INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN PROGRESSIVE EDUCATION & DEVELOPMENT

OPEN ACCESS JOURNAL
Vol 14, Issue 3, (2025) E-ISSN: 2226-6348

# Acceptance of Artificial Intelligence (AI) In Science Education: Factors Influencing Science Teachers' Intention to Use: A Systematic Literature Review

Oh Ya Wen, Nurfaradilla Mohd Nasri
Faculty of Education, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia.
Corresponding Author Email: nurfaradilla@ukm.edu.my

**DOI Link:** http://dx.doi.org/10.6007/IJARPED/v14-i3/26113

***Published Online:*** 29 August 2025

**Abstract**
Artificial Intelligence (AI) is rapidly transforming the educational landscape, with profound implications for science education. However, the successful integration of AI-based tools depends on science teachers' acceptance and their ability to effectively incorporate these technologies into their instructional practices. This systematic review examines the acceptance of AI in science education by analyzing the factors influencing science teachers' intention to use AI-based tools and the challenges associated with AI adoption. Following PRISMA guidelines, this review includes 12 empirical studies published between 2021 and 2025. The results indicate that teachers' intention to use AI is primarily influenced by the Technology Acceptance Model (TAM), which is rooted in the Theory of Reasoned Action (TRA) and its extension, the Theory of Planned Behavior (TPB). Some studies also incorporate other models, such as TPACK and path analysis frameworks. Key influencing factors include technological perceptions, psychological attributes, social influences, and pedagogical considerations. The review further highlights challenges that impede AI integration, including inadequate training and professional development (PD), technological and infrastructural limitations, pedagogical concerns, and ethical considerations. The findings of this review provide valuable insights for educators, policymakers, and researchers aiming to promote effective and equitable AI adoption in science education.
**Keywords:** Artificial Intelligence (AI), Science Teachers, Technology Acceptance Model (TAM), Influencing Factors, Challenges

## Introduction

The rapid advancement of the Fourth Industrial Revolution (Industry 4.0) has significantly transformed education through the integration of emerging technologies such as artificial intelligence (AI), automation, big data analytics, the Internet of Things (IoT), machine learning, robotic, and smart systems (Adib Rashid & MD Ashfakul Karim Kausik, 2024). These innovations have reshaped the educational landscape by enabling intelligent automation, real-time data-driven decision-making, and adaptive learning systems, fundamentally altering how education is delivered and experienced. As digital transformation accelerates, learning now extends beyond traditional classrooms into technology-supported environments that seamlessly blend physical and virtual spaces (Mhlongo et al., 2023). The growing synergy between technology-enhanced learning and conventional teaching highlights the need for educators to adopt digital tools that enhance engagement and support diverse learning needs.

Among these technological advancements, AI has emerged as a particularly transformative force, revolutionizing various aspects of education, including science education. As AI has evolved from rule-based expert systems to sophisticated machine learning and deep learning models, it can analyze vast amounts of data, recognize patterns, and make decisions with minimal human intervention (Xu et al., 2021). These capabilities have led to AI-powered tools that enhance teaching and learning through intelligent content creation, automated administrative tasks, and personalized learning experiences (Leh, 2022). In science education, AI plays a crucial role in enabling interactive simulations, virtual laboratories, real-time scientific data analysis, and intelligent tutoring systems (ITS), making complex concepts more accessible to students. Furthermore, AI-driven platforms such as adaptive learning environments, virtual tutors, and intelligent assessment tools optimize pedagogical approaches by making science education more efficient, engaging, and student-centered.

The need for AI integration in education became even more evident during the COVID-19 pandemic, which disrupted traditional face-to-face learning and accelerated the adoption of digital technologies in education (Chua & Valencia, 2020; Ng et al., 2023; Pantelimon et al., 2021). With educational institutions forced to transition to online and hybrid learning models, AI-driven technologies such as adaptive learning platforms, virtual reality classrooms and AI-based assessment systems that provide real-time feedback played a crucial role in maintaining continuity in education (Charllo, 2021). The pandemic highlighted the limitations of conventional teaching approaches and demonstrated the potential of AI to provide personalized learning experiences, address diverse student needs, and improve efficiency and accessibility in education (Singh et al., 2024). As a result, the post-pandemic education landscape is now more reliant on digital transformation, underscoring the importance of equipping teachers, especially science educator with the necessary skills and knowledge to effectively integrate AI into their teaching practices.

Moreover, the evolution of AI and automation has profound implications for the future workforce. Many traditional jobs are becoming obsolete due to AI-driven automation, while new career opportunities for high-skilled workers, particularly in healthcare and STEM-related fields are expected to rise (McKinsey Global Institute, 2017). As AI continues to reshape industries, education must adapt by integrating AI-powered tools to equip students with the necessary skills for these evolving career paths. According to the World Economic Forum's Future of Jobs Report (2020), approximately 85 million jobs could be displaced by 2025 due to automation and AI. However, around 97 million new jobs requiring advanced digital skills and AI proficiency are expected to be created, highlighting the urgency for individuals to reskill and upskill to remain competitive in the job market.

This shift is particularly crucial for Generation Z, a generation that has grown up in a technology-driven environment and exhibits distinct characteristics in learning and the workplace (Pichler, 2021). Unlike previous generations, Generation Z learners are more accustomed to using new technologies and have higher expectations for its integration into education (Chan & Lee, 2023). As such, traditional teaching methods may no longer be sufficient to meet the needs of these tech-savvy learners. To prepare students for the demands of the AI-driven workforce, educators must embrace AI as an essential component of modern education. Science teachers, in particular, play a pivotal role in leveraging AI to enhance scientific inquiry, foster problem-solving skills and create engaging STEM-based learning experiences. Their acceptance of AI is therefore critical to ensuring the successful integration of AI-powered tools in science classrooms.

However, teachers' willingness to adopt AI in their teaching practices depends on several factors, including their anxiety (AN), self-efficacy (SE), attitudes towards AI (ATU), perceived ease of use (PEOU) and perceived usefulness (PU) of AI (Wang, Liu & Tu, 2021). Research on the Technology Acceptance Model (TAM) suggests that these factors significantly influence educators' intentions to use AI-based technologies in teaching. Despite the growing awareness of AI's potential in education, many teachers remain hesitant due to concerns about job displacement (Gocen & Aydemir, 2021), lack of technical expertise (Kohnke, Moorhouse & Zou, 2023), and ethical considerations (Akgun & Greenhow, 2022; Wah & Paridah Daud, 2025). Professional development (PD) programs and targeted AI training initiatives are therefore necessary to equip educators with the skills and confidence needed to effectively implement AI in teaching and learning (Ayanwale et al., 2022).

Given these developments, this systematic literature review aims to examine the acceptance of AI in science education, with a specific focus on factors influencing science teachers' intention to use AI-based tools in their teaching practices. By analyzing existing research, this study seeks to identify key determinants that facilitate or hinder AI adoption in science education, providing valuable insights for policymakers, educators, and researchers in shaping AI-integrated teaching practices. As AI continues to redefine the future of education, understanding the factors influencing teachers' acceptance of AI is critical for fostering a technology-driven and future-ready learning environment.

## Literature Review

### *AI in Science Education*

The evolution of education has witnessed significant transformations, from traditional rote learning to modern, technology-enhanced pedagogies. In the twenty-first century, AI has emerged as a powerful tool in education, reshaping teaching methodologies and student learning experiences. According to Huang & Qiao (2022), AI in education (AIEd) primarily serves two purposes: (1) enhancing teaching and learning by improving teaching effectiveness and instructional approaches; and (2) teaching students about AI, equipping them with fundamental AI knowledge and skills to interact with AI-driven systems. However, in the context of this study, the primary focus is on the first aspect—the use of AI as an instructional tool in science classrooms and its acceptance among science teachers.

In science education, AI applications have been increasingly integrated to enhance instructional delivery, foster scientific inquiry, improve student engagement, and boost academic performance. First, AI enhances science instruction by providing intelligent tutoring systems (ITS), adaptive learning platforms, and AI-powered content recommendation systems to facilitate personalized learning experiences. For instance, AI-driven platforms such as Squirrel AI and Century Tech offer real-time feedback and scaffolded learning experiences, ensuring that students receive appropriate support at every stage of their science learning process. These platforms analyze students' learning behaviors, strengths, and weaknesses, enabling teachers to adjust instructional materials and provide tailored support based on individual needs (Eyikorogha & Chigozie, 2024; Olafare, 2024; Villegas-Ch, Arias-Navarrete, & Palacios-Pacheco, 2020). Research by Agbo et al. (2021) further indicates that AI-powered learning platforms help bridge knowledge gaps among students with diverse learning abilities by providing customized resources and support. Consequently, AI-driven instruction enables teachers to move beyond the traditional one-size-fits-all model, fostering a more personalized and adaptive learning environment that accommodates diverse student needs and enhances overall learning outcomes.

Beyond instructional delivery, AI fosters scientific inquiry by equipping students with tools that enable data-driven experimentation, hypothesis testing, and real-time data analysis. AI-powered virtual labs and simulations allow students to conduct interactive experiments in a risk-free environment (Groenewald et al., 2024; Kumar et al., 2021; Srinivasan et al., 2022). This approach addresses common challenges such as limited laboratory resources, safety concerns, and accessibility constraints (Mohamed Edali et al., 2024). Platforms like Labster and PhET simulations allow students to conduct experiments, learn lab techniques, and understand complex scientific concepts without the constraints of a physical lab, enhancing inquiry-based learning through interactive digital experiences (Akamu et al. 2024; Diab et al., 2024; Salame & Samson, 2019). Additionally, tools like Google Teachable Machine (GTM) support scientific inquiry by enabling students to train machine learning models without prior coding experience, helping them to explore AI-driven data classification and pattern recognition in scientific investigations (Herdliska & Zhai, 2023). These AI applications facilitate modern scientific exploration by integrating advanced technologies into the learning process. Research indicates that AI-supported scientific inquiry strengthens problem-solving, critical thinking, and laboratory skills, ultimately deepening students' understanding of scientific concepts (Ramadahan & Irwanto, 2018).

