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Artificial Intelligence in STEM Education

The Paradigmatic Shifts in Research, Education, and Technology

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Artificial Intelligence in STEM Education

Artificial intelligence (AI) opens new opportunities for STEM education in K-12, higher education, and professional education contexts. This book summarizes AI in education (AIEd) with a particular focus on the research, practice, and technological paradigmatic shifts of AIEd in recent years.

The 23 chapters in this edited collection track the paradigmatic shifts of AIEd in STEM education, discussing *how* and *why* the paradigms have shifted, explaining *how* and *in what* ways AI techniques have ensured the shifts, and envisioning *what* directions next-generation AIEd is heading in the new era. As a whole, the book illuminates the main paradigms of AI in STEM education, summarizes the AI-enhanced techniques and applications used to enable the paradigms, and discusses AI-enhanced teaching, learning, and design in STEM education. It provides an adapted educational policy so that practitioners can better facilitate the application of AI in STEM education.

This book is a must-read for researchers, educators, students, designers, and engineers who are interested in the opportunities and challenges of AI in STEM education.

Editor Biographies

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Artificial Intelligence in STEM Education: Current Developments and Future Considerations

Fan Ouyang, Pengcheng Jiao, Amir H. Alavi, and Bruce M. McLaren

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1.1 Introduction

During the last decade, applications of artificial intelligence (AI) methods in various academic fields have significantly increased due to the rapid development of data processing and computing technologies. Artificial Intelligence in Education (AIEd) is a well-established, interdisciplinary field that uses AI methods to facilitate instruction, learning, and decision-making processes (Hwang et al., 2020; Holmes et al., 2019; Roll & Wylie, 2016; O'Shea & Self, 1986; Self, 2016). AIEd can assist instructors in various instructional processes, such as automatically evaluating students' performance (Smith et al., 2019), providing recommendations and feedback to students (Bywater et al., 2019), or identifying at-risk students (Holstein et al., 2018; Hung et al., 2017). AIEd can also support student learning processes, such as tutoring students (VanLehn, 2006, 2011), providing learning materials based on students' need (Chen, et al., 2020), diagnosing students' strengths, weaknesses, and knowledge gaps (Liu et al., 2017), supporting student self-regulated learning (Aleven et al, 2016; Azevedo et al, 2008), or promoting collaboration between learners (Aluthman, 2016; Walker et al., 2009). AIEd can help administrators and managers monitor attrition patterns across colleges or departments and make decisions about their program developments (Hwang et al., 2020). Different AI techniques (e.g., artificial neural networks, ANN; deep learning, DL) have been successfully deployed to provide intelligent learning–teaching environments for building prediction models, learning recommendation, detecting behavior, etc. (Chen et al., 2020; Scruggs et al., 2020).

The emergence and continued work of AIEd has provided extensive opportunities for innovations in the field of science, technology, engineering, and mathematics (STEM) education (Xu & Ouyang, 2022). STEM education focuses on the integration of the subjects in STEM to improve students' interdisciplinary domain knowledge and understanding, as well as higher-order thinking and problem-solving skills (Kennedy & Odell, 2014; McLaren et al., 2010). STEM education usually faces challenges such as generating STEM problems, tracking students' learning, and evaluating their performance. The implementation of AI within instructional systems has the potential to solve developmental challenges in STEM education through creating active, interactive, or adaptive learning environments, automatically generating STEM problems and exercises, and evaluating or predicting students' performances (Alabdulhadi & Faisal, 2021; Jeong et al., 2019; Walker et al., 2014). For example, Yannier et al. (2020) introduced a mixed-reality AI system supported with computer vision algorithms to create and follow children's active learning behaviors in STEM education. In this book, Chapter 3 by Yannier et al. further introduces a new genre of Intelligent Science Stations,

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a mixed-reality system that bridges the physical and virtual worlds to improve children's inquiry-based STEM learning. In addition, intelligence tutoring systems (ITSs) equipped with machine learning (ML) techniques have been used to predict students' learning preferences and time to complete specific tasks, and categorize them into clusters of similar properties to form learning groups (Alabdulhadi & Faisal, 2021). Yağci and Çevik (2019) proposed automatic AI-based algorithm models to predict the academic students' achievements in science courses (physics, chemistry, and biology) and put forward suggestions to facilitate students' successful learning.

Currently, AI-directed STEM education, AI-supported STEM education, and AI-empowered STEM education are known as three main paradigm shifts transforming AI in STEM. This opening chapter discusses various aspects of these paradigm shifts supported by the AIEd frameworks. Their capacity to design AI-based STEM educational methods is highlighted. The chapter provides further insight into the advantages, disadvantages, and future trends of AI applications in STEM education.

