frontiers | Frontiers in Education

TYPE Original Research
PUBLISHED 21 May 2025
DOI 10.3389/feduc.2025.1577285

OPEN ACCESS

EDITED BY
Clifford A. Shaffer,
Virginia Tech, United States

REVIEWED BY
Faruk Arici,
Bayburt University, Türkiye
Hasan Celal Balıkçı,
Harran University, Türkiye

*CORRESPONDENCE
Othman Abu Khurma
othman.abukhurma@ecae.ac.ae

RECEIVED 15 February 2025
ACCEPTED 29 April 2025
PUBLISHED 21 May 2025

CITATION
Alarabi K, Alabidi S, Tairab H, Pagani LS, AlSadrani B and Abu Khurma O (2025) AI's impact on science education: a study of ant and bee mindsets in UAE science classrooms.
Front. Educ. 10:1577285.
doi: 10.3389/feduc.2025.1577285

AI's impact on science education: a study of ant and bee mindsets in UAE science classrooms

Khaleel Alarabi [1], Suzan Alabidi [1], Hassan Tairab [2], Linda S. Pagani [3,4,5], Badriya AlSadrani [6] and Othman Abu Khurma [7]*

[1]College of Education, Al Ain University, Al Ain, United Arab Emirates, [2]College of Education, United Arab Emirates University (UAEU), Al Ain, United Arab Emirates, [3]School of Psycho-Education, Université de Montréal, Montréal, QC, Canada, [4]CHU-Mère-Enfant Sainte-Justine, Université de Montréal, Montréal, QC, Canada, [5]School Environment Research Group, Université de Montréal, Montréal, QC, Canada, [6]College of Education, United Arab Emirates University (UAEU), Al Ain, United Arab Emirates, [7]Emirates College for Advanced Education, Abu Dhabi, United Arab Emirates

Introduction: Although Artificial intelligence (AI) has the potential to revolutionize educational practices worldwide, particularly within the science domain, the integration of such technologies in education remains a challenge. This study investigates science teachers' perspectives regarding AI and examines how its integration influences teaching and learning processes. The research employs the metaphor of a dedicated ant farm and a co-operative beehive to analyze the potential of AI for enhancing science education. Two primary mindsets are identified: ant-like and bee-like thinking. This conceptualization illustrates how science teachers in the UAE perceive the integration of AI into education. Two research questions guided the study design: (1) How do science teachers perceive the impact of AI on science education's effectiveness and outcomes? (2) What insights do science teachers have regarding the integration of AI into traits related to ant-like or bee-like thinking?

Methods: Consequently, a cross-sectional survey was carried out, designed to collect data from 104 science teachers who voluntarily participated in this study using a specifically developed and validated questionnaire.

Results: The findings indicate that the majority of teachers reported a high or extraordinarily high level of understanding of the impact of AI integration in science education, which implies strong agreement with its potential influence.

Discussion: The study's findings offer a metaphor-based framework that showed a wide range of responses to the ant-like thinking and bee-like thinking metaphors, highlighting the complexity of science teacher perceptions. These findings diagonalized the need for more evident conceptual framing and further research on how such metaphors (heuristic tools) can be used to influence teacher understanding and classroom application of AI in a science learning context.

KEYWORDS

AI, science teachers, ant-like thinking, bee-like thinking, UAE

1 Introduction

1.1 AI's role in education

Artificial intelligence (AI) is a computer system that simulates human processes and intelligence. Current technology has developed programs that characterize or mimic human nature and behavior (Holmes and Porayska-Pomsta, 2022). Technology can simulate human behavior when trained using learning algorithms (Darayseh, 2023). Ideally, AI uses a large amount of information, observes patterns, and predicts a future state (Jarrahi, 2018; Lee and Hauskrecht, 2021). AI deploys critical skills such as learning, creativity, reasoning, and self-correction. There are four general types of AI: reactive machines, self-awareness, theory of mind, and limited-memory machines (Chung et al., 2022). These types of AI offer various benefits to the users. By automating tasks, AI's growth and development have transformed the labor market. Generative AI tools have also become critical in business, education, and healthcare (Darayseh, 2023; Al Arabi et al., 2023).

1.2 AI challenges in teacher adoption

AI has various disadvantages, including a deep technical understanding, the fact that it is expensive, and that it results in human unemployment (Korinek and Stiglitz, 2019; Dwivedi et al., 2021). However, the benefits of AI far outweigh its weaknesses, particularly in education and healthcare. The gaming and healthcare sectors in the United Arab Emirates (UAE) primarily employ AI (Darayseh, 2023; AlArabi et al., 2023).

The implementation of AI in education continues to pose a significant challenge. In the field of science education, policies aimed at integrating AI into the curriculum have yet to be implemented. Consequently, the UAE remains behind in the adoption of new technologies and platforms. Although there are plans and steps to implement AI in science education, these strategies require further improvement. Therefore, it is crucial to conduct research to explore the potential applications of AI in science education.

1.3 Theoretical grounding for metaphorical frameworks

Thinking involves processing information, remembering facts, and applying knowledge to various scenarios (Rumelhart, 2017; Tairab et al., 2020). Thinking also entails making assumptions, testing the idea against evidence and data, constantly updating opinions in line with results, and generating new conclusions (Baron, 2023; Khalil et al., 2023). Lake et al. (2016) stated that humans have inherent thought biases that require evaluation against the existing evidence. There are various types of human thinking in science (Gibson et al., 2023; Shodiyev, 2023; Alarabi et al., 2024).

Of the numerous cognitive models that guide scientific inquiry, metaphorical explanations of thinking styles and behaviors can offer revealing perceptions of how humans think about problem-solving and collaboration. Teachers use these metaphors and analogies, rather than literal comparisons, to describe certain behavioral tendencies or personality traits in the thinking of some species. This describes their thinking in a way that categorizes their predominant behavioral tendencies or mindsets. Metaphors simplify and offer a framework for understanding different modes of thinking or organizational styles (Moffett, 2024; Shodiyev, 2023). For example, ants are often associated with diligence, perseverance, and strong work ethics (Sabouret, 2021; Foltýnek et al., 2023). In terms of behavior, they are methodical, hardworking, and focused on tasks. They may prioritize efficiency, organization, and productivity. Ant-like thinking may involve meticulous planning, attention to detail, and willingness to work diligently toward long-term goals (Sabouret, 2021). The chief strength of ant-like mindsets is their thought processes, which promote efficiency, thoroughness, and strong work ethics (Foltýnek et al., 2023). However, as a weakness, such thought processes may also lead to a lack of flexibility or innovation if individuals become too focused on their assigned tasks and fail to see a bigger picture (Sabouret, 2021).

Figure 1 illustrates ant-like thinking, characterized by meticulous planning, attention to detail, and strong commitment to long-term goals. This mindset fosters efficiency, discipline, and perseverance, thereby ensuring systematic task completion. However, its rigidity may hinder adaptability and innovation as individuals may become overly focused on structured and predefined objectives.

Conversely, bee-like thinking emphasizes individual skills, wherein a group's collective intelligence surpasses that of an individual. Bees communicate and coordinate effectively to achieve common objectives, explore ideas, and collaborate with diverse groups (Sabouret, 2021). AI utilizes beelike thinking to develop tools that facilitate individual expertise and learning through collaboration with diverse individuals. Beelike thinking provides optimal solutions for problems that require innovation and creativity. Both species operate in a highly organized manner within their group, each performing specialized roles to ensure the success of the colony. Significantly, narrow-mindedness is a characteristic of ants, whereas open-mindedness is associated with bees. Ultimately, the relative efficacy of ant-like and bee-like thinking depends on the context and specific objectives of the current situation. In numerous instances, a combination of both approaches may prove the most effective as it leverages the strengths of each while mitigating their potential weaknesses (Olga and Nadezhda, 2022; Ouyang and Jiao, 2021). Intelligence can enhance the overall learning experience of science education by incorporating both ant-like and bee-like principles. It possesses the potential to create dynamic, adaptive, and collaborative learning environments that better prepare students for future challenges while fostering critical thinking, creativity, and effective problem-solving skills (Olga and Nadezhda, 2022; Ouyang and Jiao, 2021).

Figure 2 illustrates beelike thinking, which emphasizes collective intelligence, adaptability, and collaboration. This mindset fosters innovation by integrating diverse perspectives and dynamic problem-solving approaches. Individuals engage in open communication and cooperative exploration to generate creative solutions. However, its reliance on group interactions may lead to inefficiencies or delays in decision-making.

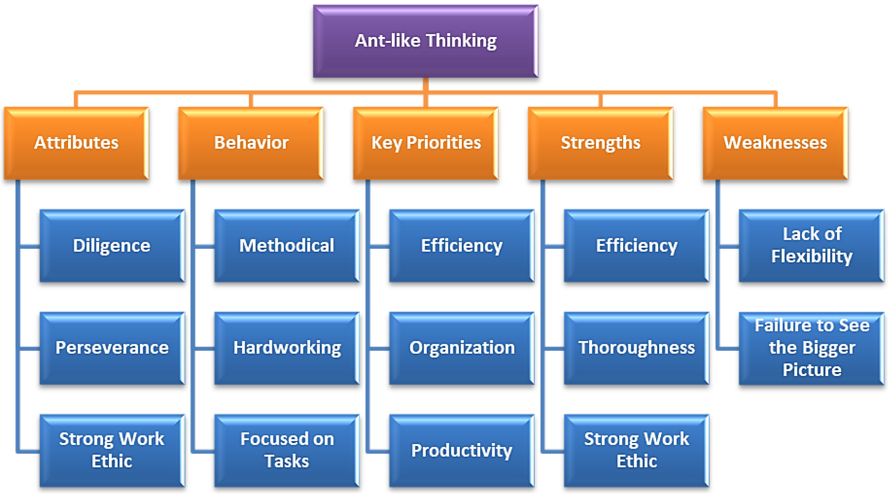

FIGURE 1
Ant-like thinking.