Moreover, AI significantly enhances student engagement by creating immersive and interactive learning experiences. Okunade (2024) highlights that AI integration in science education enables interactive simulations, virtual experiments, and immediate feedback, allowing students to engage actively in the learning process. For example, AI-driven augmented reality (AR) and virtual reality (VR) applications, such as Google Expeditions and Merge Cube, facilitate the creation of simulated learning environments that enhance student presence and support inquiry-based learning beyond physical constraints (Cowin, 2020). These technologies integrate immersive simulations, virtual laboratories, and interactive visualizations, enabling students to explore complex scientific concepts in a dynamic and experiential manner (Haleem et al., 2022). This not only deepens students' understanding of scientific topics, but also fosters curiosity and enthusiasm for learning. Additionally, Ayeni (2024) emphasizes that AI-driven gamification enhances student engagement by providing adaptive challenges and tailored feedback across various science subjects. However, Strmečki, Bernik, and Radošević (2015) caution that a gamified learning environment must be carefully designed with clear instructions and well-integrated gaming elements to ensure students remain focused on learning objectives rather than becoming distracted.

Lastly, AI contributes to academic performance improvements by enabling adaptive learning pathways and early intervention strategies. By providing real-time feedback and deep insights into students' strengths and weaknesses, AI helps instructors make data-driven decisions and develop personalized interventions tailored to individual learning needs (Kamalov, Calonge, & Gurrib, 2023). Supporting this, López-Zambrano, Torralbo and Romero (2021) highlight that AI leverages educational data mining and learning analytics to identify learner characteristics, predict academic outcomes, and assist educators in providing targeted support to at-risk students, ultimately reducing the likelihood of academic failure. This adaptive capability allows students to receive immediate feedback and customized learning pathways, ensuring that misconceptions or gaps in their understanding of scientific concepts are promptly addressed (Mavroudi, Giannakos & Krogstie, 2018). Consequently, several studies have demonstrated that the integration of AI in science education significantly enhances students' academic performance.

For instance, Zhang and Leong (2024) reported that students in experimental groups showed notable improvements across all subjects, particularly in mathematics and science, which require logical reasoning and analytical thinking. Similarly, Heeg and Avraamidou (2023) found that AI applications integrated into science curricula positively impacted students' learning achievements, ensuring that they successfully met curriculum objectives. In addition, Topal et al. (2021) emphasized that AI-powered chatbots enhance science instruction by improving student learning outcomes and engagement. Supporting these findings, Almasri (2024), in a systematic review of empirical research on AI in science education, concluded that AI tools have consistently demonstrated a positive impact on students' academic performance. Overall, the integration of AI in science education transforms traditional teaching methodologies, enhances student engagement, and supports academic achievement. The growing adoption of AI-driven technologies in science classrooms signifies a shift towards more adaptive, interactive and data-informed pedagogical approaches, paving the way for a more effective and personalized learning experience.

*Theoretical Frameworks for AI Acceptance in Science Education*
The Technology Acceptance Model (TAM), introduced by Davis (1989), is grounded in the Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen (1975) and its successor, the Theory of Planned Behavior (TPB; Ajzen, 1985). These theories suggest that beliefs influence attitudes, which shape intentions and ultimately drive behavior. TAM builds on this theory to explain how individuals accept and use technology in various contexts, including education. Over the years, researchers have extended the model by incorporating additional variables to address its limitations and improve its applicability in different settings. These extensions include TAM2 (Venkatesh & Davis, 2000), the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003), and TAM3 (Venkatesh & Bala, 2008). Despite the evolution of TAM, its core premise remains consistent: users' intention to adopt technology is primarily influenced by PU, PEOU and ATU (Davis, 1989; Granić & Marangunić, 2019). PU refers to the extent to which a user believes that a technology enhances their job performance, while PEOU represents the degree to which a user perceives the technology as effortless to use. These variables shape a user's attitude toward the technology, ultimately determining their behavioral intention to use it.

In science education, TAM has been widely used to study teachers' acceptance of various digital tools, including AI (Al Darayseh, 2023; Alshorman, 2024), mobile applications (Ateş & Garzón, 2022), and augmented reality (Ateş & Gündüzalp, 2025). To provide deeper insights into AI adoption, researchers have extended TAM by incorporating psychological and contextual factors. For instance, Schiavo, Businaro, and Zancanaro (2024) integrated AI literacy and AI anxiety into TAM, revealing that AI literacy enhances PEOU and PU, thereby fostering AI acceptance. However, AI anxiety exerts a minor negative effect, partially mediating the relationship between literacy and acceptance. Similarly, Tekin (2024) identified SE and AI anxiety as key factors influencing teachers’ behavioral intention to use AI, with PU and PEOU emerging as the strongest predictors. Zhang et al. (2023) further examined gender differences in AI adoption, revealing that gender moderates the relationship between AI anxiety and PEOU, emphasizing the need to consider diverse user experiences in AI implementation.

Expanding on this, Kong, Yang and Hou (2024) examined Generative AI adoption among primary and secondary school teachers in Hong Kong using an extended TAM framework incorporating SE and subjective norm. A survey of 367 teachers revealed that SE, PU, and attitude were critical in shaping behavioral intention, while subjective norm also played a significant role. The study emphasized the need for teacher training programs to enhance AI-related skills and pedagogical knowledge, alongside policy support to foster AI adoption in education. Complementarily, Hazzan-Bishara, Kol, and Levy (2025) examined teachers' adoption of Generative AI by incorporating both external (AI exposure, information credibility, institutional support) and internal factors (intrinsic motivation, SE). Their study found that credible AI exposure enhances PU, ultimately influencing adoption intention, while institutional support directly and indirectly fosters motivation and SE. These findings highlight the need for educational policymakers to prioritize infrastructure, technical support, and PD, such as Generative AI training programs to drive effective AI integration in schools.

*Challenges of AI integration in Education*

Despite its transformative potential, the integration of AI in education presents several challenges that hinder its widespread adoption. One of the primary concerns surrounding AI integration among teachers is ethical considerations related to data privacy, algorithmic bias, and job displacement. AI-powered educational platforms collect vast amounts of teacher and student data, raising concerns about data security, surveillance, and potential misuse of personal information. For example, Abd-Alrazaq et al. (2023) found that large language models (LLMs) like GPT-4 may inadvertently disclose student and teacher personal information, including names, email addresses, phone numbers, prompts, uploaded images, and generated images. OpenAI may then use this data for service enhancement, research activities, fraud prevention, and legal compliance, potentially sharing it with third parties without explicit user consent. Additionally, AI systems can monitor and analyze students’ thoughts and ideas, raising concerns about surveillance mechanisms that may infringe upon student privacy (Zhai, Wibowo & Li, 2024). These risks underscore the urgent need for robust data protection measures in education.

Moreover, biases inherent in training data can perpetuate stereotypes in educational content (Ng, Chan & Lo, 2025), reinforcing inequalities and discrimination against marginalized groups (Ferrara, 2023). To mitigate this, educators and students must develop

AI literacy skills (Chiu, 2023), enabling them to critically assess AI-generated content and foster more inclusive learning environment. Furthermore, there is also growing apprehension among educators about AI replacing traditional teaching roles (Nikitina & Ishchenko, 2024). This raises concerns about job displacement and diminished autonomy, as AI's increasing presence in education threatens teachers' leadership. Research by Ghamrawi, Shal & Ghamrawi (2023) suggests that educators risk becoming mere implementers of algorithm-driven instruction, limiting their ability to exercise leadership and make pedagogical decisions. This perceived loss of control reduces their capacity to tailor lessons to students' needs. Consequently, it fosters tension and reluctance to embrace new technology in the classroom (Chan & Tsi, 2023).

Apart from ethical considerations, many educators lack the necessary skills and confidence to integrate AI effectively into their teaching practices (Su, Ng & Chu, 2023). A report by Education Week revealed that 45% of teachers feel uncomfortable with integrating AI technologies they have encountered or expect to use in the near future (Langreo, 2023). This discomfort largely stems from a lack of AI literacy and insufficient pedagogical knowledge for the effective implementation of AI in teaching (Kim & Kwon, 2023; Luckin & Cukurova, 2019). Moreover, the availability of PD opportunities in AI remains limited and inconsistent across educational institutions (Arvin et al., 2023; Tan, Cheng, & Ling, 2025), further hindering its widespread implementation. Without adequate training, educators may struggle to utilize AI tools optimally, limiting their potential to enhance teaching and learning. Therefore, Bekdemir (2024) and Kandlhofer (2016) highlight the urgent need for comprehensive AI training programs that address educators' knowledge gaps and equip them with the necessary skills for effective AI integration in subject-area teaching.

**Research Objectives and Questions**

This study aims to explore the acceptance of AI in science education by examining the factors influencing science teachers' intention to use AI-based tools in their teaching practices. Grounded in the TAM, this systematic literature review seeks to provide a comprehensive understanding of the determinants that facilitate or hinder AI adoption in science classrooms. The findings from this study will offer valuable insights for educators, policymakers, and researchers in developing effective strategies for AI integration in science education.

*Research Objectives*

The specific objectives of this study are as follows:
1. To analyze the extent to which science teachers accept and use AI-based tools in science education.
2. To identify the key factors that influence science teachers' intention to adopt AI in teaching.
3. To examine the challenges and barriers that hinder the effective implementation of AI in science education.

*Research Questions*

To achieve these objectives, the following research questions will guide this study:
1. What is the current level of AI acceptance and adoption among science teachers in science education?
2. What are the key factors that influence science teachers' intention to use AI-based tools

in teaching?
3. What challenges do science teachers face in integrating AI into their teaching practices?

## Methodology

This section details the process used to retrieve articles related to science teachers' acceptance of AI in science education. The systematic review process was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework (Page et al. 2021). Articles were identified through a comprehensive search across several databases, including Scopus and Web of Science (WoS). Following the initial identification, the review process continued with rigorous screening based on titles and abstracts, followed by an assessment of full-text eligibility and subsequent exclusion of studies that did not meet the predefined criteria. This multi-phase procedure ensured that only the most relevant and high-quality articles were included for further analysis, ultimately facilitating the synthesis of key determinants, theoretical frameworks, and empirical findings on science teachers' intentions to use AI-based tools in their instructional practices.