1.2 Paradigmatic Shifts of AI in STEM Education

AIEd has undergone several research, practice, and technological paradigmatic shifts in its brief history (Ouyang & Jiao, 2021). The first major shift is *AI-directed* (i.e., learner-as-recipient) education, which is based on behaviorism theory (Skinner, 1953, 1958). In this paradigm shift, the primary role of AI technology is to present STEM knowledge and/or course content to students, who receive the service of knowledge representations and learning pathways provided by AI systems. For example, Stat Lady Intelligent Tutoring System (Shute, 1995), Cognitive Tutors (Koedinger et al., 1997), and ASSISTment Builder (Razzaq et al., 2009) are categorized within this paradigm. The theoretical underpinning of the second paradigm called *AI-supported* (i.e., learner-as-collaborator) education is cognitive and social constructivism, in which the AI provides learning supports as the core component and students act as active collaborators to learn and progress. For example, dialogue-based tutoring systems (DTSs) (Pai et al., 2021) and exploratory learning environments (ELEs) (Rosé et al., 2019) are categorized in this paradigm. The theoretical underpinning of the third paradigm called *AI-empowered* (i.e., learner-as-leader) education is complex adaptive system theory, in which AI serves as a dynamic agent for empowering students' active learning. Students in this paradigm can be effective leaders who actively interact with AI systems and dynamically adjust self-directed learning. Emerging concepts such as human-centered AI systems (Riedl, 2019), human–AI collaboration (Hwang et al., 2020), or human-centered artificial intelligence in education (Yang et al., 2021) can be categorized into this paradigm.

Figure 1.1 shows the number of AIEd publications between 2010 and 2020. As seen, there has been a growing interest in studies related to all three paradigmatic shifts. Interestingly, a large portion of these studies are dealing with AI-supported and AI-empowered paradigms (Figure 1.1).

Although these paradigmatic shifts are general educational frameworks, they can also be applied to STEM education more generally. This process involves gradual reshaping of STEM education from the teacher-directed instruction mode to the student-centered

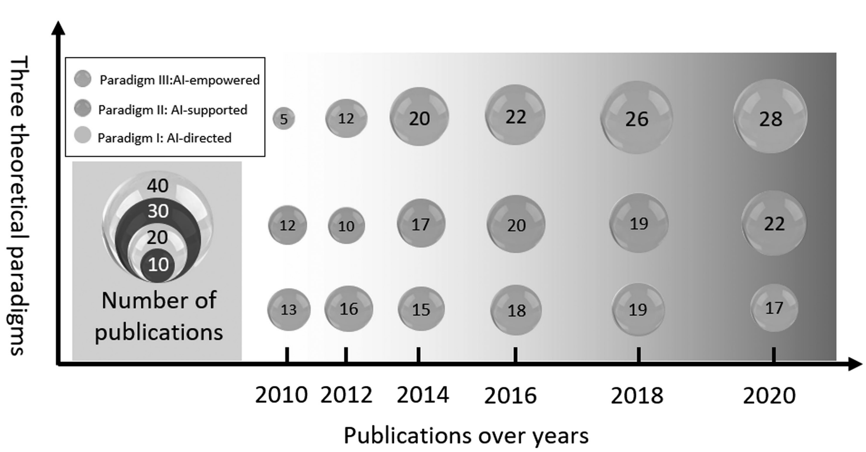

FIGURE 1.1
Number of publications related to AIEd under three theoretical paradigms.

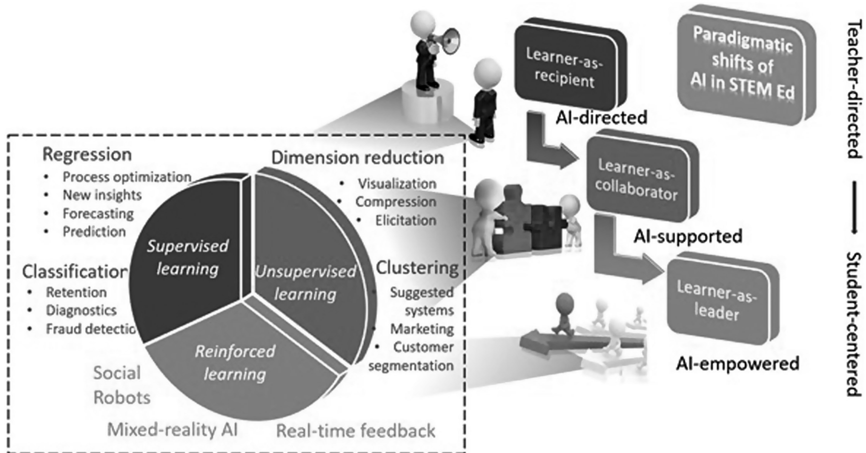

FIGURE 1.2
The shifts of three paradigms of AIEd in STEM education.