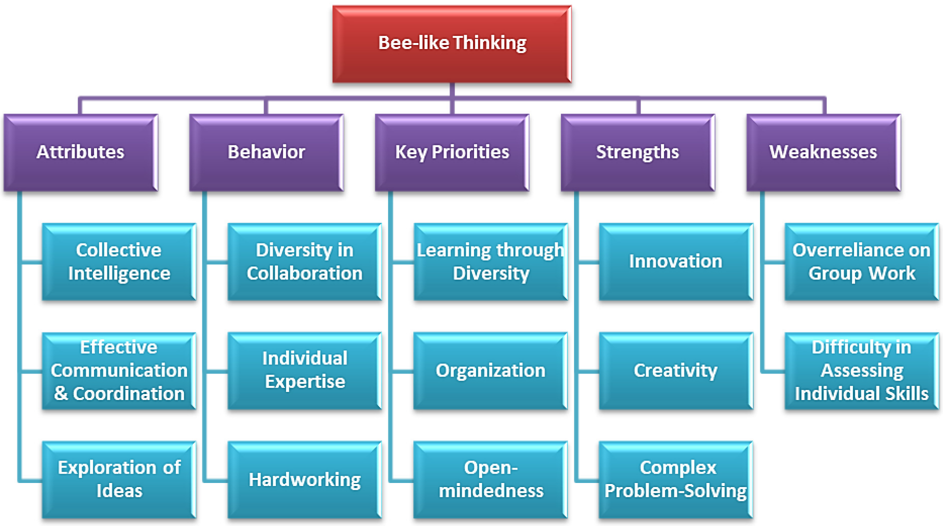

FIGURE 2
Bee-like thinking.

1.4 Rationale for the chosen metaphors

To frame teachers' cognitive approaches (thinking styles) to AI integration in science education, this study adopts these metaphors of ant-like thinking and bee-like thinking. The rationale is that ant-like thinking represents structured, collective, and task-driven behavior; this is aligned with a set of traits that align with traditional, procedural science learning (Zohar and Dori, 2003), Where teachers emphasize structure, diligence, and incremental task execution related to their teaching practices, therefore, these traits are often linked with early or cautious stages of AI adoption in science teaching pedagogies. In contrast, bee-like thinking symbolizes adaptability, creativity, and synthesis, reflecting the cognitive flexibility required to fully leverage AI's interdisciplinary potential (Sawyer, 2006), which also aligns with constructivist and connectivist perspectives (Siemens, 2005) that cover or capture traits such as adaptability, collaboration, and systems-level thinking. More specifically, for teachers, these metaphors can help them interpret their cognitive and emotional responses to AI in science education. Therefore, by linking these cognitive metaphors to established learning theories, the study moves beyond symbolism to provide a framework that explains observed variations in their attitudes toward the integration of AI in teaching science, revealing underlying mindsets toward innovation and change. The use of these metaphors can also highlight a broader issue in the field, which is the gap between AI's transformative capabilities in science education and its limited acceptance by schools, teachers, and learners (Holmes et al., 2019).

Science classrooms throughout the UAE adhere predominantly to traditional teaching and learning methodologies. This approach limits the potential of AI to personalize learning, enhance comprehension, and foster creativity. Students lack access to AI-powered tools that can promote inquiry, facilitate experimentation, or encourage the critical analysis of intelligent outputs. Consequently, this deficiency not only diminishes the potential for problem solving and future innovation but also potentially impedes efforts to address global challenges, thereby hindering economic growth. The current situation is characterized by a significant disparity between the inherent capabilities of AI in science education and its limited accessibility and acceptance by educational institutions, teachers, and students. Despite AI's capacity to facilitate learning, generate innovative solutions, and support academic advancement across various disciplines, the UAE's educational landscape lacks a comprehensive understanding of its advantages in scientific education (Marquez et al., 2022). This has created a disconnect between the students and the global academic community. These disparities can be mitigated by developing a more comprehensive understanding and improved communication regarding AI in education, as it has the potential to assist learners in mastering specific scientific concepts and skills. This approach would revolutionize science education and create a more inclusive and globally competitive learning environment throughout the UAE. Therefore, there is an urgent need to advocate the widespread dissemination of information regarding the broader benefits of technology utilization in science education.

2 Purpose of the study

This study aimed to investigate the current practices of science teachers in the UAE. Specifically, in the context of potentially incorporating AI into science education, there are two main mindsets (ant-like and bee-like). By focusing exclusively on the current methodological practices of both ants and bees, collectively, it is mindset-like. Thus, the integration of AI tools and methodologies into science education could potentially identify the current approaches, challenges, and opportunities. Moreover, this study represents an inquiry into a comprehensive understanding and foundation for feasible future advancements. The unexplored domain in which AI and science education intersect establishes the groundwork for AI development and integration across various educational domains. Therefore, these findings can serve as a catalyst for a new era of learning in which technology empowers and inspires teachers and students to think critically about any subject matter. Consequently, two research questions were addressed: (1) How do science teachers perceive the impact of AI on the effectiveness and outcomes of science education? (2) What insights do science teachers have regarding the integration of AI into traits related to ant-like or bee-like thinking?

3 Significance of study

Although researchers, such as González et al. (2017) and Zhai et al. (2021), have extensively discussed AI's contribution to the development of teaching, learning, and instruction, there is a dearth of research on AI and its applications in the UAE. This study aims to bridge this research gap by enhancing the efficiency of teachers' classroom practices by applying AI to both teaching and learning processes. Furthermore, this study uses analogies of ants and bees to reshape teachers' perspectives on teaching strategies, such as cooperative learning, problem-solving, and analytical thinking, potentially facilitating effective science learning. The findings of this study underscore the potential utility and integration of AI capabilities in the teaching and learning processes, providing learners with a range of innovative and engaging educational experiences. Moreover, this study draws comparisons between the cooperative methods of ant and bee colonies, and more efficacious science learning. Additionally, the findings of this study will be valuable in enhancing professional development programs for science teachers to effectively implement AI in their instructional practices.

4 Literature review

4.1 Theoretical framework

The relationship between AI and science education is predicated on the mechanisms of information retention and learning in individuals (Ng et al., 2023). Cognitive learning perspectives, which elucidate the construction and development of knowledge, serve as the foundation of this study. From a cognitive learning perspective, the primary assumption is that mental processes play a critical role in how individuals learn and form an understanding (Johnson, 2019; Khalil et al., 2023). Student cognition is integral to the cognitive processes that are essential for learning (Adnan et al., 2021; Liu et al., 2024). By processing substantial volumes of data generated during learner interactions and data analysis, AI in science education influences learners' cognitive processes by accelerating their semantic processes (Ng et al., 2023; Al Arabi et al., 2023). Consequently, knowledge construction facilitates learners in identifying patterns, assessing the relevance of learning experiences, and making data-driven decisions for constructing knowledge. According to the cognitive learning theory, individual cognition determines learners' affective and behavioral responses (Slovic et al., 2004). This is particularly salient in science education, where thoughtful abstraction is crucial for understanding and interpreting information that appears concrete or simplified (Luckin and Cukurova, 2019; Alarabi et al., 2022). AI facilitates such learning processes as it engenders a gradual progression from concrete to abstract information, which ultimately promotes mastery (Johnson, 2019). AI also influences individuals' beliefs. For instance, when students internalize the notion of not being proficient in physics, they perceive it as challenging. In such cases, AI assists students to make physics more cognitively accessible. If subject complexity is high, students can request AI to further simplify it until it becomes manageable. Thus, after assisting learners in the initial physics tasks, AI altered learners' perspectives by facilitating the comprehension of increasingly complex concepts. The integration of AI in science education is gradually reshaping pedagogical approaches by enabling personalized, creative, and interactive learning environments. As highlighted in Arıcı's (2024) review, AI technologies (e.g., ChatGPT) can autonomously generate instructional content that is ideal for a teaching pedagogy that simulates scientific phenomena for more straightforward interpretations and quicker acquisition of their concepts and supports hands-on learning through realistic virtual scenarios (Krenn et al., 2022). It is worth mentioning that this incredible potential can confirm a deeper understanding of complex concepts and reduce cognitive demands to get over any delay or hindered understanding of advanced complicated scientific phenomena (Arıcı, 2024).

Another potential element of AI is the enhancement of deep work in the learning process from the elementary school to university levels (Perrotta and Selwyn, 2020). Specifically, learners can engage in meaningful abstraction for extended periods without distractions, which may influence their learning and cognitive processes. In the contemporary context, such higher-level thinking has become more challenging for learners than in distracted environments (Dignum, 2019). However, by facilitating problem resolution, AI enables learners to engage in higher-level cognitive processes that are essential for learning (Perrotta and Selwyn, 2020). For instance, when initiating an essay, most word-processing programs implement corrections and provide improved sentence structure. Grammarly is an AI tool that offers a correct sentence structure. ChatGPT facilitates the writing process. When learners experience cognitive obstacles, they can obtain support that maintains their cognitive engagement with the task at hand (Johnson, 2019). According to a recent survey of more than 1,600 researchers worldwide, many scientists anticipate that AI will soon become central to research practices (Van Noorden and Perkel, 2023).