*The Review Protocol (PRISMA)*

PRISMA is a standardized guideline initially published in 2009 to enhance the transparency and accuracy of systematic reviews. It provides a structured approach for reporting why a review was conducted, how it was performed, and what was found. However, advancements in systematic review methodologies and terminology led to the release of PRISMA 2020, which introduces improved reporting guidance, a 27-item checklist, and revised flow diagrams to ensure that systematic reviews are comprehensive, replicable, and applicable across various research domains (Page et al. 2021). PRISMA plays a critical role in systematic reviews by enabling researchers to synthesize existing knowledge, identify research gaps, and establish future research priorities. It helps address questions that individual studies may not fully answer, highlights methodological inconsistencies in primary research, and contributes to the development and evaluation of theories within a given field. By promoting structured and transparent reporting, PRISMA enhances the credibility, reliability, and usability of systematic reviews for researchers, educators, and policymakers.

*Resources*

To ensure a comprehensive and high-quality selection of relevant literature, this study utilizes two well-established academic databases: WoS and Scopus. These databases are widely recognized for their extensive coverage of peer-reviewed research across various disciplines, including education and technology. WoS, managed by Clarivate, is a comprehensive and authoritative research database that serves as the world's leading citation index. Its Core Collection includes records from high-impact journals, open-access publications, conference proceedings, and scholarly books. WoS provides robust citation tracking and analytical tools, making it valuable for identifying influential studies and understanding research trends.

Scopus, managed by Elsevier, is another leading abstract and citation database that covers a broad spectrum of scientific and academic literature. It includes peer-reviewed journals, conference papers, and book chapters from diverse subject areas. Scopus is particularly known for its extensive coverage of international research and strong citation analysis capabilities. By utilizing both WoS and Scopus, this study ensures a rigorous and unbiased selection of high-quality, peer-reviewed research on AI acceptance in science education. Their combined use enhances the reliability, credibility, and comprehensiveness of the literature synthesis, ensuring relevance to the study’s focus.

*Systematic Searching Strategies*

The systematic searching strategy consists of three main stages: identification, screening, and eligibility (Figure 1).

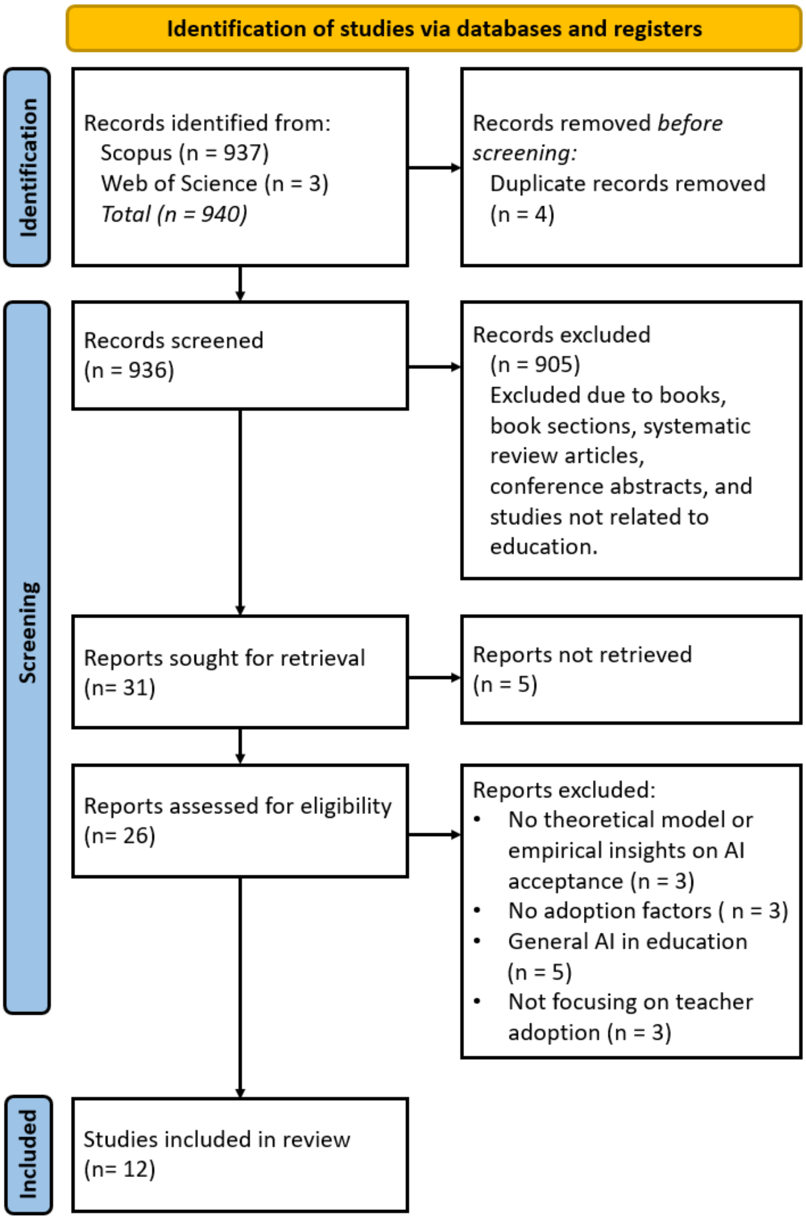


Figure 1. Flow diagram of the study.

*Identification*

The identification phase involves a systematic process of finding related terms, synonyms, and variations for the main keywords of this study, namely AI, science education, and technology acceptance among science teachers. The purpose of this stage is to enhance the search strategy and maximize the retrieval of relevant articles for the systematic literature review.

The search process relied on previously established keywords, online thesaurus tools, and database-suggested terms from Scopus and WoS. Boolean operators such as AND, OR, and parentheses were strategically used to refine the search results and reduce irrelevant records. Additionally, phrase searching and truncation techniques were applied to improve precision and recall in retrieving relevant studies.

To ensure a comprehensive and optimized search strategy, the search queries were structured in a single-line format to allow immediate evaluation of retrieved references and efficient optimization. Furthermore, predefined proximity structures in database queries helped enhance retrieval accuracy (Bramer et al., 2018). The final search strings used for both Scopus and WoS are shown in Table 1.

Table 1
*The search string used for the systematic review process.*

| Database | Keywords Used |
|---|---|
| Scopus | TITLE-ABS-KEY((“artificial intelligence” OR “AI”) AND (“science education” OR “teaching science” OR “STEM education”) AND (“acceptance” OR “technology acceptance” OR “TAM” OR “intention to use” OR “adoption”) AND (“science teachers” OR “teacher perception” OR “teacher attitude” OR “self-efficacy”)) |
| Web of Science (WoS) | TOPIC: ("artificial intelligence" OR "AI") AND ("science education" OR "STEM education") AND ("teacher acceptance" OR "technology adoption" OR "intention to use" OR "self-efficacy") |

*Screening*
The screening phase involved filtering a vast collection of citations from research databases to identify studies for full-text screening and eventual inclusion in the review (Polanin et al., 2019). First, four duplicate records from Scopus and WoS were removed using Zotero, an automated reference management tool for deduplication. After this, 936 records were screened, with 905 excluded for being books, book sections, systematic review articles, conference abstracts, or studies unrelated to education. Among the 31 studies sought for retrieval, five were inaccessible, leaving 26 for eligibility assessment. Since all retrieved articles were originally in English, the risk of misinterpretation was minimized. To ensure relevance, only articles published between 2021 and 2025 were considered, as AI adoption in education has gained significant momentum during this period (Table 2).

Table 2
*Inclusion and exclusion criteria*

| Criterion | Eligibility | Exclusion |
|---|---|---|
| **Timeline** | Between 2021 to 2025 | <2021 |
| **Literature type** | Empirical studies, full conference papers | Systematic reviews, books, book sections, conference abstracts/ proceedings |
| **Language** | English | Non-English |
| **Scope** | Related to the acceptance of AI in science education from the perspective of science teachers. | Not related to the acceptance of AI in science education from the perspective of science teachers. |

*Eligibility*

The final eligibility stage began with 26 remaining articles. This stage was critical, as the titles, abstracts, and main content of all articles were thoroughly examined to ensure they met the inclusion criteria (Table 2) and were suitable for this study in addressing the research objectives. To further refine the scope, only studies that specifically focused on the acceptance of AI in science education from the perspective of science teachers were considered. Additionally, studies employing TAM or similar theoretical frameworks were prioritized, but studies without an explicit theoretical model were included if they provided valuable empirical insights into AI acceptance among science teachers. During this process, three studies were excluded for lacking a theoretical model or empirical insights, three studies were removed for not examining factors influencing teachers' AI adoption, five studies focused on general AI in education rather than science teachers’ adoption, and three studies emphasized AI tools and student engagement instead of teacher adoption. Studies without TAM or similar models were critically assessed for empirical contributions before inclusion or exclusion. Ultimately, 14 studies were excluded, leaving 12 relevant studies for the final review.

*Exclusion Criteria*

Only articles that strictly met the inclusion criteria were retained for the final review. Studies were excluded based on several factors, including systematic review articles, books, book sections, conference abstracts or proceedings, non-English publications, and studies published before 2021. Additionally, articles that did not focus on AI acceptance in science education from the perspective of science teachers were excluded. While studies using TAM or similar theoretical frameworks were prioritized, those without an explicit theoretical model were excluded only if they lacked valuable empirical insights into AI acceptance among science teachers. These criteria ensured the selection of high-quality and relevant data aligned with the research objectives. Figure 1 illustrates the procedure followed in this study.

## Results

*General Findings and Background of the Articles*

A total of 12 selected articles were reviewed and categorized into three themes based on the research models used: TAM, TPB, and other models. This classification provides a structured understanding of the theoretical foundations guiding AI adoption in science education. Additionally, the background of the selected articles was analyzed based on the publication years and countries in which they were conducted.

