Abstract

We have entered the Fourth Industrial Revolution, which has brought widespread digital transformation with advanced and broadened technologies including artificial intelligence (AI). To help students prosper in a world full of AI applications, it is important for us to offer students sufficient AI-integrated learning opportunities across different subjects, including science. In this position paper, a pedagogical approach to AI-integrated science education through facilitating epistemic discourse is proposed. To establish a foundation for this integration, epistemic similarities and differences between how scientific knowledge is constructed and how AI agents learn are compared, referring to Chinn et al.'s (2014) epistemic cognition framework that attends to epistemic aims, ideals, and processes. Four bins of instructional strategies for facilitating epistemic discourse in AI-integrated science classrooms is suggested, which will help students more readily act as informed knowledge constructors, critics, and users of AI and science, who can pose questions that matter to their lives.

초록

우리는 지금 인공지능(AI)을 비롯한 최첨단의 기술로 광범위한 디지털 변혁을 가져온 4차 산업혁명의 시대를 살아가고 있다. AI 기기 및 시스템이 일반화된 세상에서 관련 역량을 갖춘 주도적 삶을 살아가기 위하여, 학생들에게 과학을 포함한 다양한 과목에서 충분한 AI 통합학습기회를 제공하는 것은 중요한 일이라 할 수 있다. 이 연구에서는 인식론적 답안을 축진하는 AI 통합과학교육에 대한 교육학적 접근법을 제안하고자 한다. 이러한 통합적 기반을 마련하기 위해 인식론적 목표, 개

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1 Introduction

During a science class in which my students and I (Won) discussed how we could utilize biological knowledge in our real lives, one student, Gina, noted the following:

When my father was diagnosed with pancreatic cancer, the doctor forced my family to decide whether or not to allow him to undergo a surgery that could risk his life. By then, we had already visited several doctors who each seemed to possess a slightly different outlook. I already had learned about cancer from my biology class, but making a decision about my father’s cancer was a completely different thing. I was freaked out. I wished there was something like an AI [artificial intelligence] that could give my family an answer, an answer we could trust and know wouldn’t go wrong.

Immediately, the other students rushed to their laptops and began searching online to see if this kind of AI existed, saying “there should be one out there.” However, while I appreciated their eagerness, I paused the class and said the following:

I deeply appreciate your active listening to Gina and your willingness to find an AI out there that could help her problem. But let’s slow down first and imagine, what kind of AI are we looking for? How can an AI’s diagnosis or recommendations help Gina avoid “going wrong”? Do we trust the information because AI said it? Why? How do we know that AI will make better and smarter decisions than doctors?
This opening vignette describes a moment in which a spontaneous conversation about artificial intelligence (AI) emerged in a science classroom. People today, including students, rely on numerous products and services that contain AI agents in varying facets of daily life (Kurzweil, 2005). As such, the current discourse in learning spaces such as science classrooms often leads to situations in which students find relevant applications for AI that relate to their learning content (e.g., using AI for cancer diagnosis and consultation, as exemplified by the opening vignette). AI, as one of the newest fields of science and engineering, refers to “the study of agents that receive percepts from the environment and perform actions” (Russell et al., 2010, p. viii). Agents that use AI (AI agents, hereafter) contain automatic learning algorithms that use massive amounts of complex data and concurrent feedback systems through which they make their performance of any given task to be more trustworthy—that is, more accurate, rational, and reliable.

As the opening vignette reveals, I stopped the students from rushing to search online so that I could prompt them to make epistemic considerations about the trustworthiness of using AI for cancer diagnosis and consultation. “Epistemic” refers to beliefs about knowledge and knowing—in other words, “beliefs as personal, implicit or explicit, assumptions about the nature, source, and justification of knowledge” (Mason, 2016, pp. 375–376). Epistemic discourse involves intra- or inter-personal consideration of whether and how much to trust statements that exhibit knowledge and knowing (e.g., hypothesis, explanations, evidence, solutions, and predictions, to name a few). We can facilitate epistemic discourse by engaging ourselves and others in questions like “how do I (we) know that I (we) know?” “do I (we) believe this information said to be evidence?” and even “do I (we) believe the expert’s prediction?” Questions like these help us to examine the trustworthiness of the processes in which we construct, justify, evaluate, and then use knowledge statements as the basis of decisions and actions. Similarly, in the opening vignette, I asked questions to facilitate epistemic discourse related to AI and science in the classroom. This paper is concerned with such discourse in effort to help students learn and examine the epistemic aspects of AI and science, particularly in response to the recent increasing demand for AI-integrated education in the countries like South Korea (Korea, hereafter), seeking to lead the era of digital transformation by raising prepared young people.

To help young people prosper in a world full of AI applications, it is important for us to offer students sufficient AI-integrated learning opportunities across different subjects, including science. In this position paper, I propose a pedagogical approach to AI-integrated science education: integration through facilitating epistemic discourse. This approach draws on the assumption that
scientific knowledge construction and AI agents’ learning possess some key epistemic similarities and differences, and it also draws on the idea that engaging students in classroom discourses examining these epistemic features is a potentially useful way to integrate science and AI learning. This approach will help students strengthen competencies in critically understanding and utilizing science and AI in their lives.

I seek to answer two research questions:
1. What does epistemic discourse in AI-integrated science classrooms look like?
2. What are some instructional strategies for facilitating such epistemic discourse?

I will answer these questions as I develop my argument in three sections. In the first section, I examine the ontological standing of AI-integrated science education by situating the problem space of this paper in the context of the digital transformation era and the demand for AI and AI-integrated education (Long & Magerko, 2020; Parliament, 2018; Schwab, 2017; Van Brummelen & Lin, 2020). I review how AI-integrated science education has been studied and implemented by narrowing down the scope of this paper to AI-integrated science education at the secondary level in Korea and in other countries around the world. Second, I propose the idea of AI-integrated science teaching through facilitating epistemic discourses in classrooms. To establish a foundation for this integration, I compare epistemic similarities and differences between how scientific knowledge is constructed and how AI agents learn (answering the first research question). As a tool for comparative analysis, I refer to Chinn et al.’s (2014) epistemic cognition framework. I then suggest a set of instructional strategies for facilitating epistemic discourse in AI-integrated science classrooms (answering the second research question). Lastly, I discuss the expected outcomes of undertaking my proposed pedagogical approach, and I consider the implications of this approach in terms of the policy support for teacher professional development and collaboration in Korea. I conclude this paper by briefly discussing directions for future research.