The current study employs two metaphors to explain how behaviors are formulated or will be formulated according to given parameters within the context or the community. Metaphors of ant-like and bee-like thinking, which are derived from the principles of swarm intelligence (Nayyar and Nguyen, 2018; Critchlow, 2023) and Distributed Cognition Theory (Hollan et al., 2000; Green, 2013). These fields of study illustrate how decentralized decision making and emergent behaviors develop from the interactions of simple agents within complex environments. Ant-like thinking is characterized by sequential, rule-based, and reinforcement-driven problem-solving, similar to how ants utilize pheromone trails to determine optimal paths (Garnier et al., 2007). This approach aligns with structured procedural learning methods in education. Conversely, beelike thinking emphasizes exploration, adaptability, and distributed communication (Wise et al., 2014), reflecting dynamic, networked, and inquiry-based learning strategies that are important as highlighted in the UAE science curricula (Khurma and El Zein, 2024). Research on cognitive learning theory supports these metaphors, indicating that sequential learning (ant-like) is beneficial for novices, whereas more exploratory approaches (bee-like) benefit advanced learners. Furthermore, Csikszentmihalyi's (2014) flow theory proposes that alternating structured and flexible learning modes can enhance engagement and cognitive efficiency.

4.2 Historical perspective

Alan Turing's 1950 publication of "Computer Machinery and Intelligence" marked the inception of artificial intelligence (AI). Subsequently, in 1952, Arthur Samuel developed a program capable of autonomously playing checkers (Woolridge, 2022). AI experienced rapid advancement in the late 1950s and the 1960s, with the creation of programming languages, films, and books (Garnfinkel and Grunspan, 2018; Fleck, 2018). AI progressed at a more moderate pace in the 1980s and the early 1990s as investors were scarce due to the global economic downturn (Woolridge, 2022; Lee, 2018). Despite the economic challenges of this period, comparable software from 1970 onward facilitated the launch of the Hubble telescope and sequencing of the entire genome in the 1990s (Hagen, 2000; Levay, 2021). Significant advancements across scientific disciplines have occurred since the early millennium (Lee, 2018; Woolridge, 2022). In 2011, Apple introduced Siri, which was the first AI virtual assistant. In 2020, OpenAI initiated GPT-3 testing, followed by the development of DALL-E in 2021 (Woolridge, 2022). In 2022, OpenAI launched ChatGPT, which enabled essay composition (Lund et al., 2023). Through intuitive processing, AI operates through multiple imputations of large datasets. By analyzing the behavioral patterns within these datasets, AI modified the algorithms to generate estimates. Dignum (2019) asserted that the initial step involves the engineer inputting data into a program. Text, videos, and images can serve as input data. Data context and desired outcomes were defined. The second step entails data processing, during which AI determines the computational approach. Contingent upon pre-programmed data, AI interprets real-time information to adhere to specific behavioral patterns. Following the processing, the data output was obtained through prediction (known as imputation). AI can correct and adjust errors (Johnson, 2019). The final stage is an assessment in which the AI analyzes the data and estimates the probability of its predictions. There are various types of AI. The first is natural language processing (NLP), which enables computer programs to comprehend, modify, and generate human languages. NLP can interrogate voice and text data. ChatGPT and Siri (a voice-language assistant) exemplify NLP applications (Moore, 2019). Another category of AI is computer vision, which facilitates the generation of meaningful messages from images and video. For instance, computer vision encompasses the face and finger unlocking capabilities of a smartphone. Robotics is another form of AI. Robotics involves programming AI tools to replicate human movement (Sabouret, 2021). Starship delivery robots and Nimbo security robots are examples of robotic AI.

The metaphor "scientists should be like bees and not ants or spiders" comes from Francis Bacon's writings, in which he compares different methods of gaining knowledge and conducting scientific inquiry (Bacon, 2014; Danziger, 2002). Ants symbolize those who focus solely on empirical data collection and lack a deeper analysis or transformation. They gather facts but do not innovate or theorize. On the other hand, spiders symbolize individuals who depend on abstract reasoning, constructing theories based solely on their own ideas or previous knowledge, without empirical grounding. However, Bees exemplifies this optimal approach. They collect knowledge from external sources (similar to flowers) and transform and refine it into something new and useful (comparable to honey). The true labor of philosophy mirrors this process, as it neither depends solely on cognitive abilities nor merely stores raw data from natural history or mechanical experiments but instead transforms and processes it within the understanding (Draaisma and Vincent, 2000; Bacon, 2014). Bacon advocates scientists to embrace this balanced approach: acquiring knowledge through experimentation and observation while critically engaging with and transforming that knowledge into new theories and applications (Bunge, 2017; Jalobeanu, 2015).

4.3 AI and science education

A study by Darayseh (2023) on the acceptance of AI in science education has revealed positive outcomes. According to science teachers, AI has positive implications for ease of use, self-efficacy, and attitudes. This research indicates that both teachers and learners perceive AI as beneficial for science education. Nja et al. (2023) assessed the impact of AI on science education. The results revealed that the implementation of AI in science education enhances the ease of instruction and student learning. AI has enabled teachers to articulate concepts more effectively than traditional teaching methods have. Furthermore, Li et al. (2024) examined the performance of 23 student teachers in "Human-Human" and "Human-Machine" collaborative learning approaches. Their study found that student teachers who utilized AI-generated activities demonstrated improved critical thinking skills, completed tasks more efficiently, and experienced a reduced cognitive load. Moreover, additional researchers have discovered that AI enhances student learning in areas where students encounter difficulties (Yang et al., 2021; Chen et al., 2022). The literature indicates that AI positively influences science education by improving learning and instruction.

Abstract thought plays a critical role in science education because it provides a problem-solving system (Matthee and Turpin, 2019; Lamb et al., 2018). According to Dignum (2019), thinking provides a systematic method for offering solutions to problems experienced by people. Consequently, when one method of thinking is ineffective, an individual can explore alternatives. Different thinking methods facilitate effective problem-solving (Cocking and Mestre, 2013; Wismath and Orr, 2015). Additionally, thinking is important in science education as it distinguishes assumptions from facts. Rather than relying on abstract assumptions, thinking enables the assessment of evidence as the basis for drawing conclusions (Sjöström and Eilks, 2018). Beyond insisting on evidence, thinking in science education also evaluates the reliability of evidence (Kneusel, 2023). Science education typically requires updating evidence over time (Kuhn and Modrek, 2022). Evaluating evidence facilitates the development of new methods to draw conclusions.

AI systems emulate human cognitive processes in several ways. In terms of ant-like cognition, AI robotics replicates the characteristics of ants, including collective intelligence, task completion efficiency, and rule adherence. AI applications in science education facilitate the decomposition of problems into smaller components and provide solutions (Moore, 2019). In the context of science education, AI tools adhere to predetermined rules and accomplish tasks within specified time frames. AI can establish programs that require students to work collaboratively, thus creating an ant-like cognitive structure (Seeber et al., 2020). Furthermore, AI generates cues for learners to facilitate the process and deconstruct complex tasks. Conversely, beelike cognition promotes individual expertise and exploration of ideas from diverse backgrounds. AI employs beelike thinking when developing learning tools for students (Sabouret, 2021). AI creates tools that emulate teachers and tutors to assist learners with difficulties in developing their skills (Dignum, 2019). Moreover, AI facilitates collaboration between students and teachers from diverse backgrounds (Dignum, 2019). The varied perspectives offered foster creativity and innovation.

AI tools typically utilize decentralized processing and distributed learning, which draws inspiration from collaborative and creative beelike navigation systems (Rahmadika et al., 2022). This replicated the interconnectedness of the hive, resulting in enhanced learning efficiency, resilience, and adaptation. The objective of AI designers is to augment an extensive digital knowledge repository using collective intelligence (Saurabh et al., 2019).

5 Materials and methods

A cross-sectional survey design was chosen for its ability to efficiently collect quantifiable data from a large sample of science teachers within a particular window of time. This method facilitated the identification of overall trends in the science teachers' perceptions and awareness related to AI integration. Research acknowledges how mixed-methods design would have added richness in the form of interviews or open-ended responses, however, the scope of the current study was set toward acquiring an overview of prevalent attitudes and levels of knowledge, little, high, extremely high, etc.

A cross-sectional survey was conducted to examine science teachers' perspectives on AI integration into science education. Cohen-Mansfield et al. (2016) define questionnaires as tools for collecting self-reported data on participants' views, opinions, and experiences. Cross-sectional surveys are efficient in quickly collecting data from a broad sample of participants (Creswell and Hirose, 2019). This design elucidates the scientific community's perspective of AI in science education. Participants' perspectives on AI in science education were assessed using the Scale for AI in Science Education through Ants and Bees Thinking (AI-SEABT).

The AI-SEABT scale has been developed by a panel of subject matter faculty in science education, information and communication technology, and research experts to capture science teachers' cognitive orientations toward AI integration in their science teaching practices or used pedagogies grounded in metaphor-based cognitive theory and pedagogical literature. The scale consists of three subscales: (1) Procedural Engagement, (2) Collaborative Adaptability, and (3) Transformative Openness. The first subscale reflects ant-like thinking, aligned with behaviorist and task-oriented teaching models, focusing on individual effort, routine, and linear AI use that aims to support instruction (Zohar and Dori, 2003; Reigeluth, 2013). The second and third subscales reflect bee-like thinking: Collaborative Adaptability captures attitudes toward shared inquiry, peer-learning, and responsiveness to change—aligned with constructivist and connectivist pedagogies (Sawyer, 2006; Siemens, 2005), while Transformative Openness addresses broader epistemological beliefs (whether AI integration would affect learning, mental processes, or believing that science can be learned through inquiry) and willingness to reimagine science learning through AI. Item generation followed a deductive approach, where constructs were derived from theory and validated metaphorical frameworks, then operationalized into 5-point Likert-scale items.

To ensure the AI-SEABT scale validity, the developers reviewed and provided feedback to ensure scale validity, the feedback

TABLE 1 Cronbach's alpha values for the questionnaire.