*Articles Reviewed Based on Year*

Table 3 illustrates the distribution of selected articles from 2021 to 2025, highlighting the research trend on AI adoption in science education. Although this review focused on studies from the last five years, no publications were found for 2021 and 2022. Research in this area began to gain traction in 2023, with two studies published. This was followed by a significant surge in 2024, with nine studies, marking the peak of AI adoption research among science teachers. In contrast, 2025 has only one publication so far, which may be due to the fact that the year has just begun. This trend suggests a growing research interest, particularly in 2024, with the possibility of further publications emerging in 2025.

Table 3
*Article reviewed based on publication years*

| Author(s) | 2021 | 2022 | 2023 | 2024 | 2025 |
|---|---|---|---|---|---|
| Nja et al. | | | ✓ | | |
| Al Darayseh | | | ✓ | | |
| Alshorman | | | | ✓ | |
| Ayanwale, Adelana & Odufuwa | | | | ✓ | |
| Ramnarain et al. | | | | ✓ | |
| Mnguni et al. (Study B) | | | | ✓ | |
| Mnguni | | | | ✓ | |
| Adelana, Ayanwale & Sanusi | | | | ✓ | |
| Shi, Ding & Choi | | | | ✓ | |
| Beege, Hug & Nerb | | | | ✓ | |
| Mnguni et al. (Study A) | | | | ✓ | |
| Awofala et al. | | | | | ✓ |
| **Total** | 0 | 0 | 2 | 9 | 1 |

*Distribution of Articles Based on Countries*

Table 4 presents the distribution of reviewed articles based on the countries where the studies were conducted. Nigeria leads with four studies, indicating significant research efforts in AI adoption in science education. South Africa follows closely, contributing two individual studies and collaborating on two additional studies with Thailand and Indonesia, bringing its total involvement to four studies. Other countries, including the United Arab Emirates, Jordan, the United States, and Germany, have each contributed one study. The distribution of studies highlights a growing global interest in AI integration in science education. However, the absence of studies from Malaysia suggests a gap in research that needs to be addressed. As AI continues to revolutionize teaching and learning, Malaysia must proactively engage in AI research and integration within its education system to remain competitive on the global stage.

Table 4
*Article reviewed based on countries*

| Countries | 2021 | 2022 | 2023 | 2024 | 2025 | Total |
|---|---|---|---|---|---|---|
| Nigeria | 0 | 0 | 1 | 2 | 1 | 4 |
| United Arab Emirates (UAE) | 0 | 0 | 1 | 0 | 0 | 1 |
| Jordan | 0 | 0 | 0 | 1 | 0 | 1 |
| South Africa | 0 | 0 | 0 | 2 | 0 | 2 |
| South Africa and Thailand | 0 | 0 | 0 | 1 | 0 | 1 |
| South Africa and Indonesia | 0 | 0 | 0 | 1 | 0 | 1 |
| United States | 0 | 0 | 0 | 1 | 0 | 1 |
| Germany | 0 | 0 | 0 | 1 | 0 | 1 |

**Main Finding**

The review process in this study involved synthesizing findings related to three distinct research questions, each of which is presented separately in the following sections.

*RQ1: What is the current level of AI acceptance and adoption among science teachers in science education?*

The current level of AI acceptance and adoption among science teachers presents a complex and varied landscape. While there is a general recognition of AI's potential in education, the actual levels of readiness, acceptance, and adoption vary considerably, and widespread implementation is still emerging. Several studies indicate that science teachers exhibit varying degrees of readiness and acceptance toward AI. Alshorman (2024) highlights this complexity, noting that while teachers express a general optimism about AI's potential, significant challenges, such as limited resource access and insufficient PD, impede their readiness for AI adoption. This suggests that positive attitudes alone do not automatically lead to practical readiness. Similarly, Mnguni (2024) reveals mixed attitudes among pre-service life sciences teachers, where optimism about AI's potential coexists with reservations concerning its efficacy and impact on learner engagement. These concerns contribute to moderate to low behavioral intentions to integrate AI into life sciences teaching. Despite these challenges, some studies report a more positive inclination toward AI. For instance, Al Darayseh (2023) found a high acceptability of AI use in the classroom by science teachers, with positive correlations observed between acceptability and factors like SE, ease of use, expected benefits, attitudes, and behavioral intentions. Nja et al. (2023) also indicated a high approval for AI utilization among science teachers. Mnguni et al. (2024b) further support this trend, showing that South African and Thai pre-service teachers displayed generally favorable attitudes and behavioral intentions toward AI integration in teaching. However, it's crucial to distinguish between intention and actual adoption. Ramnarain et al. (2024) and Mnguni et al. (2024b), both focusing on pre-service teachers, primarily explore factors influencing the intention to use AI based on TPB. This emphasis on pre-service teachers suggests a growing focus on preparing future educators for AI integration.

Meanwhile, Adelana, Ayanwale, and Sanusi (2024) present a contrasting perspective, showing that even when pre-service teachers recognize AI’s usefulness, this perception alone does not guarantee adoption. Instead, factors such as facilitating conditions, knowledge, and pedagogical orientation play a significant role in determining whether teachers will ultimately integrate AI into their teaching practices. Beege, Hug, and Nerb (2024) support this notion by observing that ChatGPT is currently hardly used in the classrooms of the investigated teachers, despite high expectations for its future use. Moreover, the reviewed studies emphasize that acceptance and adoption are not uniform and are shaped by contextual factors. For example, Mnguni et al. (2024a) illustrate this through a comparative study, revealing that despite geographical and infrastructural disparities between Indonesia and South Africa, both groups of pre-service teachers share a positive outlook on AI integration in biology education. This suggests that global exposure to digital technology can foster a common understanding of AI’s educational benefits, even across different contexts.

Furthermore, several studies suggest that AI integration in science classrooms is still in its early stages. Shi, Ding and Choi (2024), through a case study, provides valuable insights into the practical realities of AI integration, examining teachers' use of a specific AI-enabled system and their perceptions during implementation. This type of research is crucial for understanding the complexities of actual adoption beyond mere acceptance or intention. Additionally, Awofala et al. (2024) highlight the influence of pedagogical beliefs on AI adoption. Their findings suggest that science, technology, and mathematics (STM) teachers with constructivist beliefs are more likely to integrate AI tools into their teaching compared to those with traditional beliefs. This underscores the role of pedagogical philosophy in shaping AI adoption.

*RQ2: What are the key factors that influence science teachers' intention to use AI-based tools in teaching?*

Science teachers' intention to adopt AI-based tools is shaped by multiple interrelated factors, including technological perceptions, psychological attributes, social influences, and pedagogical considerations. Studies on AI adoption in science education have predominantly utilized established theoretical frameworks such as the TAM, the TPB and the TPACK to analyse these influences. As summarized in Table 5, TAM remains the most widely applied model, particularly in studies conducted in Nigeria, Jordan, and the UAE. Within the TAM framework, PU and PEOU consistently emerge as key determinants of science teachers' AI adoption. For instance, Nja et al. (2023) found that ease of usage was the strongest predictor of behavioral intention to utilize AI, while Al Darayseh (2023) reported that perceived benefits and ease of use, alongside attitude, could predict 71.4% of future behavioral changes related to AI adoption. These findings reinforce that science teachers are more likely to embrace AI if they perceive it as both beneficial and easy to use.

Beyond technological perceptions, psychological factors such as self-efficacy and trust also shape science teachers' AI adoption. Studies by Al Darayseh (2023) and Alshorman (2024) highlight a positive correlation between self-efficacy and teachers' perceptions and intentions to use AI, with Alshorman (2024) further emphasizing that teachers with greater confidence in using AI tools are more likely to integrate them into their teaching. However, concerns over data privacy, security, and inadequate PD may hinder adoption. Additionally, Ayanwale et al. (2024) underscored the significance of trust in AI-based educational technologies for successful AI integration. Their study found that anxiety, preferred methods to enhance trust, and perceived benefits significantly influenced teachers' trust, while the lack of human characteristics in AI did not impact trust levels among STEAM teachers. These findings suggest that strengthening teachers' confidence and trust in AI while addressing potential concerns is essential to facilitating its effective adoption in science education.

Social influences, particularly subjective norms, play a crucial role in shaping science teachers' AI adoption. Within the TPB framework, subjective norms reflect the influence of peers, colleagues, and the broader educational community on teachers' adoption decisions. Ramnarain et al. (2024) demonstrated that subjective norms, along with AI literacy, attitude, perceived behavioral control, and perceived usefulness, significantly impact pre-service science teachers' intention to use AI. Similarly, Adelana, Ayanwale, and Sanusi (2024) and Mnguni et al. (2024b) found that pre-service biology and science teachers often adopt AI in response to professional expectations and collaborative learning environments. Cross-cultural comparisons further highlight the role of social norms, with Thai pre-service teachers exhibiting stronger normative beliefs and greater confidence in AI integration than their South African counterparts. This contrast suggests that institutional and cultural contexts shape how teachers perceive and respond to social influences in AI adoption (Mnguni et al., 2024b).

Finally, pedagogical considerations also intersect with technology adoption, as teachers' instructional beliefs and technological knowledge (TK) influence their willingness to integrate AI into teaching. Awofala et al. (2025) found that teachers with constructivist pedagogical orientations, who emphasize active learning and student-centered instruction, are more likely to integrate AI tools compared to those with traditional teaching beliefs. The TPACK framework further highlights the importance of TK and pedagogical knowledge (PK) in AI integration. Mnguni et al. (2024a) reported that Indonesian biology pre-service teachers demonstrated higher levels of TK and Technological Pedagogical Knowledge (TPK) than their South African counterparts, suggesting that stronger technological proficiency may facilitate AI adoption. While both groups had a positive outlook on AI integration, Indonesian participants perceived greater benefits, particularly in using AI to support peer collaboration. These findings underscore the need for tailored teacher training programs and equitable access to technological resources to enhance AI adoption in diverse educational contexts.