learning mode (see Figure 1.2). The following sections discuss the three paradigms of AIEd in STEM education in more detail – about the applications of the three paradigms in STEM education, the current AI applications for STEM education under these three paradigms, and related design and research.

1.2.1 Paradigm One: AI-Directed STEM Education

In the AI-directed paradigm, AI is equipped with the subject knowledge and guides the whole learning process in which the learner acts as a recipient to follow the AI-enabled learning path (Ouyang & Jiao, 2021). Behaviorism emphasizes prior systematic sequencing of learning content for the learner and guiding the learner to achieve an expected outcome (Skinner, 1953). For the AI-directed paradigm, learning is about helping learners reinforce their knowledge through a programmed instruction pattern or learning path. For instance, when learners are learning new concepts, the pattern requires immediate feedback for incorrect responses and the presentation of stimuli to guide students to mastery (Greeno et al., 1996; Schommer, 1990; Skinner, 1958). The student is required to respond to preprepared knowledge by following predetermined learning procedures and pathways and by continuously performing intended learning activities set by the AI until the desired goal is achieved (Burton et al., 2004; Holmes et al., 2019; Koschmann, 2009). Under the AI-directed paradigm, AI systems share similar characteristics to Skinner's 'teaching machine' (Skinner, 1958), which presents learners with logical subject matters and different learning pathways, that require learners to respond overtly, show they know the correct knowledge immediately, and move on to personalized learning paths (Burton et al., 2004).

For example, Shute (1995) introduces the Stat Lady Intelligent Tutoring System, which presents statistics content in a predefined order and requires learners to follow the learning sequence. Koedinger et al. (1997) use Cognitive Tutors in practical algebra curriculums to help students understand and use multiple representations of information. Mitrovic (2003) presents a Web-enabled Intelligent SQL Tutor in an introductory database course to observe students' actions and adapts to their knowledge and learning abilities. Moreover, Chin et al. (2010) and Biswas et al. (2016) use teachable agents that enable students to draw on the social metaphor of teaching to help them learn. Razzaq et al. (2009) utilize ASSISTment Builder as a tool to support teachers to effectively create, edit, test, and deploy tutor content in mathematics courses. McLaren et al. (2011) introduce a web-based intelligent tutor, namely, the Stoichiometry Tutor, to support students in chemistry learning. Overall, in the AI-directed paradigm, the AI directs the whole learning process, while the learner solves problems, engages in cognitive inquiry, and ultimately achieves learning goals by receiving AI services.

From the perspective of the AI-directed paradigm, the application of AI technologies in STEM education is a process of AI-reinforced instruction and learning. On the one hand, the instructor's teaching in STEM education is released or replaced by AI techniques. In particular, AI usually serves as a tutoring platform or a pedagogical agent to help instructors deliver teaching materials and resources, impart information and knowledge to students, and carry out teaching activities (Anderson et al., 1990; Shute, 1995). For instance, the ACT Programming Tutor system generates a production rules database for programming knowledge and presents students with a personalized learning sequence by calculating the probability of them learning these rules (Anderson et al., 1990). On the other hand, a student's learning in STEM education is reinforced through behaviorism-oriented AI techniques. For example, intelligent tutors train and supervise students mastering knowledge, completing homework, and passing examinations (Chin et al., 2010; Koedinger & Corbett, 2006; McLaren et al., 2011; Mitrovic et al., 2001; VanLehn, 2011). Consequently, the AI-directed paradigm mainly utilizes AI technology to represent knowledge in a certain instructional pattern or learning pathway, in order to impart course materials during instruction and learning in STEM education.

1.2.2 Paradigm Two: AI-Supported STEM Education

The AI-supported paradigm indicates that the AI system loosens its control and acts as a learning support system, while the role of the learner changes to that of a collaborator working with the system, focusing on the individual self-directed learning (Ouyang & Jiao, 2021). This paradigm assumes that learning occurs when learners interact with people, resources, and technology in the social environment in light of social constructivism learning (Bandura, 1986; Liu & Matthews, 2005; Vygotsky, 1978). According to this paradigm, the active and bidirectional interaction between the learner and the AI system should be formed, optimizing the learner-centered learning context. In other words, the AI system continuously collects data from the learner during the learning process as incremental input to optimize the student model, while the learner achieves better or more effective learning as a result of the interaction with the AI system (Baker & Smith, 2019; du Boulay, 2019; Rose et al., 2019). Overall, the AI-supported paradigm promotes learner-centered learning through effective interaction and ongoing collaboration between learners and the AI systems.