Constructs	No of items	Mean	Standard deviation (SD)	Cronbach alpha (α)
UAC	6	4.763	0.446	0.968
ALT	10	4.212	0.387	0.874
BLT	10	4.116	0.524	0.896

TABLE 2 Understanding of AI functionalities and levels of AI thinking.

Constructs	No of items	Questionnaire items
UAC	6	1, 2, 3, 4,5,6
ALT	10	8, 11, 13, 15, 17, 18, 21, 22, 25, 26
BLT	10	7, 9, 10, 12, 14, 16, 19, 20, 23, 24

TABLE 3 Participant characteristics.

Subject	*N*	Percentage (%)
Biology	34	32.7
Physics	46	44.2
Chemistry	24	23.1
Total	104	100

required the tool to be refined and get piloted to evaluate three important main jobs: First, their revisions to ensure the theoretical coherence with the metaphors and instructional realities of AI use in Abu Dhabi schools. Second, to ensure that the data collection tool moves beyond attitude measurement and instead, it function as a heuristic diagnostic for categorizing science teachers' dispositions toward AI integration across instructional, collaborative, and epistemological domains. Third, the revisions required piloting test to ensure item clarity across the recruited participants. Their suggestions have enhanced the instrument's construct validity. Cronbach's alpha for the internal consistency metric was calculated (Table 1). A high score of 0.913 suggests that the questions effectively capture the intended constructs. The AI-SEABT, which focuses on participants' understanding of AI functionalities and analogies, consists of 26 items (Likert-type statements) designed to provide quantitative data on participants' levels of AI awareness.

Table 2 details the categorization of the items into three core constructs: Understanding AI Capabilities (UAC), Understanding the Analogy (Ant-Like Thinking) (ALT), and Understanding the Analogy (Bee-Like Thinking) (BLT). Each questionnaire item utilizes a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

The data collection procedures were designed to guarantee consistency and ethical compliance. A purposive sampling technique was employed to recruit 104 science teachers (Physics, Chemistry, and Biology) from various schools across Abu Dhabi and Al Ain (Table 3). Participants were recruited from among those enrolled in a professional diploma program at Al Ain University, who provided informed consent to participate in the study. The researchers communicated the survey link to all program chairs and their science instructors teaching in their programs. The link to the survey starts with the informed consent section and the opt-out statement that makes participants aware of their right to stop at any time during the completion task or not to agree if they decide to, which indicates voluntary participation. The consent form section has sufficient information for participants, stating that there are no consequences for their participation, rewards, or any financial incentives. Instead, the researcher will send a thank you message and express appreciation upon the completion of the survey. There were two rounds of sharing the survey link, In the first round, researchers received 83 responses out of 210, and in the second round, 2 weeks later, when a reminder was sent out by the instructors, another 21 responses were completed.

6 Results

6.1 How do science teachers view the AI impact on the efficacy and outcomes of science education?

To address research question one, descriptive statistics [Mean (M) and Standard deviation (SD)] were calculated to analyze teacher responses regarding their understanding of AI capabilities. Table 4 presents the distribution of teachers' responses to the questionnaire understanding AI capabilities (UAC) construct. The results indicated that most teachers reported a high or very high level of understanding of AI capability items. The mean scores for the six items ranged from 3.04 to 4.57, with only one item falling below 3.41. Nevertheless, all items remained within the "high understanding" category. The highest mean score (4.57) corresponded to the statement "I believe AI has the potential to revolutionize science education," indicating a strong agreement with AI's potential impact. Conversely, the lowest mean score (3.01) was associated with the statement "I am familiar with the concept of artificial intelligence (AI)," suggesting a potential gap in teachers' baseline knowledge of AI itself.

The interpretation of mean scores in Tables 1, 2 followed a five-level scale commonly used in educational research to categorize Likert-type responses: Very High (4.21–5.00), High (3.41–4.20), Moderate (2.61–3.40), Little (1.81–2.60), and Very Little (1.00–1.80). This classification was adapted from similar scales used in previous studies analyzing teacher attitudes and perceptions (e.g., Alharbi, 2015), and was reviewed for appropriateness in the context of the current study.

6.2 How do science teachers grasp the ant-bee metaphor-AI relationship?

Descriptive statistics were calculated to analyze teachers' responses regarding their understanding of the analogy between AI and insect-like thinking. Table 5 presents the distribution of teachers' responses (physics, chemistry, and biology) based on their comprehension of the analogy between AI and ant-like thinking. For ant-like thinking biology, the teachers had the highest mean scores (M = 3.6), followed by chemistry (M = 2.1), and physics

TABLE 4 Descriptive analysis of teachers' responses for understanding AI capabilities.

Understanding AI capabilities	Mean	SD	Degree*
I am familiar with the concept of AI.	3.01	0.64	Moderate
Do you believe AI could enhance science education?	4.41	0.35	Very high
AI can explain complex scientific concepts in a way that is understandable to all students.	3.98	0.88	High
I believe AI has the potential to revolutionize science education.	4.57	1.01	Very high
AI integration in science education can improve student learning outcomes.	4.34	0.73	Very high
AI technologies can be effectively applied to real-world scenarios to teach science concepts.	4.01	0.54	High
Overall scores	4.05	0.69	High

*Very high (4.21–5.0), High (3.41–4.20), Moderate (2.61–3.4), Little (1.81–2.60), and Very little (1.0–1.80).

TABLE 5 Means scores and standard deviations for measures of AI-SEABT scale.

Type of thinking	Subject	*N*	Mean	SD
Ant-like (mean)	Physics	46	1.87	1.01
	Chemistry	24	2.1	1.0
	Biology	34	3.6	0.93
	Total	104	2.52	0.98
Bee-like (mean)	Physics	46	4.81	0.67
	Chemistry	24	4.68	0.81
	Biology	34	2.69	0.87
	Total	104	4.06	0.78

teachers had the lowest mean score (M = 1.87). Additionally, regarding beelike thinking, an analysis of mean scores showed that physics teachers had the highest mean score (M = 4.81), followed by chemistry (M = 4.68), and biology teachers had the lowest mean score (M = 2.69).

Table 6 presents the distribution of the teachers' responses based on their comprehension of the analogy between AI and ant-like thinking. Teacher responses exhibited a wide range, with the majority falling into either low or high categories. The mean score across the 10 items varied considerably, ranging from 1.45 to 4.91. Notably, only one response was classified as moderate, and two were categorized as very low. The responses for all 10 items were within the "little" category, suggesting that teachers generally do not perceive AI as functioning similarly to ant-thinking.

Table 7 illustrates the distribution of teachers' responses concerning their understanding of the analogy between AI and bee-like thinking. The teacher responses demonstrated a wide range, with the majority falling into either the very high or moderate category. The mean score across the 10 items varied substantially, ranging from moderate 2.88 to very high (4.81). Notably, two of the responses were classified in the high category. The responses for all 10 items were within the "high" category, indicating that teachers generally perceive AI as functioning similarly to bee-thinking.

In conclusion and beyond these descriptive statistics, the subscale-level trends reveal meaningful contrasts in teacher orientations toward AI integration in their teaching practices. For example, the Bee-like Thinking subscale scored highest (M = 4.06), particularly for items related to personalization, engagement, and adaptive learning, which indicates a strong alignment with constructivist and connectivist approaches (Siemens, 2005; Sawyer, 2006). In contrast, Ant-like Thinking scored lowest (M = 2.52), with minimal support for AI's role in collaboration or structured teamwork, indicating reluctance, hesitance, or feeling unconfident toward procedural or collective AI applications (Zohar and Dori, 2003). These patterns highlight a preference for individualized over task-driven uses of AI in science education.

6.2.1 ANOVA

A normality test was performed to determine if the data were normally distributed, and because the p-value of the Kolmogorov-Smirnov test was greater than 0.05, the dataset was normally distributed. Moreover, the Levene test for equality of variances was used to assess the homogeneity of the variance, and the results were not significant ($p > 0.05$). Levene's test was used for the students in the pre-test. A one-way Analysis of Variance (ANOVA) was used to determine whether there were any statistically significant differences between the three groups of science teachers and traits related to ant-like or bee-like thinking (Table 8). Regarding ant-like thinking, it was found that, at $p < 0.05$, the science teachers' groups were significantly different [F (2,101) = 246.3, p = 0.000]. Similarly, discipline had a statistically significant effect on beelike thinking scores [F (2, 101) = 285.4, p = 0.000].

Tukey's HSD *post-hoc* test was used to determine which group differences were significant (Table 9). No significant difference in ant-like thinking was found between the physics (M = 1.87, SD = 1.01) and chemistry (M = 2.1, SD = 1.0) teachers ($p > 0.05$). Moreover, biology teachers (M = 3.6, SD = 0.93) showed significantly higher levels of ant-like thinking than physics (M = 1.87, SD = 1.01) and chemistry teachers (M = 2.1, SD = 1.0) at p = 0.05. These results suggest that biology teachers had a stronger alignment with ant-like thinking skills than physics and chemistry teachers. In contrast, the results reveal that biology teachers (M = 2.69, SD = 0.87) scored significantly lower on items associated with bee-like thinking traits compared to Chemistry (M = 4.68, SD = 0.81) and Physics (M = 4.81, SD = 0.67) teachers. Chemistry and physics teachers were more likely to associate AI with bee-like thinking. There was no significant difference between chemistry and physics teachers, indicating a shared perception of AI's potential as a tool for fostering beelike thinking in science education.

TABLE 6 Descriptive analysis of teachers' responses for ant-like thinking.