2 Positionality

Before detailing my argument, I want to specify my positionality and associated limitations, as well as my efforts to mitigate these limitations. My positionality on AI integration with science teaching draws on my experience teaching secondary science in Korea and my scholarly commitments to equitable education that can support students to enhance and utilize epistemic thinking and
agency. First, my experience as a secondary science teacher in Korea prompted me to formulate the initial idea for this paper, the experience through which I observed swift shifting trends in Korea's educational agenda that had brought both continuous challenges and fresh opportunities for teachers (Kim, 2019). I perceived the current demand for AI-integrated education in Korea as one of the recent policy trends that greatly affect teachers across multiple subjects. The Korea Ministry of Education seeks curricular revision, putting forth the goal of advancing the quality of the future Korean workforce in preparation for the Fourth Industrial Revolution era, which has been said will feature AI and digital technologies (Korea Ministry of Education, 2020; Schwab, 2017). Such an economy-driven policy goal, rather than being driven by the academic legitimacy of the integration of AI, may work both as a challenge and an opportunity to transform science teaching. On the one hand, the demand for the AI integration is a challenge because science teachers are being charged with greater teaching burdens in addition to those they had already been responsible for. They will also be asked to re-educate themselves in the new disciplinary knowledge and technologies of AI to afford the integration. On the other hand, it can be an opportunity that may facilitate teachers' forward thinking about how to integrate AI if they required to, particularly if teachers seek to ensure every student's, not just specifically chosen students', access to the integrative learning opportunity. These potential challenges and opportunities pushed me to investigate how to support science teachers' AI integration in ways that will eventually benefit students' science learning, one of which is suggested in this paper. I imagine an integration approach that every science teacher can accomplish through daily classroom discourse.

Second, I bring to this paper my scholarly commitment to support students' epistemic thinking and agency. While my positionality as a science teacher-scholar whose advocacy for equitable education led me to writing this paper, it also implies – and I admit this fully – that my understanding of AI research and its epistemology is limited and leaves significant room for sophistication. To mitigate this limitation, I refer to the scholarly discussion about the epistemology of science and domain-general epistemic cognition in comparative analyses of how science constructs knowledge and how AI agents learn. One line of my research specifically attends to the epistemic aspects of scientific knowledge construction and the ways that students reason about these aspects (Kim & Alonzo, 2021). This scholarly pathway has helped me to imagine integration involving the epistemic aspects of both science and AI. I refer to the literature that discusses epistemic processes and the aims and ideals of such processes to inform this paper's analysis (e.g., Chinn et al., 2014; Duncan et al., 2018).
AI Education Through Integration

To inform the discussion of AI-integrated science teaching focused on epistemic aspects, I first examine the ontological standing of what AI-integrated education has been and has meant in the context of the digital transformation era been named the Fourth Industrial Revolution (FIR). Klaus Schwab, World Economic Forum Founder and Executive Chairman, published a book, *The Fourth Industrial Revolution* (2017), and the term has been used to describe emerging technologies and their impacts on nearly all industries in the early 21st century across economic development, policy shifts, international relations, and on individuals’ ways of perceiving, acting, and being (Philbeck & Davis, 2018). AI stands at the intersection of technologies featuring and leading the FIR, such as robotics, the Internet of Things, and advanced materials (Chakraborty et al., 2022). AI encompasses leading-edge technologies, the scholarly roots of which stem from a wide range of disciplines such as neuroscience, computer science, psychology, philosophy, and mathematics (El Naqa & Murphy, 2015). We can largely attribute the significant surge of AI research and technologies in recent years to the exponential availability of big data and machine learning (Davenport & Patil, 2012; El Naqa & Murphy, 2015). We currently use AI for various applications in our lives – from medicine and business purposes to military and social ends – and this trend will continue to increase (Kim & Park, 2017). AI can help process and find solutions to a wide range of problems people face by using agents that simulate, mimic, and automate the actions and thinking of humans (cognition, behavior, and neural networks), with the goal of gradually achieving rational perfection. Accordingly, many countries are eager to explore, invest, and take leadership in advancing AI knowledge, technologies, and infrastructures (Lee, 2020).

This paradigmatic shift in digital transformation requires people to develop and sustain competencies in commanding and communicating with AI applications: in short, AI competencies. We can exercise AI competencies through our use of AI-related knowledge and skills in our daily lives. To thrive in the world of AI, young people should have equitable access to learning opportunities that will help enhance AI competencies (Margolis & Goode, 2016). K-12 public education can function as a particularly optimal place to offer such opportunities, ensuring that a wide range of students explicitly and extensively learn AI and computing across grade levels (Association for Computing Machinery and Institute of Electrical and Electronic Engineers-Computer Science, 2020; Goel, 2017; Goode et al., 2020; Touretzky et al., 2019). This way, K-12 AI education can work toward serving not only the students envisioning career pathways for themselves in AI or computer science and engineering, but also for
every individual who will live in the rapidly developing world full of AI services and products.

3.1 Advancing AI Literacy

AI competencies can be collectively considered important constituents of AI literacy. AI literacy, as a part of a broader computing literacy, is described as a set of competencies people exercise to help their informed and critical understanding – as well as their use of – AI services and products. Researchers have asked (and are still discussing) which specific competencies constitute AI literacy. While no concrete scholarly consensus yet exists, researchers frequently mention competencies in three areas: AI knowledge, AI skills, and AI attitudes (Kim et al., 2021; Long & Magerko, 2020; Sahami, 2015). AI knowledge helps us comprehend the core concepts of AI and use it in our lives. This knowledge includes, but is not limited to, the following: definitions and types of AI, different kinds of search algorithms, the understanding of machine learning, and the kinds of various AI applications (e.g., face recognition and credit applications) as well as the methods and goals for using them (e.g., security monitoring and business efficiencies). AI skills range from the use of pre-existing AI applications to the programming and debugging that can help imagine and design AI agents. AI attitudes entail ethical and critically reflective considerations of the importance of unbiased algorithm design – and the use of AI and its repercussions.

People should be able to use AI literacy to make personal and civic decisions about and to take actions on the important issues of their daily lives (Aoun, 2017). First, AI literacy can help personal decision-making. For example, when using automatic tagging services in social networks, AI literacy can help us recognize that the social network providers may have designed automatic tagging algorithms in specific ways – which are often for commercial gain and/or biased – giving us the information necessary to use the social network service cautiously. As another example of AI literacy’s impact on personal decision-making, it may help consumers determine if the so-called AI-embedded smart product is worth the extra cost compared to a regular, cheaper-priced product. Second, AI literacy can help civic decision-making. Take for example an AI agent that measures and predicts the safety of nuclear power plants. A person’s decision to vote for or against a policy on whether to keep or eliminate a power plant should draw on a measured consideration of how and to what extent one should trust the result gleaned from the AI. As these decision-making examples suggest, AI literacy is crucial if we are to make sound decisions and avoid being fooled by the information and services offered by AI.
3.2 AI Education Across the Globe

Many countries are reconfiguring their education systems to encompass the digital transformation to center AI and to thus provide for young people’s AI literacy. In the UK, AI has been emphasized in Grade K-12 so that the next generations can establish their AI competencies (Parliament, 2018; Zimmerman, 2018). In the US, the Computing Curricular Standards 2020 describes AI education as an important requirement for all undergraduates (ACM & IEEE-CS, 2020). Korea, as one of the leading countries in high-edge technology and digital systems, has put a strong emphasis on AI education and has even revised the national curricular documents accordingly (Korea Ministry of Education, 2020; Shin & Shin, 2020). In the years following Korea’s 2022 national curricular revision, new courses focusing on data science and AI will be offered for upper secondary students – in addition to preexisting computing subjects such as middle school informatics. The national curricular revision was designed so that K-12 education will focus on AI literacy and higher education will focus on strengthening professional pipelines in the AI and computer engineering fields. For elementary students, the priority is to explore and use various types of AI tools. Secondary students are expected to engage in complex tasks and programming algorithms related to the different content taught in different school subjects, which indicates that secondary grade-levels are suited for trying out the integration of AI with different school subjects, including science.