In STEM education, various AI implementations have been established to enable effective interaction between AI systems and learners, representative of which are dialogue-based tutoring systems (Pai et al., 2021) and exploratory learning environments (Rosé et al., 2019). On the one hand, these AI systems accurately understand the learner's learning situation by tracking their learning process and collecting and analyzing multimodal data about the learner. For example, Gerard et al. (2019) present a natural language processing tool embedded in student scientific explanations in learning. This tool can automatically score students' responses based on human-designed rubrics, adaptively guide students' learning based on the scoring results, and provide real-time feedback to the teacher on learning status. On the other hand, sustained interaction between learners and the AI systems can improve understanding of the system's decision-making process and appropriate adjustments for the upcoming learning activities. For example, Caballé et al. (2014) introduce a learning resource, the Collaborative Complex Learning Resource (CCLR), in a software engineering course. CCLR virtualizes the collaborative learning process, enabling students to observe how avatars discuss and collaborate, how discussion threads grow, and how knowledge is constructed, refined, and consolidated. Berland et al. (2015) use a tool AMOEBA, with real-time analyses of students' programming progressions, to support collaboration in a programming classroom setting in real time among middle and high school students. In summary, the learner follows the predefined learning path of the AI systems in the AI-directed paradigm, while in the AI-supported paradigm, the learner and the AI systems form a continuous mutual interaction, thus facilitating the development of learner-centered learning (Ouyang & Jiao, 2021).

From the perspective of Paradigm Two, major educational subjects (i.e., instructor, student) collaborate with the AI technologies to enhance the instruction and learning process. On the one hand, the instructional process in STEM education can be understood as a complementarity process between AI and the instructor. As an assistant, AI in STEM education can help instructors carry out instructional activities through automated question generation, assessment, feedback, and monitoring. For instance, Smith et al. (2019) propose a multimodal computational model that enables a more accurate portrait of learners by automatically analyzing students' writing and drawing in science learning. Bywater et al. (2019) describe a teacher-responding tool based on natural language processing technology that automatically generates response suggestions to assist teachers in providing personalized feedback to students in a mathematics course. On the other hand, student's learning in STEM education can be understood as a collaborative process between AI and students. The AI system acts as a support tool that does not dominate the learning process, while the student works with the system and thus focuses more on the individual student's learning process. In this case, a collaborative relationship is established between AI techniques and students during STEM education. For example, Howard et al. (2017) created an intelligent dialogue agent that helps college students learn Computer Science concepts. This agent tracks the student's learning behavior and tries to guide them toward more productive behavior. Di Mitri et al. (2021) introduced CPR Tutor, a real-time multimodal feedback system for cardiopulmonary resuscitation (CPR) training, to help students correct mistakes and improve their learning performance. In this book, Chapter 15 by Zhu et al uses various machine learning methods (e.g., text classification, transition rate analysis and sequential pattern mining, network analysis, and multilevel modeling) to understand the relationships between students' learning outcomes and processes in terms of students' discourse, multifaceted engagement, self-regulation, as well as evaluation behaviors during collaborative inquiry learning. In summary, the AI-supported paradigm focuses on using AI technologies to improve learners' engaging and collaborative roles to support individualized learning in STEM education.