Despite positive attitudes and intentions, actual AI adoption remains limited, with many teachers perceiving AI as a supporting tool rather than an integral pedagogical partner (Shi, Ding & Choi, 2024). Moreover, while STEM teachers recognize AI’s benefits, concerns over risks and practical implementation challenges contribute to low adoption rates (Beege, Hug & Nerb, 2024). These findings suggest that beyond addressing technical barriers, targeted PD programs and institutional policies are necessary to bridge the gap between intention and actual AI integration in classrooms.

Table 5
*Summary of Reviewed Articles by Research Model*

| Author and Year | Study Design | TAM | TPB | Other Models |
|---|---|---|---|---|
| Nja et al., 2023 | QN | ✓ | | |
| Al Darayseh, 2023 | QN | ✓ | | |
| Alshorman, 2024 | QN | ✓ | | |
| Ayanwale, Adelana & Odufuwa, 2024 | QN | ✓ | | |
| Ramnarain et al., 2024 | MM | | ✓ | |
| Mnguni et al., 2024b | QN | | ✓ | |
| Mnguni, 2024 | QL | | ✓ | |
| Adelana, Ayanwale & Sanusi, 2024 | QN | | ✓ | |
| Shi, Ding & Choi, 2024 | QL | | | Not Specified |
| Beege, Hug & Nerb, 2024 | QN | | | Path Model |
| Mnguni et al., 2024a | QN | | | TPACK |
| Awofala et al., 2025 | QN | ✓ | | |

[1] QL = Qualitative, [2] MM = Mixed Method, [3] QN = Quantitative

*RQ3: What challenges do science teachers face in integrating AI into their teaching practices?*

The reviewed literature highlights several challenges that science teachers face when integrating AI into their teaching practices. One significant barrier is the lack of adequate training and PD opportunities tailored to AI integration. For instance, Alshorman (2024) found that although Jordanian science teachers were motivated to learn about AI, they expressed dissatisfaction with the training programs available to them. This indicates a need for structured and targeted PD to bridge the gap between teachers' interest and their preparedness for AI adoption. Similarly, Mnguni et al. (2024a) emphasized that South African pre-service teachers struggled with limited exposure to AI due to inadequate training, particularly in rural areas, leading to disparities in TPACK compared to their Indonesian counterparts who benefited from comprehensive AI-focused training.

Technological and infrastructural challenges also play a significant role in hindering AI adoption. Mnguni et al. (2024b) observed that while Thailand's advanced digital infrastructure supports broader AI adoption, South Africa faces substantial limitations that hinder its implementation. Mnguni (2024) further highlighted that pre-service life sciences teachers in rural South Africa struggle with unreliable internet access, limited hardware, and frequent electricity shortages, making AI integration impractical. These infrastructural deficiencies exacerbate the digital divide, restricting equitable access to AI tools and limiting their effective use in science classrooms.

Additionally, pedagogical concerns further complicate the integration of AI. Research by Shi, Ding, and Choi (2024) found that AI-based systems like Inq-ITS were less effective for students with low English proficiency, as they struggled with text-based feedback. This forced science teachers to spend extra time providing support, making AI integration more demanding. Moreover, pre-service science teachers in South Africa expressed concerns about AI's efficacy, its impact on student engagement, and its alignment with existing teaching styles (Mnguni, 2024). Beege, Hug, and Nerb (2024) also noted that the lack of clear administrative recommendations and integration into the curriculum left many educators uncertain about how to best implement AI in their classrooms, emphasizing the need for more structured pedagogical frameworks.

Finally, ethical considerations present additional hurdles. Alshorman (2024) reported that data privacy and security issues are major concerns among educators, emphasizing their awareness of data management risks and the ethical aspects of educational technology. This highlights the need for robust data protection measures and policies on the ethical use of AI tools in education. In addition, Awofala (2024) noted that traditional educational beliefs contribute to skepticism, with some educators viewing AI as a threat to conventional teaching methods and even fearing that it may replace teachers' roles. Such concerns raise ethical questions about the potential dehumanization of the classroom and the erosion of teacher-student relationships. These challenges underscore the need for comprehensive strategies that address training gaps, infrastructure limitations, pedagogical concerns, and ethical considerations to ensure the successful and responsible integration of AI in science education.

**Discussions**

This systematic literature review aimed to explore the acceptance of AI in science education by examining the factors influencing science teachers' intention to use AI-based tools and the challenges they face in integrating AI into their teaching practices. The findings provide valuable insights into the current state of AI adoption, the key determinants of teachers' intentions, and the obstacles hindering effective implementation. The review highlights a complex and evolving landscape regarding AI acceptance and adoption in science education. While there is a general consensus that AI holds significant potential to enhance teaching and learning, the actual level of adoption remains varied (Alshorman, 2024). This disparity is consistent with previous research that highlights the gap between positive perceptions of AI and its actual integration into classroom practices (Galindo-Domínguez et al., 2023; Woodruff, Hutson & Arnone, 2023). Other factors, such as targeted support, access to resources, ethical guidelines, and PD, play crucial roles in ensuring successful integration (Filiz, Kaya, & Adiguzel, 2025; Hazzan-Bishara, Kol, & Levy, 2025).

The focus on pre-service teachers in several studies included in this review signals a proactive approach to preparing future educators for an AI-enhanced educational environment. This emphasis aligns with the increasing calls for teacher education programs to incorporate technology integration skills, including AI literacy, to ensure that new teachers are equipped to leverage these tools effectively (Bekdemir, 2024; Kohnke et al. 2025; Rütti-Joy, Winder & Biedermann, 2023).The comparative studies included in this review further underscore the importance of contextual factors in shaping AI adoption in science education. For instance, Mnguni et al. (2024a) and Mnguni et al. (2024b) found differences in pre-service teachers' TPACK and normative beliefs between South Africa, Indonesia and Thailand, highlighting the need for culturally and educationally sensitive approaches to AI integration. Overall, the findings suggest that AI integration in science education is an evolving field, with acceptance and adoption influenced by a complex interplay of individual, contextual, and technological factors.

A central focus of the reviewed literature is identifying the key factors that influence science teachers' intention to use AI-based tools. The TAM and the TPB have been frequently employed as theoretical frameworks, providing valuable insights into the determinants of AI adoption. PU and PEOU consistently emerge as significant predictors of teachers' intention to use AI (Al Darayseh, 2023; Awofala et al., 2024; Nja et al., 2023). Teachers are more likely to adopt AI tools if they believe these tools will enhance their teaching effectiveness, improve student learning outcomes, and streamline their administrative tasks (Gârdan et al., 2025; Zhang et al. 2023). However, the perceived complexity of AI tools and the effort required to learn and use them can hinder adoption (Molefi et al., 2024).

SE, or teachers' confidence in their ability to use AI tools, is another critical factor. Research consistently demonstrates a strong positive association between higher SE and a greater intention to use AI in teaching science (Al Darayseh, 2023; Alshorman, 2024). Herzallah and Makaldy (2025) further emphasize this relationship, identifying teacher SE as a pivotal psychological mechanism that bridges the gap between theoretical acceptance of AI and its practical implementation in the classroom. This aligns with social cognitive theory (Bandura, 1977), which posits that self-belief is a fundamental driver of behavior. Therefore, targeted efforts to enhance teachers' SE through comprehensive training and continuous support are essential for successfully integrating AI into science education.

In addition to the core constructs of TAM and TPB, this review identifies other significant factors influencing AI adoption among science teachers. Ayanwale et al. (2024) highlighted the importance of trust in AI-based technologies, noting that factors like anxiety, preferred methods to increase trust, and perceived benefits significantly influence teachers' trust. Subjective norms, or the social influence of colleagues and institutions, also shape teachers' intentions. Ramnarain et al. (2024) found that subjective norms, along with AI literacy, attitude, perceived behavioral control, and perceived usefulness, significantly impact pre-service science teachers' intention to use AI.

The TPACK framework also plays a crucial role in AI integration, as effective use of AI requires teachers to be proficient with the tools and understand how they enhance pedagogical practices. Mnguni et al. (2024a) found that Indonesian pre-service teachers had higher levels of TK and TPK than their South African counterparts, highlighting disparities in AI-related competencies. Such differences underscore the need for targeted PD to ensure equitable AI adoption. Sun et al. (2023) demonstrated that a TPACK-based professional development program significantly improved in-service computer science teachers' AI knowledge, teaching skills, and self-efficacy. This reinforces the importance of equipping teachers with both technological and pedagogical competencies to facilitate meaningful AI integration. In summary, AI adoption is shaped by a complex interplay of technological, psychological, social, and pedagogical factors, all of which must be considered when designing interventions to support science educators.

The reviewed literature also highlights several challenges faced by science teachers in integrating AI into their teaching practices, which can hinder effective adoption. A recurring issue is the lack of adequate resources and training (Alshorman, 2024). Many teachers report limited access to AI tools, insufficient PD opportunities, and a lack of ongoing support, leading to low self-efficacy and anxiety regarding AI use. This underscores the importance of institutional support in AI integration. Molefi (2024) emphasizes that teachers with proper training and guidance are more confident and likely to adopt AI, while inadequate support can discourage its use. Thus, overcoming these challenges through access to AI tools, PD programs, and continuous support is crucial for successful AI adoption in science education. Moreover, concerns about data privacy and security also pose significant challenges (Alshorman, 2024). Teachers have expressed concerns about the ethical implications of AI usage, emphasizing the need for clear ethical policies and guidelines to ensure its responsible and effective use in education (Funa & Gabay, 2025).

Practical limitations and pedagogical challenges further complicate AI integration. Shi, Ding and Choi (2024) found that AI-based systems were less effective for students with low English proficiency, increasing demands on teachers' time. Mnguni (2024) noted that pre-service science teachers in South Africa expressed concerns about AI's efficacy, its impact on student engagement, and its alignment with existing teaching styles. These findings highlight the need for careful consideration of the diverse needs of students and the potential impact of AI on teaching practices. As a whole, the challenges of AI integration into science education include training gaps, resource limitations, pedagogical adaptations, and ethical considerations. Overcoming these challenges will require concerted efforts from educators, policymakers, and technology developers to provide adequate support, address ethical concerns, and foster a positive environment for AI integration.