Understanding ant-like thinking	Mean	SD	Degree*
AI can create collaborative learning environments where students work together on science problems.	1.92	1.10	Little
AI can facilitate peer-to-peer learning and knowledge sharing in science.	2.04	1.09	Little
In my classroom, I prefer collaborative learning activities where students work together towards a common goal.	3.58	0.66	High
AI can promote strong communication and teamwork skills in science classrooms.	1.45	1.21	Very little
In your classroom, students share ideas and resources openly to achieve a common goal.	2.88	0.58	Moderate
The AI system in science would be most similar to a virtual lab assistant that guides students through pre-defined experiments.	3.45	0.87	High
AI in science education would be most effective in delivering pre-defined learning experiences.	3.91	0.76	High
AI in science would primarily focus on individual student competition.	1.75	1.25	Very little
AI would be more beneficial for students who thrive in collaborative learning environments.	2.03	0.96	Little
AI might hinder the development of critical thinking and independent learning skills.	2.15	1.31	Little
Overall scores	2.52	0.98	Little

*Very high (4.21–5.0), High (3.41–4.20), Moderate (2.61–3.4), Little (1.81–2.60), and very little (1.0–1.80).

TABLE 7 Descriptive analysis of teachers' responses for bee-like thinking.

Understanding bee-like thinking	Mean	SD	Degree*
AI could effectively cater to the diverse learning styles present in a science classroom.	2.88	0.77	Moderate
AI can provide students with individualized feedback and support in science learning.	4.08	0.89	High
In your classroom, students explore different learning paths based on their chosen area of focus.	3.31	1.03	Moderate
AI can personalize learning pathways in science based on individual student needs.	4.63	0.72	Very high
AI can enhance student interest and participation in science education	4.81	0.43	Very high
AI in science would prioritize collaborative problem-solving activities.	4.11	0.74	High
In my classroom, I prefer Individualized learning experiences where students progress at their own pace.	2.96	1.22	Moderate
Integrating AI for collaborative learning can enhance student engagement in science education.	4.49	0.84	Very high
The AI system in science would be like a personalized learning portal that adapts content based on student progress.	4.62	0.46	Very high
AI-enabled individualized learning experiences can cater to diverse student needs in science education.	4.71	0.32	Very high
Overall scores	4.06	0.74	High

*Very high (4.21–5.0), High (3.41–4.20), Moderate (2.61–3.4), Little (1.81–2.60), and very little (1.0–1.80).

7 Discussion

This study aimed to highlight the moderating role of science teachers and how their current mindset can bridge the gap in the use of AI in science education in the UAE. There is potential for increased effectiveness and efficiency in instruction. The survey findings revealed that science preservice teachers (registered as postgraduate students) have generally perceived the integration of AI in their pedagogical methods as beneficial, with consistently high average scores on the Likert scale. As previously explained, the reliability of the instrument is indicated by a Cronbach's alpha of 0.931. In addition to that, the expert input during survey development has effectively reinforced the credibility of the results and suggested that the reported perceptions accurately reflect teachers' views.

These findings confirm that the ant-like thinking and bee-like thinking metaphors offer more than symbolic value; they also function effectively as heuristic tools to interpret the pedagogical lenses through which teachers view AI and its integration in their pedagogical interventions. The high bee-like scores reflect openness to transformative, learner-centered uses of AI, while low ant-like scores suggest discomfort with its use in structured, collaborative contexts, where a possibility of "free ride" is higher, which might demotivate active adopters of AI when being assigned collective tasks. This highlights the need for targeted professional development that bridges the gap between enthusiasm for AI and readiness for its pedagogical integration (Luckin and Holmes, 2016; Holmes et al., 2019).

TABLE 8 ANOVA results for AI-SEABT -scale measure by teachers' groups.

		Sum of squares (SS)	df	Mean square (MS)	*F*	Sig.
Ant-like thinking	Between groups	44.1	2	54.6	246.3	0.000
	Within groups	22.5	101	0.42		
	Total	62.4	103			
Bee-like thinking	Between groups	58.3	2	58.7	285.4	0.000
	Within groups	5.7	101	0.66		
	Total	73.5	103			

TABLE 9 *Post-hoc* tests for AI-SEABT -scale and students' type of thinking.

						95% Confidence interval for difference[a]	
Dependent variable	(I) groups	(J) groups	Mean difference (I–J)	Std. error	Sig.	Lower bound	Upper bound
Ant-like thinking	Biology	Chemistry	1.50*	0.086	0.012	−0.37	0.04
	Biology	Physics	−0.23*	0.065	0.020	0.07	0.02
	Physics	Chemistry	1.73*	0.073	0.91	1.12	1.65
Bee-like thinking	Biology	Chemistry	−0.199*	0.094	0.016	−0.72	−0.07
	Biology	Physics	0.13	0.084	0.005	0.47	0.83
	Chemistry	Physics	−2.12*	0.077	0.67	−0.35	−0.044

*The difference is statistically significant at the $p < 0.05$ level. [a]The confidence intervals were calculated and interpreted using post-hoc multiple comparison adjustments.

7.1 AI impact on the efficacy and outcomes of science education

Although science teachers generally perceive AI as having significant potential for science education, their comprehension of the underlying concepts may require further development. When implemented effectively, AI facilitates scientific learning, which is crucial for academic success. Nevertheless, there may be some discrepancies in the interpretation; however, the findings have consistently demonstrated a robust optimistic outlook on the potential of AI in science education. The strong belief that AI can transform science education received the highest mean score, 4.57. This emphasizes teachers' shared recognition of the transformative potential of AI in enhancing educational pedagogy and objectives. Therefore, this study corroborates previous research indicating that AI is an effective tool for improving teachers' teaching methods and student achievement (Al Arabi et al., 2023; Darayseh, 2023; AlArabi et al., 2023; Liu et al., 2024). Nevertheless, this investigation underscores the limited knowledge of AI among teachers, as evidenced by their relatively low mean score (3.01) for familiarity with AI concepts. This finding suggests that, while teachers acknowledge the significance and potential of AI, there is a need to enhance their understanding of its fundamental principles and applications in the field of science. The results of this study support the findings of other studies that demonstrate the importance of teachers acquiring more knowledge of AI's capabilities to fully utilize it in various educational contexts to enhance student performance, particularly in science classes (Al Arabi et al., 2023; Darayseh, 2023; AlArabi et al., 2023; Zhang, 2022; Dignum, 2019).

7.2 Teacher's understanding of the nexus between the two mindsets of ant and bee metaphor and AI

The wide range of responses to Question Two indicates that science teachers generally do not perceive AI as functioning similarly to ant-like thinking and demonstrate variability in their beliefs regarding AI's capabilities. Specifically, the findings suggest that teachers generally perceive AI as functioning in a manner similar to bee-like thinking. The ant-like thinking model facilitates straightforward understanding and acquisition of knowledge through step-by-step procedures, potentially simplifying comprehension for a broader range of learners (Sadedin and Duenez-Guzman, 2012). This aligns with previous studies that have examined how AI can expedite the learning process by providing clear rules and structured learning pathways (Al Arabi et al., 2023; Sadedin and Duenez-Guzman, 2012; Liu et al., 2024), demonstrating that AI can enhance understanding and facilitate comprehension. Furthermore, AI systems promote behavior that is analogous to that of bees. Beelike thinking prioritizes individualization, expertise, and diversification. These findings indicate that AI has the potential to serve as an essential tool for struggling students as it can construct a robot that communicates with students on an individual basis (Sadedin and Duenez-Guzman, 2012; Liu et al., 2024). The findings also demonstrated the application of AI for visual, auditory, and spatial purposes. Consequently, learners who struggle to comprehend oral ideas can be presented in visual or auditory formats. Learners can also engage in the learning process, which can readily promote their adaptability (Dignum, 2019). In science education, learners possess diverse strengths and modalities. According to Kneusel (2023), AI enhances all these by modifying the learning formats.

Ant-like thinking and bee-like thinking metaphors have been wisely chosen and effectively employed in this study as heuristic tools to explain science teachers' affective and cognitive predispositions toward adopting AI. Their role in this study exceeded strict or nominal categorizations since they, as creative heuristics utilized tools, enabled more complex descriptions of the contribution of implicit pedagogical beliefs to the adoption process. Heuristics, usually used frequently in cognitive science and education research, serve to simplify complex decision-making and do abstract thinking, especially when dealing with concepts that require imagination or formulating mental images, more practical and usable (Gigerenzer and Gaissmaier, 2011; Reigeluth, 2013). Ant-like thinking, in this context, is a procedural and conservative style that adheres to behaviorist methodologies, with AI viewed primarily as a tool for efficiency or automation, as it is required when conducting experiments or implementing science-based inquiry that needs to follow a specific list of procedures to test out a hypothesis or follow logical steps to answer the inquiry questions critically.

Bee-like thinking, on the other hand, is more in line with constructivist and socio-cognitive approaches, emphasizing innovation, distributed learning, and epistemic collaboration (Sawyer, 2006; Siemens, 2005). These metaphors provide a fruitful analytic lens for examining patterns in teachers' responses—both on the surface level of attitudes and the cognitive frames through which AI is envisioned and evaluated. By using this heuristic framework, we move beyond simplistic "tech-ready" or "tech-resistant" teacher labels and instead identify clusters of thinking indicative of varying degrees of epistemological openness, pedagogical risk-taking, and systemic sensitivity. This approach is aligned with the incremental requests for the co-creation of knowledge when involving learners in science lessons. Investing in collaborative efforts to develop skills, generate hypotheses in group-based settings, and create new evidence-based scientific conclusions. This approach is in line with current calls for more interpretive and theory-informed models of educational technology research (Luckin and Holmes, 2016; Holmes et al., 2019). While not prescriptive in a deterministic sense, the model is of practical utility for forecasting likely concerns or support behaviors in AI adoption, for example, some of these teachers, who aren't usually or routinely willing to exert efforts in innovating customized pedagogies, might prefer to adopt it as it may get them the "free ride" when a collective task is being assigned to them officially.