1.2.3 Paradigm Three: AI-Empowered STEM Education

Driven by learner agency and instructor agency, the AI-empowered paradigm brings together multiple learners and instructors using AI as a support engine to empower quality instruction and learning. The complexity theory as the theoretical foundation of the AI-empowered paradigm holds education as a complicated intelligent system (Mason, 2008), which enhances learner intelligence through a collaborative approach between multiple agents. Moreover, stakeholders in this system should realize that AI technology is part of a complex system that consists of teachers, students, and other humans from the point of view of system design and application (Riedl, 2019). Numerous emerging concepts are proposed to build synergistic collaboration in the complex system by considering human conditions, expectations, and contexts. These typical concepts include human–machine cooperation (Hoc, 2000), human-centered AI systems (Riedl, 2019), human–AI collaboration (Hwang et al., 2020), human-centered artificial intelligence in education (Yang et al., 2021), etc. In the AI-empowered paradigm, AI enables augmented intelligence by providing learners and teachers with higher transparency of the learning process, more accurate feedback, and more practical advice (Riedl, 2019; Yang et al., 2021). AI systems support teachers in improving their understanding of the teaching and learning process, interpretation and personalized learning-oriented support, further enhancing student-centered learning activities (Baker & Smith, 2019; Holmes et al., 2019; Roll & Wylie, 2016). The learners, with empowerment of AI, lead their learning processes, hedge the risks of AI-automated decisions, and develop more effective learning (Gartner, 2019). Overall, the trends in the AI-empowered paradigm reflect the ultimate goal of AI applications in education, which is to enhance human intelligence, capability and potential (Gartner, 2019; Law, 2019; Tegmark, 2017).

Human–machine cooperation systems can achieve the AI-empowered goal by integrating AI technologies and human decision-making in STEM education. On the one hand, emerging intelligent technologies (e.g., deep learning, brain–computer interfaces, etc.) facilitate the collection and analysis of multimodal data, while ensuring transparency and accuracy. For example, Arguedas et al. (2016) use a fuzzy logic model to provide emotional feedback in an online technology course. In this way, students' emotional data is collected by AI technologies to make a more accurate representation of their emotions, enabling students to be aware of their own emotions, assess these emotions, and provide appropriate affective feedback. In turn, the role of AI has changed as human–artificial cognition has evolved (Hwang et al., 2020). On the other hand, humans can dynamically optimize the decision-making process for teaching and learning through the AI's intelligent, personalized feedback. For example, Yağci and Çevik (2019) use artificial neural networks to predict students' academic achievements in science courses (physics, chemistry, and biology) and put forward suggestions to support students. Holstein et al. (2019) use Lumilo, wearable, and real-time learning analytics glasses, to help teachers support students' learning in AI-enhanced physical classrooms. In this book, Chapter 3 by Yannier et al. introduces a new genre of Intelligent Science Stations, a mixed-reality systems that bridge the physical and virtual worlds to improve children's inquiry-based STEM learning. Chapter 21 by Hutt et al designs a new app that leverages user modeling techniques (e.g., behavior and affect-sensing) to direct interviewers to learners at critical, theory-driven moments as they learn with AIEd technologies in the classroom. The research uses machine learned models to gain a deeper insight into students' behaviors and their motivations in a qualitative way, thus furthering AIEd research. In summary, in the AI-empowered paradigm, emphasis is placed on generating adaptive, personalized learning through a synergistic interaction, integration, and collaboration between artificial intelligence systems and human intelligence (Arguedas et al., 2016; Yağci & Çevik, 2019; Yannier et al., 2020).

From the perspective of Paradigm Three, the applications of AI in STEM education will transform into a new level, namely, AI-enhanced co-design processes. Educational subjects (i.e., instructor, student) take agency and decide how to use AI technologies to enhance their instruction or learning processes and qualities (Bower, 2019). On the one hand, instructors take advantage of AI technologies to predict students' performance, identify the potential risk students, and analyze students' engagement, thereby improving STEM education (Hussain et al., 2018; Yağci & Çevik, 2019; Yannier et al., 2020). For instance, Hussain et al. (2018) use machine learning techniques to analyze students' engagement in an online social science course, and instructors can use the analysis results to adjust their teaching and thus promote students' engagement. On the other hand, in STEM education, students can use the right AI technology to avoid decision-making risks and become the owners of their own learning. In this case, AI provides personalized learning path recommendations and corresponding knowledge graphs to support student learning, based on the understanding of a student's knowledge structure and learning preferences (Arguedas et al., 2016; Chi et al., 2018; Wang et al., 2017). For example, a knowledge graph presents connections between knowledge points and concepts through graph structure, enabling students to differentiate and master complex concepts in STEM education (Chi et al., 2018; Wang et al., 2017). Based on the learner-centered principle, the AI-empowered paradigm uses AI technologies to make learners the center leader in STEM education, where learners become active participants rather than passive receivers.