4 Toward AI Education for All Through Integration

*AI is relevant to any intellectual task; it is truly a universal field*

Russell et al., 2010, p. 2

There has been an increasing research and policy movement calling for integrating AI into other subjects’ instruction (Korea Ministry of Education, 2020; Luckin et al., 2016). Such calls for integration point out that students can broaden their participation in AI and develop students’ literacy in both AI and other integrated subjects by learning AI not only in the computing subjects that have been considered home for AI education, but also in other subjects. Van Brummelen and Lin (2020) describe three approaches to achieving AI-integrated education: “(1) relating an AI tool or concept to the core subject, (2) relating content from the core subject to AI, and (3) noticing overlapping concepts in AI and the core subject” (p. 8). These tactics suggest that integration builds on the equal standing of concepts and tools of the respective subjects being integrated. AI-integrated education, as such, means that
AI knowledge and skills are connected to the core concepts and skills of the respective subjects.

AI-integrated education differs from using AI as content learning tools and from general AI education (Korea Foundation for the Advancement of Science and Creativity [KOFAC], 2020). The former type of education uses AI services and products as learning tools to advance the teaching and learning of any subject (Kim & Park, 2019). All subject teachers can implement this type of education by determining the kinds and characteristics of AI and using them in the necessary areas of instruction. Teachers can use instructional AI agents such as translators, intelligent cameras, and automated assessment tools that offer feedback service. Using AI tools in this way is often misunderstood as AI integration; however, it is not, because using AI as a tool does not necessarily require teachers and students to make more conceptual connections between AI and other subjects at the same level of depth as the integration requires.

The latter type of AI education—general AI education—aims to teach basic and advanced concepts and principles of AI and programming in computing subjects (Lee, 2020). As this requires professional knowledge and skills involving AI, this should be thoroughly taught by computing teachers who have majored in computer science and related disciplines. AI education can also support students’ experience with AI and programming by using educational applications such as the Teachable Machine (Carney et al., 2020), Machine Learning for Kids (Lane, 2020), and the MIT App Inventor (Massachusetts Institute of Technology App Inventor, n.d.). These tools help students to experience programming and to learn how to train AI agents with ease.

When compared to the two types of education discussed above, AI-integrated education requires a more organic and more equal meshing between the core concepts and skills of AI and other subjects (Shin & Shin, 2020). AI-integrated education means that a subject teacher possesses a general understanding of AI to the extent that they can relate it to some concepts and practices from their own subject. Subject teachers can also use the educational applications listed above for integration. For example, students can create data by recording words correctly (as guided by a teacher) and incorrectly, and the students can use this data to train a classification model developed by MIT App Inventor, which helps students to program the model’s learning algorithms (Van Brummelen & Lin, 2020). Also, students may engage in a discussion about what determines correctness. Students can then use the app they invented to further help them learn correct pronunciations. This is an example of integration that will facilitate students’ training of the AI model with data they purposefully generate based on the categories of pronunciation data they have established and help them take the criteria of correctness into consideration.
4.1 How Is AI Integrated Into Science Education?

The demand for AI integration in science education is not an exception. The two subjects seem to share some commonality in that they are both considered subjects that function to strengthen the national workforce and that they entail data-driven epistemic processes. First, as I noted earlier, the demand for AI integration has largely been driven by an economic rather than an academic rationale, with the aim of efficiently strengthening the national workforce so that they can use AI knowledge and skills in order to make profit (Parliament, 2018; Zimmerman, 2018). Similarly, science has been framed a subject that can function to raise the quality workforce preparation in STEM fields (Korea Ministry of Education, 2020). Second, researchers (e.g., Shin & Shin, 2020) have found the utility of integrating students’ science and AI learning, highlighting overlaps in the processes of scientific knowledge construction and AI’s data processing, particularly in that they collect and analyze data to generate conclusive explanations (science) and predictions/actions (AI). In short, if integration is demanded, one useful approach would be paying attention to the epistemically similar (and different) parts in the processes of scientific knowledge construction and AI learning and generating prediction, solutions, and actions.

Teachers can help students’ learning of science and AI by providing instruction on the similarity between the two and by scaffolding students’ use and comparison of AI and science in ways that can help students better understand them both, respectively and relationally. For example, Heinze et al. (2010) undertook a Scientists-in-Schools program in Australia where AI scientists partnered with K-6 schoolteachers to design a curriculum that taught the history of science behind AI development and provided instruction regarding the two disciplines’ connections to physics and neuroscience. Similarly, in their study with US teachers, Van Brummelen and Lin (2020) developed an integrative curriculum that teachers could use to effectively support students’ science practices and concepts related to understanding and operating AI. In the US, Krakowski et al. (2020) implemented a student internship program in which students from a small group of advanced science learners first learned computing concepts such as sequences, loops, and debugging and then applied this programming knowledge to designing an algorithms model to collect and analyze data from a coral reef ecosystem under threat.

Likewise, recent studies and practices in Korea have been actively engaged with this topic. Kim and Park (2017) developed and applied an instructional model that utilized computer games to engage sixth grade students in training and testing AI. Shin (2020) analyzed the unit of “energy and daily lives” to
examine the possibility of integrating AI, co-designing and piloting the unit with teachers. These studies indicate that science is a subject we can readily integrate with AI, for science practices such as data collection, classification, and representation can benefit from using AI (Shin & Shin, 2020; Van Brummelen & Lin, 2020).

While this emerging area of research offers rich potential for integrative teaching and learning of science and AI, there are still at least three things we should carefully consider: how to integrate, who should teach it, and for whom. First, regarding how to integrate, most programs implemented in the previous studies had students use online AI applications and engage in programming. These applications were primarily skill oriented and applied to specific topics such as classification, rather than relating to the core concepts and practices of AI and science at equal standing. This pattern can misrepresent integration as merely the technical use of advanced AI skills in science classrooms.

The second consideration centers on who should teach the integrated programs. Pre-existing AI-integrated programs have been facilitated by researchers, teachers, and schools/local districts with an interest in or access to AI integration projects (Bernstein et al., 2021). Because these previous programs utilized AI tools and programming skills that are often new to science teachers, science teachers, if they are asked to implement the programs, may feel that they should learn the new knowledge and skills about AI. Indeed, it is imperative that science teachers learn new knowledge and skills in order to be prepared for AI-integrated teaching. However, teachers may feel a lack of capacity, time, and resources, making it difficult to add AI knowledge and skills on top of the already overwhelming demands assigned to teaching science (Vazhayil et al., 2019). My intent is not to say that learning and knowing about AI and programming does not benefit science teachers. Even the instructional strategies I suggest in what follows require, to some extent, learning about AI. What I mean is that we should be respectful of the division of labor and expertise between science and computing teachers. Integration ultimately requires pedagogical collaboration between different subjects and teachers who are responsible experts for the respective subjects they teach.