**Limitations**

This systematic literature review, while providing a comprehensive analysis of AI acceptance among science teachers, is subject to certain limitations. Firstly, the selection of research papers in this review was inherently influenced by the search terms and strategies employed. While a rigorous and thorough search was intended, it is acknowledged that alternative search terms might have identified additional relevant articles for inclusion. Secondly, the search strategy was limited to the Scopus and WoS databases, which may have resulted in the exclusion of relevant studies indexed in other databases or repositories. Thirdly, the geographical distribution of the included studies was uneven, with a significant number of studies originating from Nigeria and South Africa, which may limit the generalizability of the findings to other cultural and educational contexts. Finally, the review relied on the authors' interpretation of the included studies, introducing a potential for subjective bias in the synthesis of findings.

## Conclusion

This systematic review explored the acceptance of AI in science education, analyzing the factors influencing science teachers' intention to use AI-based tools and the challenges they encounter. The review highlights an evolving landscape where AI's potential to enhance science education is recognized, but actual adoption is complex and uneven. The analysis indicates that while science teachers' intention to use AI is driven by factors like perceived usefulness, ease of use, self-efficacy, and social influence, successful integration is impeded by challenges related to training, technology, pedagogy, and ethical concerns. A strategic and comprehensive approach that prioritizes targeted training, infrastructural support, pedagogical guidance, and ethical safeguards is essential to effectively harness the transformative potential of AI in science education.

## References

Abd-Alrazaq, A., AlSaad, R., Alhuwail, D., Ahmed, A., Healy, P. M., Latifi, S., Aziz, S., Damseh, R., Alrazak, S. A., & Sheikh, J. (2023). Large Language Models in Medical Education: Opportunities, Challenges, and Future Directions. *JMIR Medical Education, 9*(1), e48291.

Adelana, O. P., Ayanwale, M. A. & Sanusi, I. T. (2024). Exploring Pre-Service Biology Teachers' Intention to Teach Genetics Using an AI Intelligent Tutoring-Based System. *Cogent Education, 11*(1). https://doi.org/10.1080/2331186X.2024.2310976

Adib Bin Rashid & MD Ashfakul Karim Kausik. (2024). AI Revolutionizing Industries Worldwide: A Comprehensive Overview of Its Diverse Applications. *Hybrid Advances, 7*, 100277. https://doi.org/10.1016/j.hybadv.2024.100277

Agbo, F. J., Afolayan, O. T., & Olaniyi, O. (2021). AI-Based Learning Platforms and Personalized Education in Nigerian Universities. *Journal of Educational Technology, 15*(2), 45-60.

Ajzen, I., (1985). From intentions to actions: A theory of planned be-havior. In J. Kuhl & J. Beckmann (Eds.) *Action control. From Cognition to Behavior* (pp. 11-39). Springer Verlag: Berlin, Heidelberg.

Akamu, E. J., High, R., Iloghalu, U. B., Ahmed, Y., & Jeffers-Francis, L. K. (2024). Exploring the Use of Videos and Virtual Simulations in College Microbiology Lab Courses: Student Perception and Pros and Cons. *Trends in Higher Education*, *3*(4), 861-871. https://doi.org/10.3390/higheredu3040049

Akgun, S., & Greenhow, C. (2022). Artificial Intelligence in Education: Addressing Ethical Challenges in K-12 Settings. *AI Ethics 2*: 431-440. https://doi.org/10.1007/s43681-021-00096-7

Al Darayseh, A. (2023). Acceptance of Artificial Intelligence in Teaching Science: Science Teachers' Perspective. Computers and Education: *Artificial Intelligence, 4*, 100132. https://doi.org/10.1016/j.caeai.2023.100132.

Almasri, F. (2024). Exploring the Impact of Artificial Intelligence in Teaching and Learning of Science: A Systematic Review of Empirical Research. *Res Sci Educ, 54*, 977-997. https://doi.org/10.1007/s11165-024-10176-3

Alshorman, S. (2023). The Readiness to Use AI in Teaching Science: Science Teachers' Perspective. *Journal of Baltic Science Education, 23*(3), 432-448. DOI: 10.33225/jbse/24.23.432

Arvin, N., Hoseinabady, M., Bayat, B., & Zahmatkesh, E. (2023). Teacher Experiences with AI-based Educational Tools. *AI and Tech in Behavioral and Social Sciences, 1*, 26-32. DOI:10.61838/kman.aitech.1.2.5

Ateş, H., Garzón, J. (2022). Drivers of Teachers' Intentions to Use Mobile Applications to Teach Science. *Educ Inf Technol, 27*, 2521-2542. https://doi.org/10.1007/s10639-021-10671-4

Ateş, H., & Gündüzalp, C. (2025). The Convergence of GETAMEL and Protection Motivation Theory: A Study on Augmented Reality-Based Gamification Adoption among Science Teachers. *Educ Inf Technol*. https://doi.org/10.1007/s10639-025-13480-1

Ayanwale, M. A., Adelana, O. P., & Odufuwa, T. T. (2024). Exploring STEAM Teachers' Trust in AI-Based Educational Technologies: A Structural Equation Modelling Approach. *Discover Education, 3*, 44. https://doi.org/10.1007/s44217-024-00092-z

Ayanwale, M. A., Sanusi, I. T., Adelana, O. P., Aruleba, K. D., & Oyelere, S. S. (2022). Teachers' readiness and intention to teach artificial intelligence in schools. *Computers and Education: Artificial Intelligence, 3*, 100099. https://doi.org/10.1016/j.caeai.2022.100099

Ayeni, N. F. (2024). Teaching Science Education in an Era of Artificial Intelligence. *European Journal of Computer Science and Information Technology, 12*(5), 36-42. https://eajournals.org/ejcsit/wp-content/uploads/sites/21/2024/08/Teaching-Science-Education.pdf

Awofala, A. O. A., Bazza, M. B., Ojo, O. T., Oladipo, A. J., Olabiyi, O. S., & Arigbabu, A. A. (2025). Structural Equation Modeling of Nigerian Science, Technology and Mathematics Teachers' Adoption of Educational Artificial Intelligence Tools. *Digital Education Review, 46*, 51-64. https://doi.org/10.1344/der.2025.46.51-64

Bandura, A. (1977). Self-efficacy: Toward a Unifying Theory of Behavioral Change. *Psychological Review, 84*(2), 191-215. https://doi.org/10.1037/0033-295X.84.2.191

Beege, M., Hug, C., & Nerb, J. (2024). AI in STEM Education: The Relationship between Teacher Perceptions and ChatGPT Use. *Computers in Human Behavior Reports, 16*, 100494. https://doi.org/10.1016/j.chbr.2024.100494

Bekdemir, Y. (2024). The Urgency of AI Integration in Teacher Training: Shaping the Future of Education. *International Journal of Didactical Studies,* 3(1), 37-41. DOI:10.51853/jorids/15485

Bramer, W. M., de Jonge, G. B., Rethlefsen, M. L., Mast, F., & Kleijnen, J. (2018). A Systematic Approach to Searching: An Efficient and Complete Method to Develop Literature Searches. *Journal of the Medical Library Association: JMLA*, *106*(4), 531-541. https://doi.org/10.5195/jmla.2018.283

Chan, C. K. Y., & Tsi, L. H. Y. (2023). The AI Revolution in Education: Will AI Replace or Assist Teachers in Higher Education?. DOI:10.48550/arXiv.2305.01185 [08 March 2025]

Chan, C. K. Y., & Lee, K. K. W. (2023). The AI Generation Gap: Are Gen Z Students More Interested in Adopting Generative AI such as ChatGPT in Teaching and Learning Than

Their Gen X and Millennial Generation Teachers?. *Smart Learning Environments, 10*(60), 1-23. https://doi.org/10.1186/s40561-023-00269-3

Charllo, B. V. (2021). Remote Learning Challenges and Solutions: The Role of AI in Bridging Educational Gaps during the Pandemic. *Journal of Scientific and Engineering Research, 8*(7), 285-293. https://jsaer.com/download/vol-8-iss-7-2021/JSAER2021-8-7-285-293.pdf

Chiu, T. K. F., Moorhouse, B. L., Chai, C. S., & Ismailov, M. (2023). Teacher Support and Student Motivation to Learn with Artificial Intelligence (AI) Based Chatbot. *Interactive Learning Environments*, *32*(7), 3240-3256. https://doi.org/10.1080/10494820.2023.2172044

Cowin, J. B. (2020). Digital Worlds and Transformative Learning: Google Expeditions, Google Arts and Culture, and the Merge Cube. *International Research and Review*, *10*(1), 42-53. https://files.eric.ed.gov/fulltext/EJ1293151.pdf

Chua, C. P., & Valencia, L. D. (2020). The Role of Artificial Intelligence in Education Amidst of the COVID-19 Pandemic. In *ICPSR Conference* (pp. 1-6). https://www.researchgate.net/publication/343691393_The_Role_of_Artificial_Intellig ence_i n_Education_Amidst_of_the_COVID-19_Pandemic

Davis, F. D. (1986). *A Technology Acceptance Model for Empirically Testing New End-user Information Systems: Theory and Results.* Doctoral Dissertation, MIT Sloan School of Management, Cambridge, MA.

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease Of Use, and User Acceptance of Information Technology. *MIS Quarterly, 13*(3), 319-340. DOI: 10.2307/249008

Diab, H., Daher, W., Rayan, B., Issa, N., & Rayan, A. (2024). Transforming Science Education in Elementary Schools: The Power of PhET Simulations in Enhancing Student Learning. *Multimodal Technologies and Interaction*, *8*(11), 105. https://doi.org/10.3390/mti8110105

Eyikorogha, Q., & Chigozie, J. N. (2024). Artificial Intelligence: A Resource Tool for Academic Service Delivery in Nigeria. *International Journal of Public Administration and Development Studies (IJPADS),* *1*(1), 17-19. http://ijpads.com/index.php/ijpads/article/view/3/3

Ferrara, E. (2024). Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies. *Sci*, *6*(1), 3. https://doi.org/10.3390/sci6010003

Filiz, O., Kaya, M. H., & Adiguzel, T. (2025). Teachers and AI: Understanding the Factors Influencing AI Integration in K-12 Education. *Educ Inf Technol*. https://doi.org/10.1007/s10639-025-13463-2

Fishbein, M., & Azjen, I. (1975). *Belief, Attitude, Intention and Behavior.* Reading, MA: Addison-Wesley.