1.3 Discussion and Future Considerations

AI systems can truly revolutionize STEM education via reducing teacher burdens, personalizing learning experiences for students, and transforming the roles of teacher and student. Furthermore, AI technologies can free teachers and students from redundant, elementary tasks and focus on more advanced, complicated tasks (Holstein et al., 2019; Hwang et al., 2020; VanLehn, 2011). For example, automatic evaluation techniques help reduce instructors' assessment tasks, while automatic translation tools improve the efficiency of students' language learning (Xu & Ouyang, 2021). AI applications can help instructors create and convey course content and materials (Razzaq et al., 2009) and provide students with tailored learning experiences, such as personalized tutoring (Mitrovic, 2003; Yang & Zhang, 2019). These techniques can also work as a supplementary assistant to serve STEM education and help teachers and students understand the teaching and learning process and the environment by continuously tracking data on the learning process (Figaredo, 2020; Papamitsiou & Economides, 2014). For example, AI-enabled algorithms and modeling can be used to predict students' learning performance (Yağci & Çevik, 2019), while wearable devices can be utilized to track students' learning behaviors (Holstein et al., 2019). AI in STEM education can potentially transform the teacher–student relationships from teacher-directed to student-centered learning. In traditional STEM courses, instruction refers to the effective transfer of teachers' knowledge and skills to students, which is characterized by teacher-directed, performance-oriented, and highly structured teaching model (DynaGloss, 1998). In contrast to the traditional modes where the teacher plays a substantial leadership role, designing and leading the teaching and learning process, the role of the teacher may shift to that of a supporter, collaborator, and facilitator in AI-enabled STEM education (Xu & Ouyang, 2021).

However, there are major challenges ahead of AI applications in STEM education, including the ambiguity of the responsibility of AI, overreliance on AI technologies, AI bias, and invasion of data privacy. When AI functions as a part in STEM education, it can partially take on human responsibilities but can hardly replace humans, as AI-empowered agents lack social competence and self-reflection even if they possess human-like intelligence. In STEM education, instructors are expected to impart knowledge to students, proactively reflect on instructional strategies, and adapt teaching appropriately based on the understanding of student learning (Collinson, 1996; Turner-Bisset, 2001). Peers can collaborate and communicate with students in different learning situations and establish interactions in social life (Muhisn et al., 2019). Therefore, relevant questions are raised: *Can AI replace instructor responsibilities in STEM education?* Whether and how does *the use of AI technology improve the quality of STEM education and improve teaching?*(Xu & Ouyang, 2021). Although AI can free teachers and students from redundant tasks in STEM education, it still lacks the ability to solve critical problems (Gary, 2019; Selwyn, 2016). For example, how to develop learners' interest and motivation and foster a desire to learn. Hence, when using AI techniques in STEM education, teachers need to consider why and how they should use AI. Are the reasons for using AI to reduce their workload or improve efficiency? Will the use of AI technology lead to decreased students' performance or other ethical issues? Third, privacy is a key challenge in applying AI in STEM education. To some extent, AI technologies such as educational data mining and learning analytics have the potential to enhance the teaching and learning process in STEM education. However, in the complex process of collecting, storing, transmitting, and using data, it may easily cause the disclosure of personal privacy or improper use of data (Zawacki-Richter et al., 2019). Before applying AI in STEM education, instructors should consider the risks of using technologies and pay attention to protecting students' privacy.

AI applications and research need to address the complexity of STEM education. The challenge is how to match the complexity of learning processes with the complexity of AI systems and the complexity of educational contexts (Ouyang & Jiao, 2021). AI technology should be designed to offer constant communications with and updates to instructors and students, to align AI models with learners' learning values, and to support the emergent, changing learning processes (Segal, 2019). Furthermore, AI applications should also consider how to empower stakeholders in reflecting on teaching and learning processes and goals, and accordingly how to inform AI systems to adapt and lead an iterative cycle of design, instruction, and development.

Development of AIEd in STEM education has experienced paradigm shifts from the traditional teacher-centered approach to the AI-enabled, learner-centered strategy (Ouyang & Jiao, 2021). The AI techniques have been thoroughly involved in AIEd to ensure such instructional changes, from designing teaching strategy using machine learning to predict learners' performance, and from capturing learners' responses using natural language processing (NLP) to analyzing learners' reactions using pattern recognition (PR) in teaching (Chen et al., 2020; Ouyang & Jiao, 2021; Xu & Ouyang, 2021). According to the AI technique perspective, the characteristics of AI technologies and algorithms contain automaticity, intelligence, and self-adapting, which might prompt another paradigmatic shift of AIEd in STEM education. In the future, AIEd can be developed for achievements in three main directions. The first direction is to apply AI techniques to analyze multimodal data from the instruction and learning process. It has potential to eliminate misunderstandings between learners and instructors, eventually improving students' learning quality and performance in STEM education (Belpaeme et al., 2018). The second direction is to build an AI-empowered virtual learning environment for the STEM education to better represent and convey knowledge that is difficult to understand or practice in real-world environments (Mystakidis et al., 2021). AI techniques not only can support the design and implementation of virtual environments, but also can provide learners with real-time feedback, personalized learning materials, and suggestions of learning paths. For example, the application of augmented reality (AR) in STEM education can spatially merge virtual and physical worlds with the support of digital devices (e.g., handheld devices, portable, glasses) (Riegler et al., 2019). In AR-based STEM education, AI techniques have the potential to improve students' understandings of abstract concepts and knowledge through visible and touchable artifacts (Ke & Hsu, 2015; Mystakidis et al., 2021). Third, collaboration, inclusion, and equity are involved as a paradigm shift for AI in STEM education. For example, Roscoe et al. propose Chapter 23 that AI algorithm models need to be disaggregated to include more nuanced variables and effects related to participants' social identities. Tang et al. in Chapter 22 argued that AI applications designed and implemented to support collaborative learning should be further strengthened, such as how AI supports group formation and students' interactions.