Lastly, we should ask, “integration for whom?” Students may have disparate access to AI-integrated learning opportunities depending on their teachers’ or school leaders’ interests, experiences, access, and expertise in AI education and research. If students happen to have science teachers equipped with interest and expertise in AI – and happen to attend schools that emphasize and lead in AI-integrated education – these students may have more readily available access to AI-integrated science learning opportunities than their counterparts.
Such disparity can contribute to maintaining the status quo of unequal access to learning opportunities. If the goal is AI-integrated education for all, we – as science teachers and researchers – should be able to find and suggest meaningful ways of integration (how to integrate) that can facilitate pedagogical collaboration (who integrates) in support of all students’ integrative learning experiences (for whom should we integrate).

5 Proposal: AI-Integrated Science Teaching Through facilitating Epistemic Discourse in Classrooms

Based on the literature review and attendant reflection about how to integrate AI with science, I propose one way of integration between science and AI, particularly in secondary science classrooms, that can take place through facilitating everyday epistemic discourse. I first discuss the epistemic similarities and differences between science and AI and then use the discussion to suggest a set of instructional strategies that can facilitate epistemic discourse.

5.1 The Foundation of Epistemic Discourse: Scientific Knowledge Construction and AI Machine Learning

As disciplines, science and AI are complex and broad. Many research fields use the term “science.” In general, science refers to “the pursuit and application of knowledge and understanding of the natural and social world following a systematic methodology based on evidence” (Science Council, 2014, para 1). While specific ways of doing science can differ across domains, they share the common feature of “commitment to data and evidence as the foundation for developing claims” (National Research Council, 2012, p. 26). Meanwhile, AI refers to the study of agents that receive information and data from the environment and are trained by feedback and mistakes (Russell et al., 2010). While the specific ways AI agents learn can differ according to the types and purposes of agents, they share common features such as gradually perfecting rational and human-like actions and thinking as they learn.

Science and AI entail epistemic endeavors aimed at generating intellectual outcomes such as knowledge claims (science) and meaningful information for solutions and predictions (AI). It is critical to offer rich discourse and activities in classrooms that center on parallel examinations of epistemic underpinnings between scientific knowledge construction and AI agents’ computational learning (Ceccucci et al., 2015; Computer Science Teacher Association [CSTA], 2020; NRC, 2012). To compare some epistemic similarities and differences
between scientific knowledge construction and AI agents’ computational learning, I referred to Chinn et al.’s (2014) framework of epistemic cognition. Their framework focuses on the aims and ideals of epistemic processes.

– Epistemic aims (What are the desired outcomes of epistemic processes?)
– Epistemic ideals (What are the criteria used to evaluate whether the aims are achieved?)
– Reliable epistemic processes (What are the processes to achieve the aims?)

This framework draws on philosophical, psychological, and educational research that supports the importance and interplay of the aims, ideals, and processes in epistemic thinking (Chinn et al., 2011; Chinn & Rinehart, 2016). The utility of this framework has been proven by its application to following studies such as the establishment of grasp of evidence (Duncan et al., 2018) and socio-scientific decision-making (Kim & Alonzo, 2021). Applying Chinn et al.’s (2014) framework to this study’s epistemic consideration of science and AI, we can understand science AI as epistemic processes that aim to produce desired intellectual outcomes, by seeking to observe epistemic ideals (e.g., reliable, valid, complete, and consistent evidence). As such, I will discuss some similarities and differences in the epistemic aims, ideals, and processes of science and AI that science teachers can highlight through their classroom discourse and practices.

For my illustrative comparison in the framework of epistemic aims, ideals, and processes, I have examined work that has suggested what students learn about how science works and how AI works, respectively. For research about how science works, I referred mostly to Duncan et al. (2018), Gott et al. (2015), and Walton and Zhang (2013). For research regarding how AI works, I referred to Bernstein et al. (2021), El Naqa and Murphy (2015), and Russell et al. (2010). I chose these references drawing on the wide range of dialogue with literature and sought to identify discussions that give descriptions and implications about epistemic aims, ideals, and processes of scientific knowledge construction and AI’s machine learning. Particularly, I refer to the literature that offers an extensive set of epistemic concepts and processes helpful for understanding data and evidence and weighing their trustworthiness in their respective fields. They also offered rich sources of comparisons by elaborating the meanings and criteria of epistemic concepts (e.g., what makes good data, evidence, reliability, and validity) and processes (e.g., what makes data collection, processing, and analysis reliable). I also referred to additional work as I found they helped refine my comparative analysis on the epistemic aspects of science and AI (e.g., Allchin, 2020; Bengio et al., 2013; Chinn & Rienhert, 2016; Long & Magerko, 2020; Weed, 2008).
5.2 Epistemic Aims of Science and AI

Epistemic aims refer to achieving desired outcomes through undertaking reliable epistemic processes. The epistemic aims of science include producing outcomes such as trustworthy scientific knowledge claims and quality evidence. Scientific knowledge claims explain natural and social phenomena. Evidence supports scientific claims. Epistemic products, such as hypotheses determined to be valid using strong evidence, also exist to help achieve trustworthy claims and evidence (Chinn & Rienhert, 2016; Duncan et al., 2018). The epistemic aims of AI include producing outcomes such as trustworthy solutions, actions, and predictions (Russell et al., 2010). Actions, solutions, and predictions can be advanced as AI agents gradually work toward rational perfection through learning processes such as machine learning. This means that the qualifiers (trustworthy, quality, rational, and perfect) are determined by epistemic ideals as discussed below.

In short, the epistemic aims of science and AI have both differences (in the specific types of outcomes) and similarities (in their shared demand for high quality outcomes). The specific types of outcomes they each aim to achieve differ, as doing science is aimed at explaining phenomena, while using AI is more aimed at obtaining solutions and predictions regarding phenomena. One important similarity is that the two disciplines both aim at producing intellectual outcomes of a high quality. Another similarity is the defeasibility of the intellectual outcomes: that is, their being “evidence-based but inherently prone to the possibility of error” (Walton & Zhang, 2013, p. 174). Because scientific claims and AI-informed solutions and predictions are defeasible, the epistemic processes of doing science and training AI agents both seek to address, mitigate, and minimize inevitable errors.

