731–746. Available from: <https://doi.org/10.1007/s11191-024-00508-0>.
- [54] Timmons, A.C., Duong, J.B., Simo Fiallo, N., Lee, T., Vo, H.P.Q., Ahle, M.W., Comer, J.S., Brewer, L.C., Frazier, S.L. and Chaspari, T., 2023. A call to action on assessing and mitigating bias in artificial intelligence applications for mental health. *Perspectives on psychological science : a journal of the Association for Psychological Science*, 18(5), pp.1062–1096. Available from: <https://doi.org/10.1177/17456916221134490>.
- [55] Udourioh, G.A., Ikegwu, A.C. and Nweke, P.I., 2025. Artificial Intelligence-Driven Innovations in Chemistry Education: Transforming Teaching and Learning Practices. In: P.A. Okebukola, ed. *Handbook in Artificial Intelligence and Quality Higher Education: A book in honour of Abubakar Adamu Rasheed*, vol. 1. Sterling Publishers, pp.379–388. Available from: <https://www.scribd.com/document/838856513>.
- [56] U.S. Department of Education, Office of Educational Technology, 2023. *Artificial Intelligence and the Future of Teaching and Learning: Insights and Recommendations*. Washington, DC: U.S. Department of Education. Available from: <https://www.ed.gov/sites/ed/files/documents/ai-report/ai-report.pdf>.
- [57] Vygotsky, L.S., 1978. *Mind in Society: Development of Higher Psychological Processes*. Harvard University Press. Available from: [https://w.pauldowling.me/rtf/2021.1/readings/LSVygotsky\\_1978\\_MindinSocietyDevelopmentofHigherPsycholo.pdf](https://w.pauldowling.me/rtf/2021.1/readings/LSVygotsky_1978_MindinSocietyDevelopmentofHigherPsycholo.pdf).
- [58] Williamson, B. and Eynon, R., 2020. Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology*, 45(3), pp.223–235. Available from: <https://doi.org/10.1080/17439884.2020.1798995>.
- [59] Winkelmann, K., Keeney-Kennicutt, W., Fowler, D. and Macik, M.L., 2017. Development, Implementation, and Assessment of General Chemistry Lab Experiments Performed in the Virtual World of Second Life. *Journal of Chemical Education*, 94(7), pp.849–858. Available from: <https://doi.org/10.1021/acs.jchemed.6b00733>.
- [60] Yakin, A., Khang, A., Muthmainnah, M., Elngar, A.A., Siripipatthanakul, S. and Limna, P., 2024. Unraveling the Quantum Robotics Influence: Transforming Social Interaction for the Future. In: A. Khang and K.C. Rath, eds. *The Quantum Evolution: Application of AI and Robotics in the Future of Quantum Technology*. Boca Raton, FL, USA: CRC Press, Taylor & Francis Group, pp.349–372. Available from: <https://doi.org/10.1201/9781032642079-17>.
- [61] Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F., 2019. Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education*, 16(1), pp.1–27. Available from: <https://doi.org/10.1186/s41239-019-0171-0>.
- [62] Zhai, X., P. H. and Krajcik, J., 2022. Applying machine learning to automatically access scientific models. *Journal of Research in Science Teaching*, 59(10), pp.1765–1794. Available from: <https://doi.org/10.1002/tea.21773>.