1.4 Structure of the Book

This opening chapter of the book presents an overview of recent advances in the area of AIEd. Underpinned by the AIEd paradigm frameworks, the chapter illustrates how AI in STEM can be observed through the three paradigmatic shifts of AI-directed STEM education (learner-as-recipient), AI-supported STEM education (learner-as-collaborator), and AI-empowered STEM education (learner-as-leader). The book is structured into five sections:

- Section I: AI-Enhanced Adaptive, Personalized Learning
- Section II: AI-Enhanced Adaptive Learning Resources
- Section III: AI-Supported Instructor Systems and Assessments for AI and STEM Education
- Section IV: Learning Analytics and Educational Data Mining in AI and STEM Education
- Section V: Other Topics in AI and STEM Education

Section I: AI-Enhanced Adaptive, Personalized Learning, includes four chapters. The present chapter introduces Intelligent Science Stations. Experiments indicate that the automated reactive guidance, made possible by a specialized AI computer vision algorithm, can provide personalized interactive feedback to children. Chapter 2 by Biswas and Hutchins combines AI and machine learning methods to support curriculum and learning environment design in an earth sciences module, and then developed analytics to analyze middle school students' learning performance and behaviors in the environment. The integrated methods provide an understanding of students' learning pathways as they transition from applying their conceptual knowledge to constructing computational models to solve an engineering design problem. Chapter 3 et al. by Yannier introduces a new genre of Intelligent Science Stations, a mixed-reality system that bridges the physical and virtual worlds to improve children's inquiry-based STEM learning. Chapter 4 by Rau presents a series of studies of sense-making and perceptual fluency in problem-solving activities that enhances students' learning of STEM content knowledge and describes how learning analytics reveal that prior knowledge affects students' interaction with representational competency supports. Chapter 5 by Pacella et al. develops an Adaptive LEArning for Statistics (ALEAS) app to provide an adaptive learning environment that allows students to assess their own knowledge in statistics. Learners are assessed by two multivariate methods: (i) for each topic, a multidimensional latent-class IRT model is defined, in which dimensions corresponding to the students' ability are measured; (ii) within each area, archetypal analysis allows integrating and comparing the students' performances. Chapter 6 by Faramand et al. proposes a methodology of intelligent learning dashboard focusing on SPOL and discusses how to construct mechanisms for adaptive formative assessment and student engagement detection with the state-of-the-art AI techniques, how to design and integrate these technologies in intelligent learning dashboards, and how to include these mechanisms in the course learning design loop to ensure data collection and pedagogical connection.

Section II: AI-Enhanced Adaptive Learning Resources includes three chapters. Chapter 7 by Matsuda et al. proposes PASTEL, a pragmatic method to develop adaptive and scalable technologies for next-generation e-learning. PASTEL is a collection of methods to assist courseware developers to build adaptive online courseware. The chapter provides details about the PASTEL technology and results from its early-stage evaluations. Chapter 8 by Shin and Gierl introduces a technology-enhanced framework based on machine learning and natural language processing techniques to understand and evaluate science articles. The chapter reveals that the best model can identify an interpretable topic to accurately classify the science articles based on their curriculum standards. Chapter 9 by Demartini et al. enhances the comprehension of teaching and learning within the educational domain by leveraging data gathered along the student learning life cycle. The integrated data mining and machine learning techniques make this conceptual platform an adaptative and innovative tool to develop reinforcement and personalization of educational experiences.