5.3 Epistemic Ideals of Science and AI

Epistemic ideals are statements used to examine whether the epistemic aims have been achieved, and they include the statements that qualify epistemic concepts (e.g., data and evidence), processes (e.g., scientific practices and machine learning algorithms), and outcomes produced (e.g., knowledge claims and predictions). Epistemic ideals help unpack what is meant by quality (e.g., trustworthy, valid, reliable, and consistent) and how and when epistemic concepts, processes, and outcomes achieve a certain level of quality. Some epistemic ideals applied to science and AI are similar (e.g., valid evidence to answer the questions asked by doing science or by training AI agents) while others differ (e.g., data in science versus data in AI). To illustrate, I must discuss some epistemic ideals of data, evidence, knowledge claims in science, and predictions in AI.
5.3.1 Data and Evidence

The word “data,” in general, refers to a set of values of quantitative or qualitative variables (Gott et al., 2015). Accumulated data does always mean evidence. To be considered evidence, data undergoes epistemic processes that can justify its legitimacy as further described below. The important epistemic ideal that can help scientific data become evidence includes accuracy (in measurement), validity (to answer the research question), pattern (by reducing confounding variables), and size (by taking large samples from the population). AI designers have programmed AI agents to collect data by drawing on a significant amount of information – usually messy, large, and multidimensional – from the environment in which the agents operate (Banko & Brill, 2001; Bengio et al., 2013). The important epistemic ideal of data in AI is a large and extensive volume of millions to trillions of bytes of data. Often the importance of the “bigness” of data in AI makes a trade-off with the epistemic ideal of accuracy greatly expected for scientific data, which is an important epistemic difference for students to compare (Russell et al., 2010).

Evidence is the core epistemic concept both in scientific knowledge construction and in AI learning. In scientific knowledge construction, data becomes evidence through the assigning of weight to the data. Data can be weighed to become evidence or not, depending on the quality of epistemic processes that involve data collection and the ensuing evidentiary practices of analyzing, evaluating, interpreting, integrating, and using evidence (Duncan et al., 2018). There are different epistemic ideals that determine quality evidence such as reliability, validity, completeness, coherence, and consistency (Gott et al., 2015). In particular, validity is an important epistemic ideal for scientific evidence as it is determined by whether the evidence answers the research/inquiry question(s) asked (Walton & Zhang, 2013). Evidence in AI learning is similarly described as “instantiations of some or all of the random variables describing the domain” (Russell et al., 2010, p. 802). Thus, in AI agents’ learning, representativeness is an important epistemic ideal that makes data become evidence; data are considered evidence when it represents well enough the population from which the data are collected.

5.3.2 Knowledge Claims (Science) and Solutions and Predictions (AI)

Scientific knowledge claims and AI’s solutions and predictions are major epistemic outcomes in science and AI, respectively. Two of the common epistemic ideals of the outcomes are defeasibility and probability. These epistemic ideals complement one another. Scientific knowledge claims and AI’s solutions/predictions can be defeasible (that is, can be refuted later), but to mitigate this defeasibility, science- and AI-based claims and predictions are presented with
rigorously calculated probabilities that explain how much they can answer the questions or problems they have been asked to solve, offering a reference for users to boost trust.

There are also differing epistemic ideals that are particularly important to scientific knowledge claims and to AI's solutions predictions. Epistemic ideals particularly important to scientific knowledge claims include the claims' coherence with data, evidence, and method design, as well as their consistency with other scientific knowledge claims proven to be trustworthy (Duncan et al., 2018; Walton, 2005). Epistemic ideals particularly important to the predictions AI offers are optimality (Will the prediction offer the best decision?) and time-efficiency (Has the prediction been made quickly?; El Naqa & Murphy, 2015). The rationality of AI agents is also an important epistemic ideal. AI agents learn gradually in an effort to maximize the success of performance, based on built-in prior knowledge and newly acquired information. Here, AI designers define the criteria of success through the process of creating and operating specific algorithms (Russell et al., 2010).

5.3.3 Fairness as Epistemic and Ethical Ideal

I propose fairness as an epistemic ideal across epistemic processes of science and AI, by synthesizing the ethical considerations of the work I have referenced. Fairness is an important ethical ideal that we should use to consider the strengths and weaknesses of epistemic outcomes generated by science and AI and to critically use the outcomes they produce (Allchin, 2020; Long & Magerko, 2020). While fairness can be variously defined for different concepts, processes, and outcomes, the core idea is whether or not the outcomes such as scientific knowledge claims and AI's solutions and predictions are (un)biased, or have resulted from (un)biased processes (Ng et al., 2021; Sharon & Baram-Tsabari, 2020).

I must also address fairness in light of the social impacts that science, AI, and their intellectual outcomes can create. Fairness through this lens can include at least two ideals for those who engage in the epistemic endeavors, such as scientific investigators and AI designers:

– Scientific investigators and AI designers are conscientious, unbiased, and unaffected by funding sources, personal interests, and political/economic influence.
– The prior knowledge, evidence, and data the scientific investigators and AI designers use are extensive and exhaustive, not partial or skewed.

These are ideals to consider in addition to the trustworthiness of the intellectual outcomes themselves, because who produces the outcomes and whether or not and how they take an ethical stance can significantly affect the quality of outcomes they produce.
5.4 Reliable Epistemic Process

Broadly speaking, epistemic processes of science are collectively called scientific methods, which involve varying inquiry practices and skills. Scientific methods in general refer to the practical ways to find reliable answers to questions we have asked about the world around us by using evidence and constructing and testing explanations and predictions (Beecher-Monas, 2007). In AI, learning algorithms are important epistemic processes through which AI agents improve performance. One form of learning algorithm is called the machine learning algorithm, which makes AI agents learn “from the surrounding environment and previous experiences, with or without a teacher” (El Naqa et al., 2015, p. ix). While the specifics of these two epistemic processes – scientific methods and machine learning algorithms – vary, they also share some similarities, as implied by Russell et al. (2010), who note, “AI has finally come firmly under the scientific method” (p. 25). As such, if this comparative approach to the epistemic processes of scientific methods and AI learning algorithms is used for students’ learning, it can offer one way to learn AI and science integratively by helping students better grasp each process while considering the other. Also, when students engage in epistemic consideration in repeated and increasingly sophisticated ways, it may be more likely that students use the knowledge of epistemic processes into examination of scientific knowledge claims and predictions/solutions offered by AI agents.

To compare, I will illustrate the two epistemic processes focusing on the phases that share similarities – (1) data collection and processing and (2) data analysis and evidence evaluation (model testing) – and produce findings and predictions in a probabilistic manner. I will then briefly note some differences and explain another important epistemic process: using epistemic outcomes.

5.4.1 Data Collection and Processing

The early phase of scientific knowledge construction involves data collection and processing – as does AI’s machine learning. Several epistemic concepts

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1 According to the types of feedback, there are three main types of machine learning: unsupervised, supervised, and reinforcement. Supervised learning involves the early phase of learning from agent designers’ teaching with a set of known data and built-in prior knowledge. Unsupervised learning allows agents to learn without explicit feedback or prior knowledge offered. AI agents cluster input data and identify potentially meaningful information. Reinforcement learning means that the agents receive some sets of rewards or punishments as they learn (for example, when AI agents engage in games that have a win and fail system, the agents can learn via reinforcement). Crosscutting the different ways of machine learning are some common learning phases that can also be related to phases of scientific methods such as data collection, data processing, data analysis, and model testing (or evaluating evidence).
dealing with data collection and processing can be discussed in AI-integrated science classrooms.