7.2.1 Disciplinary variations in perceived AI contributions to ant- and bee-like thinking

The ANOVA results presented in Table 8 reveal statistically significant differences among science teachers from different specializations: biology, chemistry, and physics; these differences are in their perceptions of AI's role in fostering and reinforcing both ant-like and bee-like thinking ($p < 0.001$). These findings indicate that the way AI is understood to support different cognitive dispositions in science education is not uniform across these three disciplines "physics, biology, and chemistry." This is a very critical result that was emphasized previously by interesting literature that highlighted how teachers' practices, beliefs, and perceptions vary and are shaped by their disciplinary epistemologies (Becher and Trowler, 2001). More specifically, the significant F-values for both constructs ($F = 246.3$ for ant-like and $F = 285.4$ for bee-like thinking) suggest a strong effect of disciplinary background on how AI is perceived by teachers to interact with structured, methodical reasoning (ant-like thinking) *vs.* creative, synthetic reasoning (bee-like thinking). This means that these findings are fully and sufficiently aligned with studies emphasizing that pedagogical interpretations and perceptions of technology adoption in teaching and learning are mediated by subject-specific teaching traditions and emphasis on the curriculum (Cohen and Ball, 1999; Mishra and Koehler, 2006).

The *post-hoc* comparisons using Tukey's HSD provided in Table 9 show that biology teachers significantly outperformed their physics and chemistry counterparts in endorsing AI's potential to enhance ant-like thinking or at least to advocate for its appropriateness for such thinking styles according to their biology specialization. This is interesting and could indicate critical reasons that may be attributed to biology's inherent emphasis on skills such as structured observation, categorization, and empirical investigation that are appropriate with the nature of its topics—these skills well aligned with ant-like traits of methodical and stepwise reasoning (Michael, 2006; Nehm and Ha, 2011). In addition, research suggests that biology education often relies on memorization and hierarchical organization of factual content, such as anatomical terms, cellular processes, and taxonomic classifications (Khodor et al., 2004; Momsen et al., 2010). Such content demands naturally foster cognitive routines that mirror ant-like processing—systematic, detail-focused, and accumulative in nature. Conversely, bee-like thinking—as discussed is linked to a different set of mental abilities such as abstraction, modeling, and integrative synthesis—was more highly rated by physics and chemistry teachers, who typically engage students in conceptual modeling, simulation, and problem-solving involving multiple variables that could be totally abstract such as chemical bonds, atoms, electricity, electro waves, etc. (Redish and Burciaga, 2003; Talanquer, 2007). These domains more readily align with AI applications such as predictive analytics, simulations, and visual modeling, which foster creative integration of knowledge (Luckin and Holmes, 2016). Hence, the disciplinary affordances of AI in science classrooms appear to shape how science teachers from different subjects perceive its value for distinct modes of scientific thinking.

Finally, AI aligns with the cognitive learning theory, which emphasizes the necessity of correct thinking and mental processes for successful learning. According to Dignum (2019), AI facilitates deep learning in science education and simplifies complex tasks, helping learners achieve optimal performance. Through simulations, teachers can acquire knowledge about AI to provide focused education even when they are absent.

In conclusion, incorporating AI into science education has significant potential to encourage diverse modes of thinking and enhance the learning experience. AI enables individuals to think in

10.3389/feduc.2025.1577285

both an ant-like and a bee-like manner, which facilitates efficient task completion, personalized learning pathways, and adaptation to various learning styles. The results of this study demonstrate that AI could transform science education by tailoring it to the unique needs and strengths of each student.

8 Limitations and future research

This study was limited to Al Ain University students in the United Arab Emirates and focused on various academic disciplines. It is conducted during the second semester of the academic year 2023/2024, with data collected and analyzed within this timeframe. Furthermore, there are several limitations to this research that need to be considered. The sample was limited to 104 science teachers who are enrolled in a professional diploma at Al Ain University, and therefore, the results may be limited in their applicability or generalizability to larger groups of science teachers, particularly those who are not engaged in professional development or from different institutions across the national or international institutions and levels of education. The use of Likert-type statements is effective and convenient for assessing general attitudes according to research (Batterton and Hale, 2017). However, it may have oversimplified participants' opinions and couldn't fully capture the richness and depth of their understanding of AI integration in teaching science. The research also relied solely on self-reported data, which may be subject to social desirability or exaggeration of AI expertise. Theoretical conceptualization of ant-like and bee-like thinking may have been a potential source of confusion, as these attributes were perhaps not concisely defined or self-interpreted consistently by all participants who are teaching in Abu Dhabi schools and are from different backgrounds and nationalities of course. Finally, the cross-sectional design provides a snapshot only at a one-time point, limiting the ability to assess change in perceptions or determine causality between AI integration and teaching quality.

The use of AI in science education has various implications, which may present a challenging perspective for science teachers. On a positive note, AI possesses the potential to facilitate personalized learning experiences. AI can be employed to monitor learners' progress, identify their strengths and weaknesses, and to develop tailored content. AI plays a crucial role in customizing learning for students with learning difficulties, enabling them to progress at their own pace (Dignum, 2019; Pratama et al., 2023). Furthermore, AI provides access to organized data. AI facilitates the distribution of materials by enhancing accessibility. It is now possible to retrieve relevant data efficiently in the desired format, which could entail an AI-enhanced learning experience. Through virtual and augmented reality, AI enables learners to simulate various scenarios. Real-world simulations using AI tools are feasible (Moore et al., 2024). In addition, AI mitigates the distance barriers and enables remote learning. The necessity of a hands-on approach has significantly impacted science education during the COVID-19 pandemic. However, AI provides solutions to this challenge and allows effective learning.

Despite its positive implications, AI also has negative outcomes in science education, which may challenge science teachers' professionalism. Although AI tools can emulate teachers, they lack the emotional intelligence of human beings, which is vital for improving students' achievement as a result (Jaberi et al., 2024). Since AI cannot adapt to situations beyond programming, human teachers continue to play an invaluable role. Another challenge with AI in education is that it creates dependence on technology. Learners who begin interacting with AI tools at a young age increasingly rely on them to provide prompts, solve problems, and write essays, leading to technological dependence (Sabouret, 2021). Moreover, learners' creativity and innovation may be compromised as they become more accustomed to AI. Therefore, it is imperative to strike a balance when implementing AI into science education.

9 Recommendations

In conclusion, AI should be implemented in science education. Personalized learning is the primary application of AI. Darayseh (2023) asserted that AI-developed machine-learning tools can monitor learners' strengths and weaknesses. The outcome of this analysis enables such tools to customize learning according to students' needs. Specifically, learners with special needs require considerable attention and time to learn. Classrooms can incorporate artificial intelligence (AI) robotics and machine learning to assist learners through educational challenges (Ali et al., 2023). Furthermore, it is recommended that AI be utilized to ensure comprehensive learning for students. Currently, teachers face significant challenges in nurturing science learners successfully. However, AI allows the distribution of learning among all students. Parents, the community, and stakeholders can all be involved in teaching as it is an ongoing process (Dignum, 2019). For instance, robots communicating with learners at home and in the community can enhance interactions outside class. This results in learning becoming a continuous process that involves all participants rather than solely concerning teachers.

The second recommendation for incorporating AI into science education is cautionary. Although AI in science education provides numerous benefits, challenges persist. Curzon et al. (2021) stated that AI gathers significant personal data that could have negative consequences if misused. Consequently, educational platforms must focus solely on curriculum achievement. Otherwise, there is a personal risk that the user information is compromised. Data protection policies and procedures should be implemented to ensure confidentiality.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. Written informed consent from the participants was not required to participate in this study in accordance with the national legislation and the institutional requirements.

Author contributions

KA: Conceptualization, Data curation, Formal Analysis, Investigation, Writing – original draft, Writing – review & editing. SA: Writing – original draft, Writing – review & editing. HT: Conceptualization, Data curation, Investigation, Methodology, Visualization, Writing – original draft, Writing – review & editing. LP: Writing – original draft, Writing – review & editing. BA: Writing – original draft, Writing – review & editing. OA: Conceptualization, Formal Analysis, Methodology, Writing – original draft, Writing – review & editing.

Funding

The author(s) declare that no financial support was received for the research and/or publication of this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The authors declare that no Generative AI was used in the creation of this manuscript.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

References

Adnan, G., Zulfikar, T., Armia, M. S., Gade, S., and Walidin, W. (2021). Impacts of inquiry learning model on students' cognitive and critical thinking ability. *Cypriot J. Educ. Sci.* 16, 1290–1299. doi: 10.18844/cjes.v16i3.5851

Alarabi, K., Al Abidi, S., Pagani, L. S., Tairab, H., Alhosani, Y., Rabbani, L., et al. (2024). Bridging the Gap: Social networks and professional development in the eyes of prospective science teachers. *Emerg. Sci. J.* 8, 192–204. doi: 10.28991/ESJ-2024-08-01-014

Al Arabi, K., Alsalhi, N. R., Almarashdi, H. S., Zakarneh, B., and Annamalai, N. (2023). The Role of Computer Simulations (CSs) and artificial intelligence on student learning: Moderating the impact of the learning environment. *Przestrzeń Społeczna* 23, 103–122.