Section III: AI-Supported Instructor Systems and Assessments for AI and STEM Education includes four chapters. Chapter 10 by Uttamchandani et al. proposes considerations that emerge in the design of orchestration assistant, an AI-supported teacher orchestration system. The theoretical possibilities are proposed for supporting pedagogy with AI. And possibilities are proposed when the teacher orchestration system is enacted, complicated, or transformed in the context of real classroom activity. Relevant design considerations are proposed for designing such AI-supported systems for teachers. Chapter 11 by Chiu et al. reviews current approaches in education that use AI technologies to provide targeted learning opportunities for teachers. This chapter leverages the ICAP framework to discuss current and future directions for AI-based tools that put teachers in-the-loop, which provides automated feedback on teachers' practices and improve students' knowledge construction. Chapter 12 by Chen and Lu proposes an overview of the mainstream learner models that are commonly used in computer-based assessments for learning as well as recent advances in learning outcome modeling. Chapter 13 by Matsumura et al. develops an automated writing evaluation system (eRevise) to support argument writing. The chapter proposes that the AWE systems communicate the features of authentic tasks, provide information that is transparent, actionable, and fair, and open up avenues for student-centered classroom collaborations.

Section IV: Learning Analytics and Educational Data Mining in AI and STEM Education includes seven chapters. Chapter 14 by Li and Lajoie introduces a theory-driven learning analytics model, which has the potential to promote the evolution of STEM education and research. This chapter presents an example study to illustrate how theory-driven learning analytics can be applied into practice in a STEM learning context. Chapter 15 by Zhu et al. discusses how learning analytics can be used to analyze students' discourse and behaviors in technology-enhanced STEM learning environments. Machine learning methods such as text classification, transition rate analysis and sequential pattern mining, network analysis, and multilevel modeling are adopted to understand the learning outcomes and processes. Chapter 16 by Nawaz et al. discusses the notion of task difficulty, how it is defined and operationalized in digital learning environments. This work further highlights how artificial intelligence and learning analytics offer opportunities to provide timely support to students when they experience task difficulties. Chapter 17 by Xu integrates inquiry learning and Web3D technology into virtual experiments in order to improve learner experiences and learning quality. A general framework is proposed, which includes three application branches: data collection and processing, learner modeling, and learning recommendation. Chapter 18 by Fan et al. reviews recent developments of ensemble learning machinery for propensity score matching and weighting. This work extends and improves the use of learning analytics for estimating treatment in the personalized medicine observational studies literature. Chapter 19 by McNamara et al. proposes that AI (and data science) can reveal nuanced patterns of student retention, persistence, and performance, but expertise in learning theory and psychological sciences is needed to suggest mechanisms and explanations for these patterns. Chapter 20 by Crossley et al. uses a widely used educational data mining technique – natural language processing – to extract linguistic attributes of students' collaborative problem-solving and links it to their final science performance.

Section V: Other Topics in AI and STEM Education deals with qualitative research and collaborative learning practice in AI and STEM education. Chapter 21 by Hutt et al. designs a new app that leverages user modeling techniques (e.g., behavior and affect-sensing) to direct interviewers to learners at critical, theory-driven moments as they learn with AIEd technologies in the classroom. The research indicates that using machine learning models to optimize researcher time helps researchers gain a deeper insight into students' behaviors and their motivations, thus furthering AIEd research. Chapter 22 by Tang et al. conducts a systematic literature review to understand the development of AI to support computer-supported collaborative learning (CSCL) in STEM education from 2011 to 2021. This review examines the overall trend of AI applications designed and implemented to support CSCL and evaluates the effects of proposed AI techniques and applications in supporting group formation and students' interaction. Chapter 23 by Roscoe et al. stresses the importance of AIEd to include more nuanced variables and effects related to demographic factors and social identities. This work also proposes that intersectional approaches are needed to represent learners' multiple identities, associated power, or privilege and to interpret observed effects.

1.5 Conclusions

This opening chapter presented an overview of recent advances in the area of AIEd and STEM education underpinned by the AIEd paradigm frameworks. We showed how AI in STEM can be observed through the three paradigmatic shifts of AI-directed STEM education (learner-as-recipient), AI-supported STEM education (learner-as-collaborator), and AI-empowered STEM education (learner-as-leader). We examined how AI applications are connected to existing educational and learning theories, the extent of which AI technologies influence teaching, and the different roles of AI in education. The capacity of the three shifts to transform the AI-based STEM educational methods was further highlighted. We discussed the future AIEd practices and research in STEM education from teacher-directed education to learner-centered learning, where learner agency, initiations, and lifelong learning are valued. Finally, summaries of the chapters included in this book are provided.

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