- The accurate collection of data depends on measuring instruments’ reliability and validity and on their calibration to minimize measurement errors. Scientific data are collected using instruments to measure the values of variables, while AI models may collect data using different sensors (visual, auditory, tactile, movement, temperature, and more) and programs for gathering information (R, Python, and application programming interfaces).

- For sample size, the greater the number of measurements, the more likely the data represent the population from which the data were collected. As sample size matters in scientific data collection, AI models learn from a massive amount of data collected (millions to trillions of bytes of data).

- While scientific data collection emphasizes accuracy (how each measure was correctly obtained in order to reduce error) and validity (whether or not one measures what one expected to measure), AI data collection mitigates the need for accuracy and validity by collecting a large volume of exhaustive and extensive data in a significantly short period of time. The time spent on data collection gets much faster in AI agents as they automatically run algorithms that specify strategies of when and how to collect which types of data.

- Data processing in science occurs prior to data analysis or concurrently with analysis. Scientific investigators process data by asking if their data are valid for answering research questions, accurately drawing on the trustworthiness of measurement and using graphic and tabular tools. In AI, data are concurrently processed to get a set of structured – that is, manageable and informative – data from the unstructured data collected.

5.4.2 Data Analysis and Evidence Evaluation (Model Testing)
In science, data analysis determines whether an accumulated set of data can serve as evidence using statistical techniques and reporting probabilities (Faigman, 2008). Because there are numerous ways of calculating error rates and probabilities, investigators’ knowledge, biases, and perspectives can affect their evaluation of data’s legitimacy as evidence – along with their interpretations of the evidence as well. The similar phase of AI’s machine learning is model testing. In this process, a model means algorithms that are advanced (trained) by receiving feedback automatically and concurrently with machine learning. The algorithms are tested and modified by receiving feedback on the AI agents’ performance and letting the AI agents operate in new and unknown environments.
The phases that follow evidence evaluation (science) and model testing (AI) show crucial differences. In scientific methods, it is critical for researchers to examine the quality of evidence in relation to the large body of preexisting knowledge and evidence from other investigations (Duncan et al., 2018). Evidence should be considered and peer-reviewed in terms of whether or not the evidence explains the target hypothesis or explains alternative hypotheses. In comparison, AI algorithms are refined by circulating back and forth between the phases that follow model testing, such as model deployment and monitoring, through which AI agents achieve the goal of gradual perfection of rationality and performance.

5.4.3 Epistemic Process for the User of Science and AI
In addition to epistemic processes of science knowledge constructors and AI designers and agents, I must also note the critical use of information as an important epistemic process required of both science and AI. The critical use of information that includes scientific knowledge claims and AI agents’ predictions may entail the following actions:
1. Being aware that scientific knowledge claims and AI’s predictions are inherently defeasible;
2. Seeking to examine the trustworthiness of providers or funders of science and AI;
3. Seeking to examine where potential biases can manifest (at different phases – data collection, analysis, interpretation, and model testing – or during the designing of methods and algorithms, and the positions and purposes of scientific methods and AI agents); and
4. Naming the power structure in which science and AI work and examining how political and economic influences have affected the work of science and AI.

These are important epistemic processes for science and AI users through which the users can exercise their agency in examining the quality of outcomes produced by scientific investigators and AI designers. This epistemic process can be connected to the epistemic and ethical ideal of fairness.

6 How to Support Epistemic Discourse in AI-Integrated Science Classrooms

Drawing on the discussion of the similarities and differences in the epistemic aims, ideals, and processes of both science and AI, I will now suggest
approaches to AI-integrated science teaching through engaging students in epistemic discourse. In the following section, I first present four bins of question prompts (what teachers can ask) and instructional strategies (when and how teachers can ask these questions) related to epistemic aims, ideals, and processes. I then consider how science teachers can potentially collaborate with computing teachers in utilizing these strategies.

6.1 Four Bins of Question Prompts and Instructional Strategies

I use the term “bin” rather than “set” or “category” to suggest freedom in using and modifying these ideas in order to meet teachers’ needs and accommodate their own senses of instructional moments and interactions. Although I present the questions and strategies under the four bins, I consider that the questions and strategies could be used at any relatable instances in science classrooms. The four bins of questions and strategies to vitalize epistemic discourse are as follows:

1. Eliciting students' initial understanding of how science works and how AI works,
2. Scaffolding students' understanding of epistemic aims, ideals, and processes,
3. Supporting students to examine the trustworthiness of scientific or AI-provided information, and
4. Supporting students to engage in their own epistemic processes.

Teachers can carefully determine whether they would introduce terms such as epistemic aims, ideals, and reliable processes by considering students' preferences, interest, and grade level. If they would prefer to use plain language students can easily access, they can introduce epistemic aims as the purpose of doing science and training AI, epistemic ideals as the criteria that will evaluate the trustworthiness of information we receive from science and AI, and epistemic processes as scientific methods and machine learning. Additionally, teachers can introduce the terms as is so that students can expand their vocabulary and discipline-specific understanding. Teachers can also carefully implement the approach to which they will scaffold and explain scientific methods and machine learning algorithms by considering their students' grade levels, the possibility of collaboration with computing teachers, and the instructional time available.

6.1.1 Eliciting Students’ Initial Understanding of How Science and AI Work

Teachers can ask questions to gauge students' initial understanding of how science works and how AI works. “Initial” means the extent to which students
can, with the help of their peers and teachers, name and order at least several phases of scientific methods and machine learning by using the terms “data” and “evidence.” Teachers can facilitate students’ further development of their definitions of what science or AI means and what each does in our daily lives. Some questions include the following:

– Which AI agent have you recently used? How closely are they related to your daily life?
– Which scientific claims have you heard these days? How do you trust them?
– What is intelligence? What is knowing?
– What is knowledge? What is a claim? What is a prediction?
– What is AI? What does AI do? What is science? What does science do? What are each of their purposes?

6.1.2 Scaffolding Students’ Understanding of Epistemic Aims, Ideals, and Processes

Teachers can ask questions to scaffold and instruct epistemic aims, ideals, and processes of science and AI. Teachers can make this process engaging by offering interactive, hands-on activities such as charts, graphics, or Venn diagrams so that students can visually express what they have learned. To scaffold this learning, teachers can use the questions below after their students complete the activities. If teachers feel concerned about their students’ understanding of the academic terms, they can unpack the terms, remaining careful not to shortchange the terms’ original meaning. The following questions demonstrate this approach:

– What should trustworthy knowledge, claims, and predictions look like? What makes knowledge, claims, and predictions sound more trustworthy to you?
– What would be “good” evidence to you? What should quality evidence look like? (Especially in terms of reliability, validity, consistency, and coherence).
– How do scientific investigators construct knowledge claims?
– How do AI designers train AI?
– What is an algorithm? What do learning algorithms mean? Why is it called “machine” learning?
– How do you think the processes of scientific methods and machine learning differ? How do you think they are similar?
– When does information become data? When does data become evidence?
– How much data do you think is sufficient, in science and in AI?
– Why is a large sample size of data considered more trustworthy than a small sample size?
- How many numbers of measurements do you consider sufficient for science and for AI learning?
- Why do scientific claims present probabilities and errors?
- If a claim (science) or a prediction (AI) is said to be true with a probability of 50% (or 70% or 95%), what does that mean? Which percentage would you trust the most?