Alarabi, K., Tairab, H., Rabbani, L., and Hamad, S. E. H. (2022). Teachers' and students' attitudes toward online physics education during the COVID-19 pandemic in UAE. *Int. J. Instruct.* 15, 293–310. doi: 10.29333/iji.2022.15417a

AlArabi, S., AlArabi, K., Alsalhi, N. R., and al Mansoori, M. (2023). The Dawn of ChatGPT: Transformation in science assessment. *Eur. J. Educ. Res.* 106, 321–337. doi: 10.14689/ejer.2023.106.019

Alharbi, B. A. M. (2015). *The Ability of Islamic Religious Education to Deliver Citizenship Education in Elementary Schools in the Kingdom of Saudi Arabia*. Exeter: University of Exeter.

Ali, N., Santos, I. M., AlHakmani, R., Khurma, O. A., Khine, M. S., and Kassem, U. (2023). Exploring technology acceptance: Teachers' perspectives on robotics in teaching and learning in the UAE. *Contemp. Educ. Technol.* 15:e469. doi: 10.30935/cedtech/13646

Arıcı, F. (2024). Examination of research conducted on the use of artificial intelligence in science education. *Sakarya Univ. J. Educ.* 14, 543–568. doi: 10.19126/suje.1485114

Bacon, F. (2014). *The New Organon or True Directions Concerning the Interpretation of Nature*. North Charleston: Createspace.

Baron, J. (2023). *Thinking and Deciding*. London: Routledge. doi: 10.1017/9781009263672

Batterton, K. A., and Hale, K. N. (2017). The likert scale what it is and how to use it. *Phalanx* 50, 32–39.

Becher, T., and Trowler, P. R. (2001). *Academic Tribes and Territories: Intellectual Enquiry and the Culture of Disciplines*, 2nd Edn. London: Open University Press.

Bunge, M. (2017). *Philosophy of Science*. London: Routledge.

Chen, X., Zou, D., Xie, H., Cheng, G., and Liu, C. (2022). Two decades of Artificial Intelligence in Education: Contributors, collaborations, research topics, challenges, and future directions. *DOAJ* 25:28

Chung, K., Le, D. T., Thaichon, P., and Quach, S. (2022). *Types of Artificial Intelligence (AI) in Marketing Management*. London: Routledge, 29–40. doi: 10.4324/9781003280392-4

Cocking, R. R., and Mestre, J. P. (2013). *The Role of Language Comprehension in Mathematics and Problem Solving*. London: Routledge, 213–232. doi: 10.4324/9780203056820-17

Cohen, D. K., and Ball, D. L. (1999). "Instruction, capacity, and improvement," in *CPRE Research Report Series*, RR-43, (New Brunswick, NJ: Consortium for Policy Research in Education).

Cohen-Mansfield, J., Hazan, H., Lerman, Y., and Shalom, V. (2016). Correlates and predictors of loneliness in older-adults: A review of quantitative results informed by qualitative insights. *Int. Psychogeriatr.* 28, 557–576. doi: \doi{10.1017/S1041610215001532}

Creswell, J. W., and Hirose, M. (2019). Mixed methods and survey research in family medicine and community health. *Fam. Med. Community Health* 7. doi: 10.1136/fmch-2018-000086

Critchlow, H. (2023). *Joined-Up Thinking*. London: Hodder Paperbacks.

Csikszentmihalyi, M. (2014). *Applications of Flow in Human Development and Education*. Cham: Springer. doi: 10.1007/978-94-017-9094-9

Curzon, J., Kosa, T. A., Akalu, R., and El-Khatib, K. (2021). Privacy and artificial intelligence. *IEEE Trans. Artif. Intell.* 2, 96–108.

Danziger, K. (2002). Metaphors of memory: A history of ideas about the mind. *J. Hist. Behav. Sci.* 38, 93–94. doi: 10.1002/jhbs.1122

Darayseh, A. A. (2023). Acceptance of artificial intelligence in teaching science: Science teachers' perspective. *Comput. Educ.* 4:100132. doi: 10.1016/j.caeai.2023.100132

Dignum, V. (2019). *Responsible Artificial Intelligence: How to Develop and Use AI in a Responsible Way*. Cham: Springer

Draaisma, D., and Vincent, P. (2000). *Metaphors of Memory: A History of Ideas about the Mind*. Cambridge, MA: Cambridge University Press, Cop.

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., et al. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *Int. J. Informat. Manage.* 57:101994. doi: 10.1016/j.ijinfomgt.2019.08.002

Fleck, J. (2018). *Development and Establishment in Artificial Intelligence*. London: Routledge, 106–164. doi: 10.4324/9780429505331-3

Foltýnek, T., Bjelobaba, S., Glendinning, I., Khan, Z. R., Santos, R., Pavletic, P., et al. (2023). ENAI Recommendations on the ethical use of Artificial Intelligence in Education. *Int. J. Educ. Integr.* 19:12. doi: 10.1007/s40979-023-00133-4

Garnfinkel, S. L., and Grunspan, R. H. (2018). *The Computer Book: From the Abacus to Artificial Intelligence, 250 Milestones in the History of Computer Science*. Available online at: https://www.amazon.com/Computer-Book-Artificial-Intelligence-Milestones/dp/145492621X (accessed November 6, 2018).

Garnier, S., Gautrais, J., and Theraulaz, G. (2007). The biological principles of swarm intelligence. *Swarm Intell.* 1, 3–31. doi: 10.1007/s11721-007-0004-y

Gibson, D., Kovanovic, V., Ifenthaler, D., Dexter, S., and Feng, S. (2023). Learning theories for artificial intelligence promoting learning processes. *Br. J. Educ. Technol.* 54, 1125–1146. doi: 10.1111/bjet.13341

Gigerenzer, G., and Gaissmaier, W. (2011). Heuristic decision making. *Annu. Rev. Psychol.* 62, 451–482. doi: 10.1146/annurev-psych-120709-145346

González, A. J., Hollister, J., DeMara, R. F., Leigh, J., Lanman, B., Lee, S. Y., et al. (2017). AI in informal science education: Bringing turing back to life to perform the turing test. *Int. J. Artif. Intell. Educ.* 27, 353–384. doi: 10.1007/s40593-017-0144-1

Green, A. (2013). Evaluating distributed cognition. *Synthese* 191, 79–95. doi: 10.1007/s11229-013-0305-1

Hagen, J. B. (2000). The origins of bioinformatics. *Nat. Rev. Genet.* 1, 231–236. doi: 10.1038/35042090

Hollan, J., Hutchins, E., and Kirsh, D. (2000). Distributed cognition: Toward a new foundation for human-computer interaction research. *ACM Trans. Comput. Hum. Interact.* 7, 174–196. doi: 10.1145/353485.353487

Holmes, W., and Porayska-Pomsta, K. (2022). *The Ethics of Artificial Intelligence in Education*. London: Routledge. doi: 10.4324/9780429329067

Holmes, W., Bialik, M., and Fadel, C. (2019). *Artificial Intelligence in Education Promises and Implications for Teaching and Learning*. Boston, MA: Center for Curriculum Redesign.

Jaberi, A., Alzouebi, K., and Abu Khurma, O. (2024). An Investigation into the impact of teachers' emotional intelligence on students' satisfaction of their academic achievement. *Soc. Sci.* 13, 244–244. doi: 10.3390/socsci13050244

Jalobeanu, D. (2015). *The Art of Experimental Natural History: Francis Bacon in Context*. Paris: Zeta Books.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Bus. Horiz.* 61, 577–586. doi: 10.1016/j.bushor.2018.03.007

Johnson, A. P. (2019). *Essential Learning Theories: Applications to Authentic Teaching Situations*. Lanham, MD: Rowman & Littlefield.

Khalil, R. Y., Tairab, H., Qablan, A., Khaleel, A., and Mansour, Y. (2023). STEM-based curriculum and creative thinking in high school students. *Educ. Sci.* 13, 1195–1195. doi: 10.3390/educsci13121195

Khodor, J., Halme, D. G., and Walker, G. C. (2004). A hierarchical biology concept framework: A tool for course design. *Cell Biol. Educ.* 3, 111–121. doi: 10.1187/cbe.03-10-0014

Khurma, O. A., and El Zein, F. (2024). Inquiry skills teaching and its relationship with UAE secondary school students' critical thinking: Systematic review of science teachers' perspectives. *Eur. J. Math. Sci. Technol. Educ.* 20:em2397. doi: 10.29333/ejmste/14155

Kneusel, R. T. (2023). *How AI Works: From Sorcery to Science*. San Francisco, CA: No Starch Press.

Korinek, A., and Stiglitz, J. E. (2019). *Artificial Intelligence and its Implications for Income Distribution and Unemployment*. Chicago, IL: University of Chicago Press, 349–390. doi: 10.7208/chicago/9780226613475.003.0014

Krenn, M., Pollice, R., Guo, S. Y., Aldeghi, M., Cervera-Lierta, A., Friederich, P., et al. (2022). On scientific understanding with artificial intelligence. *Nat. Rev. Phys.* 4, 761–769. doi: 10.1038/s42254-022-00518-3

Kuhn, D., and Modrek, A. S. (2022). Choose your evidence: Scientific thinking where it may most count. *Sci. Educ.* 31, 21–31. doi: 10.1007/s11191-021-00209-y

Lake, B. M., Ullman, T., Tenenbaum, J. B., and Gershman, S. J. (2016). Building machines that learn and think like people. *Behav. Brain Sci.* 40:e253. doi: 10.1017/s0140525x16001837

Lamb, R., Firestone, J. B., Schmitter-Edgecombe, M., and Hand, B. (2018). A computational model of student cognitive processes while solving a critical thinking problem in science. *J. Educ. Res.* 112, 243–254. doi: 10.1080/00220671.2018.1514357

Lee, J. M., and Hauskrecht, M. (2021). Modeling multivariate clinical event time-series with recurrent temporal mechanisms. *Artif. Intell. Med.* 112:102021. doi: 10.1016/j.artmed.2021.102021

Lee, K. (2018). *AI Superpowers: China, Silicon Valley, and the New World Order*. Available online at: https://en.wikipedia.org/wiki/AI_Superpowers (accessed September 25, 2018).