Funa, A. A., & Gabay, R. A. E. (2025). Policy Guidelines and Recommendations on AI Use in Teaching and Learning: A Meta-Synthesis Study. *Social Sciences & Humanities Open, 11*, 101221. https://doi.org/10.1016/j.ssaho.2024.101221

Galindo-Domínguez, H., Delgado, N., Losada, D., & Etxabe, J. M. (2023). An Analysis of the Use of Artificial Intelligence in Education in Spain: The In-Service Teacher's Perspective. *Journal of Digital Learning in Teacher Education*, *40*(1), 41–56. https://doi.org/10.1080/21532974.2023.2284726

Gârdan, I. P., Manu, M. B., Gârdan, D. A., Negoiță, L. D. L., Paștiu, C. A., Ghiță, E., & Zaharia, A. (2025). Adopting AI in Education: Optimizing Human Resource Management Considering Teacher Perceptions. *Frontiers in Education, 10*. DOI:10.3389/feduc.2025.1488147

Ghamrawi, N., Shal, T., & Ghamrawi, N. A. (2023). Exploring the Impact of AI on Teacher Leadership: Regressing or Expanding?. *Educ Inf Technol, 29*, 8415-8433. https://doi.org/10.1007/s10639-023-12174-w

Gocen, A., & Aydemir, F. (2021). Artificial Intelligence in Education and Schools. *Res Educ Media, 12*(1), 13-21. https://doi.org/10.2478/rem-2020-0003

Granić, A., & Marangunić, N. (2019). Technology Acceptance Model in Educational Context: A Systematic Literature Review. *British Journal of Educational Technology, 50*(5), 2572-2593. https://doi.org/10.1111/bjet.12864

Groenewald, E., Kumar, N., Lnu, A., & Irfan, S. (2024). Virtual Laboratories Enhanced by AI for hands-on Informatics Learning. *Journal of Informatics Education and Research, 4*(1), 560-568. DOI:10.52783/jier.v4i1.600

Haleem, A., Javaid, M., Qadri, M. A., Singh, R. P., & Suman, R. (2022). Artificial intelligence (AI) Applications for Marketing: A Literature-Based Study. *International Journal of Intelligent Networks, 3*, 119-132. https://doi.org/10.1016/j.ijin.2022.08.005

Hazzan-Bishara, A., Kol, O., & Levy, S. (2025). The Factors Affecting Teachers’ Adoption of AI Technologies: A Unified Model of External and Internal Determinants. *Educ Inf Technol*. https://doi.org/10.1007/s10639-025-13393-z

Heeg, D. M., & Avraamidou, L. (2023). The Use of Artificial Intelligence in School Science: A Systematic Literature Review. *Educational Media International*, *60*(2), 125–150. https://doi.org/10.1080/09523987.2023.2264990

Herdliska, A., & Zhai, X. (2023). Artificial Intelligence-Based Scientific Inquiry. In Zhai, X. & Krajcik, J. (Eds.), *Uses of Artificial Intelligence in STEM Education* (pp. xx-xx). Oxford, UK: Oxford University Press. http://dx.doi.org/10.2139/ssrn.4591628

Herzallah, A. M., & Makaldy, R. (2025). Technological Self-Efficacy and Sense of Coherence: Key Drivers in Teachers' AI Acceptance and Adoption. *Computers and Education: Artificial Intelligence, 8*, 100377. https://doi.org/10.1016/j.caeai.2025.100377

Huang, X., & Qiao, C. E. (2024). Enhancing Computational Thinking Skills through Artificial Intelligence Education at a STEAM High School. *Sci & Educ, 33*, 383-403. https://doi-org.eresourcesptsl.ukm.remotexs.co/10.1007/s11191-022-00392-6

Kamalov, F., Santandreu Calonge, D., & Gurrib, I. (2023). New Era of Artificial Intelligence in Education: Towards a Sustainable Multifaceted Revolution. *Sustainability*, *15*(16), 12451. https://doi.org/10.3390/su151612451

Kandlhofer, M., Steinbauer, G., Hirschmugl-Gaisch, S., & Huber, P. (2016, October). Artificial intelligence and computer science in education: From kindergarten to university. In *2016 IEEE frontiers in education conference (FIE)* (pp. 1-9). IEEE.

Kim, K., & Kwon, K. (2023). Exploring the AI Competencies of Elementary School Teachers in South Korea. *Computers and Education: Artificial Intelligence, 4*, 100137. https://doi.org/10.1016/j.caeai.2023.100137

Kohnke, L., Moorhouse, B. L., & Zou, D. (2023). Exploring Generative Artificial Intelligence Preparedness among University Language Instructors: A Case Study. *Computers and Education: Artificial Intelligence, 5*, 100156. https://doi.org/10.1016/j.caeai.2023.100156.

Kohnke, L., Zou, D., Ou, A. W., & Gu, M. M. (2025). Preparing Future Educators for AI-Enhanced Classrooms: Insights into AI Literacy and Integration. *Computers and Education: Artificial Intelligence, 8*, 100398. https://doi.org/10.1016/j.caeai.2025.100398

Kong, S. C., Yang, Y., & Hou, C. (2024). Examining Teachers' Behavioural Intention of Using Generative Artificial Intelligence Tools for Teaching and Learning Based on the Extended Technology Acceptance Model. *Computers and Education: Artificial Intelligence, 7*, 100328. https://doi.org/10.1016/j.caeai.2024.100328.

Kumar, V. V., Carberry, D., Beenfeldt, C., Andersson, M. P., Mansouri, S. S., & Gallucci, F. (2021). Virtual Reality in Chemical and Biochemical Engineering Education and Training. *Education for Chemical Engineers, 36*, 143-153. https://doi.org/10.1016/j.ece.2021.05.002

Laili Farhana Md Ibharim, Wong, Y. S., & Mazlini Adnan. (2024). Assessing Teacher Acceptance of Augmented Reality Games for STEM Education. *International Journal of Academic Research in Progressive Education and Development, 13*(3), 3418-3425. http://dx.doi.org/10.6007/IJARPED/v13-i3/22655

Langreo, L. (2023, September 30). What AI Training do Teachers Need Most? Here's What They Say. *EducationWeek*. https://www.edweek.org/technology/what-ai-training-do-teachers-need- most-heres-what-theysay/2023/09#:%E2%88%BC:text=To%20get%20educators%20more%-20comfortable,%E2%80%99t%2C%20according%20to%20experts [08 March 2025]

Leh, J. (2022). AI in LMS: 10 Must-See Innovations for Learning Professionals. https://talentedlearning.com/ai-in-lms-innovations-learning-professionals-must-see/ [08 March 2025]

López-Zambrano, J., Torralbo, J. A. L. & Romero, C. (2021). Early Prediction of Student Learning Performance through Data Mining: A Systematic Review. *Psicothema, 33*, 456-465. https://doi.org/10.7334/psicothema2021.62

Luckin, R., & Cukurova, M. (2019). Designing Educational Technologies in the Age of AI: A Learning Sciences-Driven Approach. *British Journal of Educational Technology, 50*(6), 2824-2838. https://doi.org/10.1111/bjet.12861

Mavroudi, A., Giannakos, M., & Krogstie, J. (2018). Supporting Adaptive Learning Pathways through the Use of Learning Analytics: Developments, Challenges and Future Opportunities. *Interactive Learning Environments, 26*(2), 206-220. https://doi.org/10.1080/10494820.2017.1292531

McKinsey Global Institute. (2017). Jobs Lost, Jobs Gained: What The Future of Work Will Mean for Jobs, Skills, and Wages. https://www.mckinsey.com/featured-insights/future-of-work/jobs-lost-jobs-gained-what-the-future-of-work-will-mean-for-jobs-skills-and-wages [08 March 2025]

Mhlongo, S., Mbatha, K., Ramatsetse, B., & Dlamini, R. 2023. Challenges, Opportunities, and Prospects of Adopting and Using Smart Digital Technologies in Learning Environments: An Iterative Review. *Heliyon, 9*(6), e16348. https://doi.org/10.1016/j.heliyon.2023.e16348.

Mnguni, L. (2024). A Qualitative Analysis of South African Pre-service Life Sciences Teachers' Behavioral Intentions for Integrating AI in Teaching. *Journal for STEM Education Research*. https://doi.org/10.1007/s41979-024-00128-x

Mnguni, L., Nuangchalerm, P., El Islami, R. A. Z., Sibanda, D., Ramulumo, M., & Sari, I. J. (2024a). AI Integration in Biology Education: Comparative Insights into Perceived Benefits and TPACK among South African and Indonesian Pre-service Teacher. *Asia-Pacific Science Education, 10*, 381-410. DOI:10.1163/23641177-bja10086

Mnguni, L., Nuangchalerm, P., El Islami, R. A. Z., Sibanda, D., Sari, I. J., & Ramulumo, M. (2024b). The Behavioural Intentions for Integrating Artificial Intelligence in Science

Teaching among Pre- Service Science Teachers in South Africa and Thailand. *Computers and Education: Artificial Intelligence, 7*, 100334. https://doi.org/10.1016/j.caeai.2024.100334.