6.1.3 Supporting Students to Examine the Trustworthiness of Scientific or AI-Provided Information

Teachers can use the prompts in this bin when they engage students in news articles, social media, and personal experiences related to scientific knowledge claims and AI applications. The opening vignette of this paper is one example of this approach. If AI-related conversations spontaneously emerge in science classrooms, teachers can greatly help their students grapple with the full implications of such discussions by asking questions such as the following:

- Can I base my decision-making in the information I receive from a particular AI service and product? Or should I rely on science-related news and social networking service (SNS) postings? What will be the cost and benefit of doing (or not doing) so?
- How can scientific knowledge claims and AI’s predictions be biased?
- To what extent can I trust AI agents (and their solutions and predictions)? To what extent can I trust scientists (and their claims and evidence)? What would determine the extent to which I offer my trust?
- What should I know in order to examine the trustworthiness and functions of AI and scientific knowledge claims – and the consequences of using them?

6.1.4 Supporting Students to Critically Engage in their own Epistemic Processes

Teachers can use questions in this bin as they engage students in activities designed to help them experience epistemic processes. One example of such an activity involves encouraging students to critically examine the sufficiency of textbook-informed experiments. Imagine a class in which a teacher asked students to do a confirmatory experiment on Ohm’s law. Students measure the voltage, resistance, and electric current three times, calculate the values of those variables, and find that the calculation of numeric values meets the formula of Ohm’s law. The teacher would know that the three-time measurement was just to confirm the Ohm’s law that was already considered scientific fact. Still, teachers can have students examine the rationale and sufficiency in the number of measurements by asking questions such as the following:
– Are we satisfied with just the three sample measures? Why do we measure variables a small number of times (e.g., only three times) when compared to AI, which collects millions to trillions of bytes of data in order to aid its learning?
– What if we decide to make a new set of scientific knowledge claims? How many times will you measure the resulting variables in order to test these new claims?
– What would be “good” data collection in terms of science (and in the training of AI agents)?

Teachers also can have students experience the “messy” process of data collection and processing by using statistical and analytic tools such as spreadsheets in the classroom (e.g., Hardy et al., 2022; Son & Jeong, 2020). For example, teachers can engage students in at least a single 1-hour lesson in the authentic process of collecting and processing data, which resembles a crucial aspect of the way AI learns from data. Teachers can also encourage students to explore and “play with” public data generated and stored by local and national governments and public organizations – especially when that data relates to science. Engaging students in public data may help students experience the real broadness and messiness of data, in turn teaching students the importance of processing and representation. The following questions offer some ideas for ways teachers can encourage epistemic thinking about science and AI:
– How large is the data you generated (and/or the public data you chose)? Why do you consider it large or not?
– How frequently did you measure the variables?
– Which variables did the public data measure? How frequently were the variables in the public data measured?
– How did you process the data? If there was a subset of data you did not include in the analysis, why did you make that decision?
– How do you justify your findings as trustworthy?
– If AI helps you collect, process, and analyze the data of the variables, what does such an AI look like?

Another important way to engage students in epistemic processes is through having them design an imaginary AI agent that can help solve real-world, science-related problems that matter. If the topic is relevant to students’ lived experiences, it can bring in students’ experiential knowledge more readily. Questions teachers can pose to activate this learning include the following:
– What can AI do on our behalf?
– Which problems can AI and science help us solve?
– What kind of problems would you suggest for AI to solve?
– What is a problem that matters to you?
- Which variables do you consider important to the problem? And why?
- How can we measure those variables? Also, when and how frequently?
- How can an AI agent help collect, process, and find patterns in the variables?

6.2 Synergetic Collaboration Between Science and Computing Teachers

To undertake these instructional strategies, science teachers can seek collaboration with computing teachers who are experts in computing and AI education. Computing teachers possess their content knowledge of computer science and AI, and pedagogical content knowledge of students’ computing practices, such as what aspects of programming can be challenging to secondary students and how to help students program more fluently.

Currently, I imagine at least four specific modes of collaboration between science and computing teachers, though this list is intended to be neither restrictive nor exhaustive. The first mode of collaboration involves co-planning. Science teachers and computing teachers can look into their respective curriculums, find possible overlaps, reorganize teaching schedules, and concurrently offer integrative learning opportunities to students. Second, science and computing teachers can help students engage with public data available online portals (Hardy et al., 2022). While science teachers help students explore public data, computing teachers can help students utilize the data to learn and run programming. Third, they can collaborate to help students generate data using digital interfaces. Computing teachers can help students learn how to code the measuring tools and collect data automatically based on this coding. Science teachers can then help students analyze and interpret the resulting data. Science teachers can also facilitate epistemic discourse regarding data analysis and interpretation by using some of the prompts presented above. Lastly, science and computing teachers can collaborate in scaffolding students’ AI design to solve science-related problems. While science teachers can contribute to identifying which science-related problems are worth addressing, computing teachers can contribute to helping students refine their design ideas to become achievable and realizable.

7 Discussion and Implications

So far, I have proposed a pedagogical approach to AI-integrated science teaching through engaging students in epistemic discourse. I have examined the core elements that would constitute such classroom discourse by illustrating some of the epistemological aims, ideals, and processes regarding science and AI
and suggested some instructional strategies to facilitate epistemic discourse. With these elements established, in the remainder of this paper, I will discuss expected outcomes, implications, and future research directions.

7.1 Outcomes Expected by Engaging Students in Epistemic Discourse

AI-integrated science teaching done by facilitating epistemic discourse can offer one way of supporting students’ critical and conscious thinking and action. In particular, epistemic discourse can help students pose questions as they seek to define the sources of bias, corruption, and inaccuracy, while they also work to figure out who determines which methods (science) and algorithms (AI) are used, and what the repercussions of using science and AI are.

AI-integrated science teaching through facilitating epistemic discourse can contribute to transforming classroom discourse and to concurrently developing students’ AI and science literacies. First, it can help transform science classroom discourse in ways that will support students to act as legitimate knowledge constructors, critics, and users. Facilitating epistemic discourse can disrupt the status quo that centers the absorption of so-called school science (Kim, 2021). School science includes sets of scientific knowledge that have survived the test of time for their ability to justify and evaluate trustworthiness. While the teaching of such a set of stable knowledge – knowledge now considered scientific fact – is undeniably important, focusing mostly on its delivery can sideline epistemic processes that explain how the knowledge became stable and trustworthy. The importance of this epistemic consideration becomes perhaps even greater when applied to knowledge claims appearing in social media and popular science outlets, especially because the trustworthiness of those claims may remain uncertain (Cooper et al., 2012; Ruhrmann et al., 2015; Sharon & Baram-Tsabari, 2020). Students should more actively learn not only school science but also the underlying epistemic concepts and processes so that they will be able to make informed decisions and actions when faced with knowledge claims of ambiguous trustworthiness (Kim & Alonzo, 2021). By relating the epistemic dimensions that explain how AI and science work, students can better understand each of the two. Ultimately, students will hone their critical awareness about how data collection, analysis, and evaluation function in both science and AI, offering additional clues into the myriad ways each can become biased and untrustworthy.