Levay, Z. (2021). "The power of hubble space telescope imagery," in *Space Science and Public Engagement*, ed. Y. Barel-Ben David (Amsterdam: Elsevier), 67–84.

Li, T., Ji, Y., and Zhan, Z. (2024). Expert or machine? Comparing the effect of pairing student teacher with in-service teacher and ChatGPT on their critical thinking, learning performance, and cognitive load in an integrated-STEM course. *Asia Pacific J. Educ.* 1–16. doi: 10.1080/02188791.2024.2305163

Liu, M., Zhang, L. J., and Biebricher, C. (2024). Investigating students' cognitive processes in generative AI-assisted digital multimodal composing and traditional writing. *Comput. Educ.* 211:104977. doi: 10.1016/j.compedu.2023.104977

Luckin, R., and Cukurova, M. (2019). Designing educational technologies in the age of AI: A learning sciences-driven approach. *Br. J. Educ. Technol.* 50, 2824–2838. doi: 10.1111/bjet.12861

Luckin, R., and Holmes, W. (2016). *Intelligence Unleashed: An Argument for AI in Education*. London: UCL Knowledge Lab

Lund, B., Wang, T., Mannuru, N. R., Nie, B., Shimray, S. R., and Wang, Z. (2023). ChatGPT and a new academic reality: Artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing. *J. Assoc. Inform. Sci. Technol.* 74, 570–581. doi: 10.1002/asi.24750

Marquez, J., Lambert, L., Ridge, N., and Walker, S. D. (2022). The PISA performance gap between national and expatriate students in the United Arab Emirates. *J. Res. Int. Educ.* 21, 22–45. doi: 10.1177/14752409221090440

Matthee, M., and Turpin, M. (2019). Invited paper: Teaching critical thinking, problem solving, and design thinking: Preparing IS students for the future. *J. Inform. Syst. Educ.* 30, 242–252.

Michael, J. (2006). Where's the evidence that active learning works? *Adv. Physiol. Educ.* 30, 159–167. doi: 10.1152/advan.00053.2006

Mishra, P., and Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teach. Coll. Rec.* 108, 1017–1054. doi: 10.1111/j.1467-9620.2006.00684.x

Moffett, M. W. (2024). What is a Society? Building an interdisciplinary perspective and why that's important. *Behav. Brain Sci.* 48:e51. doi: 10.1017/S0140525X24000037.

Momsen, J. L., Long, T. M., Wyse, S. A., and Ebert-May, D. (2010). Just the Facts? Introductory undergraduate biology courses focus on low-level cognitive skills. *CBE—Life Sci. Educ.* 9, 435–440. doi: 10.1187/cbe.10-01-0001

Moore, C. (2019). *Teaching Science Thinking: Using Scientific Reasoning in the Classroom*. London: Routledge.

Moore, K. C., Wood, E., Welji, S., Hamilton, M., Waswa, A., Ellis, A. B., et al. (2024). Using abstraction to analyze instructional tasks and their implementation. *J. Math. Behav.* 74:101153. doi: 10.1016/j.jmathb.2024.101153

Nayyar, A., and Nguyen, N. G. (2018). *Introduction to Swarm Intelligence*. London: Chapman and Hall, 53–78. doi: 10.1201/9780429445927-3

Nehm, R. H., and Ha, M. (2011). Item feature effects in evolution assessment. *J. Res. Sci. Teach.* 48, 237–256. doi: 10.1002/tea.20400

Ng, D. T. K., Lee, M., Tan, R. J. Y., Hu, X., Downie, J. S., and Chu, S. K. W. (2023). A review of AI teaching and learning from 2000 to 2020. *Educ. Inform. Technol.* 28, 8445–8501. doi: 10.1007/s10639-022-11491-w

Nja, C. O., Idiege, K. J., Uwe, U. E., Meremikwu, A. N., Ekon, E. E., Erim, C. M., et al. (2023). Adoption of artificial intelligence in science teaching: From the vantage point of the African science teachers. *Smart Learn. Environ.* 10:42. doi: 10.1186/s40561-023-00261-x

Olga, T., and Nadezhda, Z. (2022). Artificial Intelligence in Education: AIEd for personalised learning pathways. *Electron. J. E-Learning* 20, 639–653.

Ouyang, F., and Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Comput. Educ.* 2:100020. doi: 10.1016/j.caeai.2021.100020

Perrotta, C., and Selwyn, N. (2020). Deep learning goes to school: Toward a relational understanding of AI in education. *Learn. Media Technol.* 45, 251–269. doi: 10.1080/17439884.2020.1686017

Pratama, M. P., Rigel Sampelolo, R., and Lura, H. (2023). Revolutionizing education: Harnessing the power of artificial intelligence for personalized learning. *Klasikal* 5, 350-357. doi: 10.52208/klasikal.v5i2.877

Rahmadika, S., Fajri, B. R., Farell, G., Hadi, A., and Budayawan, K. (2022). "Recent challenges in a new distributed learning paradigm," in *Proceedings of the International Symposium on Mobile Internet Security*, (Singapore: Springer Nature Singapore), 134–144.

Redish, E. F., and Burciaga, J. R. (2003). *Teaching Physics: With the Physics Suite*, Vol. 1. Hoboken, NJ: John Wiley & Sons, 216.

Reigeluth, C. M. (2013). *Instructional-design theories and models: A new paradigm of instructional theory*. London: Routledge.

Rumelhart, D. E. (2017). *Schemata: The Building Blocks of Cognition*. London: Routledge, 33–58. doi: 10.4324/9781315107493-4

Sabouret, N. (2021). *Understanding Artificial Intelligence*. Boca Raton, FL: CRC Press.

Sadedin, S., and Duenez-Guzman, E. A. (2012). "Harnessing the swarm: Technological applications of collective intelligence," in *Pragmatic Evolution: Applications of Evolutionary Theory*, ed. A. Poiani (Cambridge: Cambridge University Press), 234–258.

Saurabh, R., Singh, N. C., and Duraiappah, A. K. (2019). “The Alternate Education for the 21st Century,” in *Proceedings of the 2019 IEEE 18th International Conference on Cognitive Informatics & Cognitive Computing (ICCI* CC)*, (Milan: IEEE), 265–271.

Sawyer, R. K. (2006). Educating for innovation. *Think. Skills Creat.* 1, 41–48. doi: 10.1016/j.tsc.2005.08.001

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G.-J., Elkins, A., et al. (2020). Machines as teammates: A research agenda on AI in team collaboration. *Inform. Manage.* 57:103174. doi: 10.1016/j.im.2019.103174

Shodiyev, J. J. (2023). The role of scientific thinking and mental development in improving human development and value. *Innovat. Dev. Educ. Activities* 2, 251–261.

Siemens, G. (2005). Connectivism: A learning theory for the digital age. *Int. J. Instruct. Technol. Distance Learn.* 2:42.

Sjöström, J., and Eilks, I. (2018). “Reconsidering different visions of scientific literacy and science education based on the concept of Bildung,” in *Innovations in Science Education and Technology*, ed. K. C. Cohan (Cham: Springer), 65–88. doi: 10.1007/978-3-319-66659-4_4

Slovic, P., Finucane, M. L., Peters, E., and MacGregor, D. G. (2004). Risk as analysis and risk as feelings: Some thoughts about affect, reason, risk, and rationality. *Risk Anal.* 24, 311–322. doi: 10.1111/j.0272-4332.2004.00433.x

Tairab, H., Al Arabi, K., Rabbani, L., and Hamad, S. (2020). Examining Grade 11 science students’ difficulties in learning about vector operations. *Phys. Educ.* 55:055029. doi: 10.1088/1361-6552/aba107

Talanquer, V. (2007). Explanations and teleology in chemistry education. *Int. J. Sci. Educ.* 29, 853–870. doi: 10.1080/09500690601087632

Van Noorden, R., and Perkel, J. M. (2023). AI and science: What 1,600 researchers think. *Nature* 621, 672–675. doi: 10.1038/d41586-023-02980-0

Wise, R., Fazey, I., Smith, M. S., Park, S., Eakin, H., Van Garderen, E. A., et al. (2014). Reconceptualising adaptation to climate change as part of pathways of change and response. *Glob. Environ. Change* 28, 325–336. doi: 10.1016/j.gloenvcha.2013.12.002

Wismath, S. L., and Orr, D. (2015). Collaborative learning in problem solving: A case study in Metacognitive learning. *Can. J. Scholarsh. Teach. Learn.* 6, 1–19. doi: 10.5206/cjsotl-rcacea.2015.3.10

Woolridge, M. (2022). *Brief History of Artificial Intelligence: What it is, Where we are, and Where we are Going*. New York, NY: Flariton Books.

Yang, S. J. H., Ogata, H., Matsui, T., and Chen, N.-S. (2021). Human-centered artificial intelligence in education: Seeing the invisible through the visible. *Comput. Educ.* 2:100008. doi: 10.1016/j.caeai.2021.100008

Zhai, X., Chu, X., Chai, C. S., Jong, M. S., Starčič, A. I., Spector, M., et al. (2021). A review of artificial intelligence (AI) in Education from 2010 to 2020. *Complexity* 2021, 1–18. doi: 10.1155/2021/8812542

Zhang, J. (2022). The influence of Piaget in the field of learning science. *High. Educ. Stud.* 12, 162–168. doi: 10.5539/hes.v12n3p162

Zohar, A., and Dori, Y. J. (2003). Higher order thinking skills and low-achieving students: Are they mutually exclusive? *J. Learn. Sci.* 12, 145–181. doi: 10.1207/s15327809jls1202_1