Molefi, R. R., Ayanwale, M. A., Kurata, L., & Chere-Masopha, J. (2024). Do in-Service Teachers Accept Artificial Intelligence-Driven Technology? The Mediating Role of School Support and Resources. *Computers and Education Open, 6*, 100191. https://doi.org/10.1016/j.caeo.2024.100191

Ng, D. T. K., Leung, J. K. L., Su, J., Ng, R. C. W., & Chu, S. K. W. 2023. Teachers' AI Digital Competencies and Twenty-First Century Skills in The Post-Pandemic World. *Education Tech Research Dev*, 71, 137-161. https://doi.org/10.1007/s11423-023-10203-6

Ng, D. T. K., Chan, E. K. C., & Lo, C. K. (2025). Opportunities, Challenges and School Strategies for Integrating Generative AI in Education. *Computers and Education: Artificial Intelligence, 8*, 100373. https://doi.org/10.1016/j.caeai.2025.100373

Nikitina, I., & Ishchenko, T. (2024). The Impact of AI on Teachers: Support or Replacement? *Scientific Journal of Polonia University, 65*, 93-99. DOI: 10.23856/6511

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. & Cornelius-Ukpepi, B. U. (2023). Adoption of Artificial Intelligence in Science Teaching: From the Vantage Point of the African Science Teachers. *Smart Learn. Environ., 10*(42). https://doi.org/10.1186/s40561-023-00261-x

Okunade, A. I. (2024). The Role of Artificial Intelligence in Teaching of Science Education in Secondary Schools in Nigeria. *European Journal of Computer Science and Information Technology, 12*(1), 57-67. https://eajournals.org/ejcsit/wp-content/uploads/sites/21/2024/02/The-Role-of-Artificial-Intelligence.pdf

Olafare, F. O. (2024). Artificial Intelligence in Educational Technology: Panacea to Efficient Instructional Delivery. In: Akpan, U.S. (eds) *Educational Broadcasting in Nigeria in the Age of Artificial Intelligence*. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-031-68530-9_15

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., & Brennan, S. E. (2021). The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *International Journal of Surgery, 88*, 105906. https://doi.org/10.1136/bmj.n71

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S. McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., Whiting, P. & Moher, D. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *Syst Rev, 10*(89). https://doi.org/10.1186/s13643-021-01626-4

Pantelimon, F.-V., Bologa, R., Toma, A., & Posedaru, B.-S. 2021. The Evolution of AI-Driven Educational Systems during the COVID-19 Pandemic. *Sustainability*, *13*(23), 13501. https://doi.org/10.3390/su132313501

Pichler, S., Kohli, C., & Granitz, N. (2021). DITTO for Gen Z: A Framework for Leveraging the Uniqueness of the New Generation. *Business Horizons*, *64*(5), 599-610. https://doi.org/10.1016/j.bushor.2021.02.021

Polanin, J. R., Pigott, T. D., Espelage, D. L., & Grotpeter, J. K. (2019). Best Practice Guidelines for Abstract Screening Large-Evidence Systematic Reviews and Meta-Analyses. *Research Synthesis Methods*, *10*(3), 330-342. https://doi.org/10.1002/jrsm.1354

Ramadahan, M. F., & Irwanto. (2018). Using Virtual Labs to Enhance Students' Thinking Abilities, Skills, and Scientific Attitudes. In *International conference on educational research and innovation (ICERI 2017)*, *Iceri*, (pp. 494–499).

Ramnarain, U., Ogegbo, A. A., Penn, M., Ojetunde, S., & Mdlalose, N. (2024). Pre-Service Science Teachers' Intention to Use Generative Artificial Intelligence in Inquiry-Based Teaching. *Journal of Science Education and Technology*. https://doi.org/10.1007/s10956-024-10159-z

Rütti-Joy, O., Winder, G., & Biedermann, H. (2023). Building AI Literacy for Sustainable Teacher Education. *Zeitschrift für Hochschulentwicklung*, *18*(4), 175-189. DOI:10.21240/zfhe/18-04/10.

Salame, I. I., & Samson, D. (2019). Examining the Implementation of PhET Simulations into General Chemistry Laboratory. *International Journal of Environmental and Science Education,* *14*(4), 207-217. http://www.ijese.net/makale_indir/IJESE_2116_article_5d3b17e193e7d.pdf

Schiavo, G., Businaro, S., & Zancanaro, M. (2024). Comprehension, Apprehension, and Acceptance: Understanding the Influence of Literacy and Anxiety on Acceptance of Artificial Intelligence. *Technology in Society, 77*, 102537. https://doi.org/10.1016/j.techsoc.2024.102537.

Shi, L., Ding, A.-C., & Choi, I. (2024). Investigating Teachers' Use of an AI-Enabled System and Their Perceptions of AI Integration in Science Classrooms: A Case Study. *Education Sciences, 14(11), 1187. https://doi.org/10.3390/educsci14111187*

Singh, T. M., Reddy, C. K. K. & Murthy, B. V. R., & Nag, A., & Doss, S. (2024). AI and Education: Bridging the Gap to Personalized, Efficient, and Accessible Learning. In *Internet of Behavior-Based Computational Intelligence for Smart Education Systems* (pp. 131-160). IGI Global. https://www.researchgate.net/publication/384843496_AI_and_Education_Bridging_the_Gap_to_Personalized_Efficient_and_Accessible_Learning

Strmečki, D., Bernik, A., & Radošević, D. (2015). Gamification in E-Learning: Introducing Gamified Design Elements into e-Learning Systems. *J. Comput. Sci.*, *11*(12), 1108–1117. DOI: 10.3844/jcssp.2015.1108.1117

Su, J., Ng, D. T. K., Chu, S. K. W. (2023). Artificial Intelligence (AI) Literacy in Early Childhood Education: The Challenges and Opportunities. *Computers and Education: Artificial Intelligence*, *4*, 100124. https://doi.org/10.1016/j.caeai.2023.100124

Sun, J., Ma, H., Zeng, Y., Han, D., & Jin, Y. (2022). Promoting the AI Teaching Competency of K-12 Computer Science Teachers: A TPACK-based Professional Development Approach. *Educ Inf Technol*, *28*, 1509-1533. https://doi.org/10.1007/s10639-022-11256-5

Tan, X., Cheng, G., & Ling, M. H. (2025). Artificial Intelligence in Teaching and Teacher Professional Development: A Systematic Review. *Computers and Education: Artificial Intelligence, 8*, 100355. https://doi.org/10.1016/j.caeai.2024.100355.

Tekin, Ö. G. (2024). Factors Affecting Teachers' Acceptance of Artificial Intelligence Technologies: Analyzing Teacher Perspectives with Structural Equation Modeling. *Instructional Technology and Lifelong Learning,* *5*(2), 399-420. https://doi.org/10.52911/itall.1532218

Topal, A. D., Eren, C. D., & Geçer, A. K. (2021). Chatbot Application in a 5th Grade Science Course. *Educ Inf Technol 26*, 6241-6265. https://doi.org/10.1007/s10639-021-10627-8

Venkatesh, V., & Bala, H. (2008). Technology Acceptance Model 3 and A Research Agenda On Interventions. *Decision Sciences, 39*(2), 273-315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of The Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science, 46*(2), 186-204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward A Unified View. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Villegas-Ch, W., Arias-Navarrete, A., & Palacios-Pacheco, X. (2020). Proposal of an Architecture for the Integration of a Chatbot with Artificial Intelligence in a Smart Campus for the Improvement of Learning. *Sustainability*, *12*(4), 1500.

Wah, K. C., & Paridah Daud. (2025). Enhancing Early Education with Artificial Intelligence: A Comparative Study of AI-Powered Learning Versus Traditional Methods. *International Journal of Academic Research in Business and Social Sciences, 15*(2), 983-999. http://dx.doi.org/10.6007/IJARBSS/v15-i2/24690

Wang, Y., Liu, C., & Tu, Y.-F. (2021). Factors Affecting the Adoption of AI-Based Applications in Higher Education: An Analysis of Teachers Perspectives Using Structural Equation Modeling. *Educational Technology & Society*, *24*(3), 116-129. https://www.jstor.org/stable/27032860

Woodruff, K., Hutson, J., & Arnone, K. (2023). Perceptions and Barriers to Adopting Artificial Intelligence in K-12 Education: A Survey of Educators in Fifty States. *IntechOpen*. DOI: 10.5772/intechopen.1002741

World Economic Forum. (2020). The Future of Jobs Report 2020. https://www3.weforum.org/docs/WEF_Future_of_Jobs_2020.pdf. [08 March 2025]

Xu, Y. J., Liu, X., Cao, X., Huang, C. P., Liu, E. K.,Qian, S., Liu, X. C., Wu, Y. J., Dong, F. L., Qiu, C. W., Qiu, J. J., Hua, K. Q., Su, W. T., Wu, J., Xu, H. Y., Han, Y., Fu, C. G., Yin, Z. G., Liu, M., Roepman, R., Dietmann, S., Virta, M., Kengara, F., Zhang, Z., Zhang, L. F., Zhao, T. L., Dai, J., Yang, J. L., Lan, L., Luo, M., Liu, Z. F., An, T., Zhang, B., He, X., Cong, S., Liu, X. H., Zhang, W., Lewis, J. P., Tiedje, J. M., Wang, Q., An, Z. L., Wang, F., Zhang, L. B., Huang, T., Lu, C., Cai, Z. P., Wang, F., & Zhang, J. B. 2021. Artificial Intelligence: A Powerful Paradigm for Scientific Research. *The Innovation, 2*(4), 100179. https://doi.org/10.1016/j.xinn.2021.100179

Zhai, C., Wibowo, S., & Li, L. D. (2024). The Effects of Over-Reliance on AI Dialogue Systems on Students' Cognitive Abilities: A Systematic Review. *Smart Learn. Environ.*, *11*(28). https://doi.org/10.1186/s40561-024-00316-7

Zhang, C., Schießl, J., Plößl, L. Hofmann, F. & Gläser-Zikuda, M. (2023). Acceptance of Artificial Intelligence among Pre-Service Teachers: A Multigroup Analysis. *Int J Educ Technol High Educ, 20*(49). https://doi.org/10.1186/s41239-023-00420-7

Zhang, H. L., & Leong, W. Y. (2024). Transforming Rural and Underserved Schools with AI-Powered Education Solutions. *ASM Sc. J., 19. https://doi.org/10.32802/asmscj.2023.1895*