Another important outcome expected from the epistemic dimension of AI-integrated science teaching is the concurrent development of AI and scientific literacies to help students pose questions. Earlier I introduced AI literacy as an expectation of K-12 AI education. Similarly, scientific literacy has been
one of the major goals of science education. Scientific literacy refers to the set of competencies for science learners involving constructing, justifying, and critiquing scientific knowledge claims – particularly those claims most relevant and important to science learners’ daily lives – along with the usefulness of the claims and information in regard to making decisions about life (Gormally et al., 2012; NRC, 2012). If the goal of science and AI education is to advance literacy and help students empower themselves as competent knowledge constructors, users, and critics, then integrating science and AI in the epistemic dimension would certainly help to accomplish this goal.

When classroom epistemic discourse is sustained, the aim is for students to develop science and AI literacies concurrently, particularly as students pose questions that matter. Solving problems is important, but AI can help us significantly in that respect. Posing questions, in contrast, is a creative and humane act done based on one’s unique lived experiences, knowledge, and community wisdom. If we expose students to learning opportunities that attend to the epistemic dimensions of science and AI, we can help students to identify and pose important questions that will help to examine the trustworthiness of given knowledge statements or predictions made by scientists or AI agents. These experiences and skills will in turn enable students to determine which issues we can use science and AI to predict and solve.

7.2 Institutional Support Needed to Actualize Integration

Individual teachers and researchers alone, however, cannot actualize AI-integrated teaching for all students. Instead, we can achieve this change by mobilizing institutional efforts that involve multiple stakeholders. First, teachers need professional development opportunities for integrated teaching. Instead of one-off or delivery-based and skill-oriented professional development, I suggest professional development opportunities that are sustainable, interactive, and integrative at the epistemic level. Such opportunities can vary in forms ranging from individual mentoring and peer teaching to communities of teacher action research and practice, and school- or district-wide summer workshops. At the core of these opportunities should be a genuine understanding of the constraints that teachers feel about the capacity, resources, time, and energy necessary to adequately establish integrative teaching and practical support such as concrete example lessons and units that teachers can apply to their classrooms (Barr & Stephenson, 2011). School leaders can also assist teachers by offering regular workshops for teachers to design and test integrative instructions between different subjects (including science and computing). School leaders can also help by reorganizing school schedules to lessen teachers’ workloads. Moreover, local school districts should offer a support
system for teachers who need resources and mentorship regarding integrative teaching in general and AI integration in particular. As still another type of support, teaching grants can be given so that teachers at the same school can be incentivized to design and implement AI-integrated teaching – especially for students from underrepresented communities.

Second, I have particularly discussed the context of AI-integrated education in Korea, which prompted the initial idea of this paper. Given Korea’s nationwide interest and emphasis on AI-integrated education across subjects, institutional support is urgently needed in order to address the shortage of computing teachers and course hours. Even if science teachers choose to pursue a collaboration with computing teachers who are experts in computing and AI education, the reality of these teachers’ working conditions may not afford them the opportunity or the willingness to collaborate. In contrast to the high national demand for AI and computing education in Korea, computing subjects are assigned only a few course hours, as indicated by informatics (the middle school computing subject) taking up only 1% over the 3 years of middle school (Korea Association of Informatics Teachers [KAIT], 2021). Due to the course-hour shortage, the government has not recruited as many computing teachers as are needed to lead both AI and AI-integrated education and computing education in general. In particular, many middle school informatics teachers have had to circulate between two to three neighboring schools in order to teach the 1-hour informatics classes (Kim, 2021). This complex situation has made informatics teachers very busy as they circulate among the different schools, making collaborative opportunities for integrated teaching nearly impossible. The complexity becomes greater when it comes to how to arrange other subjects’ course hours and the teacher workforce.

School is a political space in which different subjects have different power positions in determining the numbers of teachers, course hours, and curricular plans. School leaders, teachers, students, and parents bring different needs, values, and pedagogies (Barr & Stephenson, 2011). The long-held (and often invisible) power structure among different subjects and teachers may affect the policy decisions that have led to the low rate of recruitment of computing teachers despite the increasing demand for computing and AI education (KAIT, 2021). However, even if it is a severely challenging task given the existing power structure, fundamental change should begin from a reconsideration of the current curricular system – particularly if the goal is AI and AI-integrated education for all students. That said, if computing and other subject teachers are asked to offer AI-integrated education without curricular reorganization, it ought to be considered an undue demand that does not respect the teachers’ current workload and expertise.
What Comes Next: Research-Practice Partnership

Drawing on my discussion about expected outcomes and implications, I will conclude this paper by looking forward to the next steps for undertaking the instructional strategies of AI integration through facilitating epistemic discourse in science classrooms. Building on the pedagogical approach and attendant instructional strategies I propose, the next logical step involves undertaking a research practice partnership to further examine and implement the ideas brought forth in this paper. We can launch curricular co-design projects by inviting science and computing teachers and researchers interested in this type of integration initiative that can be concurrently administered in their own classrooms. The partnership approach will help design, pilot-test, and implement an instructional model that includes specific topics arranged with activities that center the epistemic consideration of science and AI, as well as active engagement in encouraging students to pose questions that matter. Doing so will enable the generation of empirical data and evidence from the implementation, ultimately providing for a robust evaluation of the usefulness and plausibility of the instructional model for AI-integrated science teaching in the epistemic dimension. Furthermore, the partnership project should invite students as learning experts. Students’ engagement in the instructional model – and their impressions, suggestions, and criticisms that follow – will provide a crucial source for evaluating and improving the effectiveness of the instructional model. Ultimately, the instructional model should be able to support more teachers who seek AI-integrated science teaching through their daily discourse, preparing their students to more readily act as legitimate knowledge constructors, critics, and users who pose important questions that matter to their lives.

Abbreviation

AI  Artificial Intelligence

Ethical Considerations

The data reported in this study did not require human subjects’ approval.
About the Author

Won Jung Kim is an Assistant Professor in Santa Clara University. She completed her doctoral studies at Michigan State University. Her research focuses on supporting youths’ equitable engagement with STEM in ways that matter to themselves and their communities. Seeking ways to implement justice-oriented pedagogies, she has collaborated with youth and educators in local science and community centers and conducted research-practice partnerships with pre- and in-service teachers. She is also interested in supporting and amplifying young people’s embodied STEM learning and living (e.g., dance, rap, performance, and social action) based on her science teaching years in South Korea, where she learned from her students the power of multiple ways of knowing, learning, and being. Dr. Kim is a recipient of the 2022 Outstanding Doctoral Research Award from National Association for Research in Science Teaching (NARST). She has presented her research at international and national conferences, and published her research in book chapters and journals including Science Education, Asia-Pacific Science Education, Multicultural Education Review, Forum for International Research in Education, and the Journal of Korea Association of Science Education.

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