AI-Enhanced Education: Teaching and Learning Reimagined

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Why AI in Education

Artificial Intelligence (AI) is changing the essential relationship between technology and human beings. It is reshaping the ecosystem of education and growing to be a primary focus of multinational technological corporations, education departments, and governments of countries around the world. From 2016 to 2018, the government of the United States published three documents emphasizing the importance of AI and its standing in the development of the countries: *Preparing for the Future of Artificial Intelligence* (Bundy, 2017; United States, 2016), *A National Machine Intelligence Strategy for the United States* (Carter et al., 2018), and *The National Artificial Intelligence Research and Development Strategic Plan* (National Science and Technology Council, 2019). All three documents put emphasis on education being the core application of AI. In 2019 the Open University in UK released the *Innovative Pedagogy 2019* (Ferguson et al., 2019), which points out the importance of "learning with robots" (p. 12), in order to help teachers free their time for teaching. The *Innovative Pedagogy 2020* report (Kukulska-Hulme et al., 2020) starts with Artificial Intelligence in Education as the first chapter and provides a detailed description of a possible application of AI in teaching and learning, and projects the bright future of AI development in multiple scenarios in education. Moreover, UNESCO held the conference titled "Planning Education in the AI Era: Lead the Leap" in Beijing, China, in which ten essential topics including policy formulation, learning management, teaching, and teacher development were discussed. AI is the essential power promoting educational reform.

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The current education system is insufficient to address some typical acute questions: education inequality is increasing due to the unbalanced development of the technological advancements, socioeconomic concerns, and political upheaval in some regions and countries (Facer, 2011), which cause the limited accessibility to educational resources for learners in those disadvantaged areas. Even in the countries where education is under the spotlight of national development, issues like mal-supported instructors (Schmid & Hegelheimer, 2014), engaging proper technology-enhanced pedagogy to stimulate the greatest learner potential remain top concern for instructors and educational researchers. For learners who have difficulty learning in the standard environment, their learning quality cannot be guaranteed without further attention and intervention from the instructor or the teaching system. Technologies like learning analytics and machine learning have been utilized to acquire the data about the learning experiences from numerous learners. AI grants people opportunities and hope to make education more accessible, and to identify effective new learning patterns, models, and insights to understand learning, teaching, and the roles of people engaged in those processes.

With the resources we possess so far, education is the science and practice that prepares our young generation facing the uncertainty in the future. The responsibility of educators and educational researchers is to prepare students with essential twenty-first-century skills and life-long and life-wide learning capacity. In this chapter, we first look into the technologies that are applied in AI and how they enhance education. Then, we review the applications available to education administration, teachers, and learners, and how each role might be enhanced or redefined by the affordances of AI. Finally, yet importantly, we elaborate on some concerns for future AI applications in education.

Fundamental Technologies in Educational AI

Learning Analytics

Learning analytics is the intersection of multiple academic disciplines such as education, AI, and data science, among many others. Through collecting, analyzing, and reporting students' learning data, the essential function of learning analytics is to understand and improve learning to the optimum level. More operationally, Society for Learning Analytics Research (SoLAR) defines learning analytics as the measurement, collection, analysis, and reporting of data about learners and their contexts, for understanding purposes and optimizing learning and the environments in which it occurs. There are three major elements in learning analytics: data, analytics, and action plan (Chen et al., 2020). Data refers to collecting data that provide analytical insights about learners and their learning behavior; analytics entails applying research methodologies and algorithms to produce high quality and insightful analysis; action plans are the bridge between the analytics and the desired learning objectives, through applying the insights and models gained to attain the learning purpose. According to this study, in Fig. 1, we visualized the three elements.

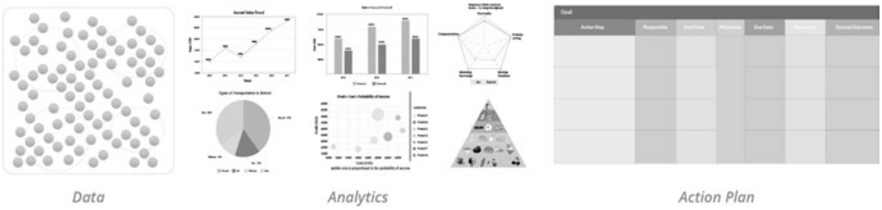

Fig. 1 Three major components of learning analytics

Levels of Learning Analytics			
Descriptive	**Diagnostic**	**Predictive**	**Perspective**
What has happened?	*Why did it happen?*	*What will happen?*	*What should I do?*
• Look at facts, figures and data to create a detailed picture. • Did the student fail a quiz? • What was mastered? • What was not mastered?	• Examining the descriptive to critically assess what really happened? • The student did ok in one area but not ok in another area? • What were the root causes such as time devoted, homework, class discussions, etc.?	• By looking at the past can we predict what will happen in the future? • If time devoted, homework, class discussions were levers such as A, B, C, then what is the impact of each lever on the future?	• How can specific outcomes be achieved by tweaking each one of the levers? • How can we apply Descriptive, Diagnostic and Predictive knowledge to achieve our learning outcomes?

Fig. 2 Four levels of learning analytics

Arroway et al. (2015) applied a hierarchy approach of understanding learning analytics, in which learning analytics could be divided into four levels: descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. We create the table in Fig. 2 to help better understand these four levels.

Descriptive analytics focuses mainly on the historical data that is collected from multiple related resources to trace the previous learning behavior of learners. Diagnostic analytics intends to identify patterns and get insights into a specific learning problem. Predictive analytics builds on historical data to develop statistical models that can forecast the future possibilities for learners. It is the process of identifying probable difficulties and creating opportunities to provide targeted support to learners. Prescriptive analytics takes another step further to consider the possible forecasted outcomes and predict consequences for these outcomes, which provides the strategic plan to intervene in the learning process in order to improve the efficiency of learning. Compared to descriptive data solely focused on historical data received, predictive analytics and prescriptive analytics are the two most widely applied types in learning analytics. One example of representative predictive analytics applications is the Course Signal system developed by Purdue University. This system applies the data collected by instructional tools within the educational institution to determine which students might be at risk, partially indicated by their effort within a course. The Course Signal system offers them support and resources to help students succeed by predicting and providing early interventions (Arnold & Pistilli, 2012).

The wide usage of learning analytics brings more accurate prediction of students' learning behavior, which allows institutes to take intervention actions, but it also projects a challenge on solving course-specific and institute-specific contexts issues, especially the instructional conditional differences (the efficiency of Learning Management system, quality of instruction, etc.), as it brings challenges to structure the models for customized analytics. Example applications and products of learning analysis in education include student and learning behavior modeling (Holstein et al., 2018; Santamaría-Bonfil et al., 2020), learning performance prediction (Ifenthaler et al., 2019), AI-assisted learning self-reflection and awareness (Buckingham Shum & Crick, 2016; Viberg et al., 2020), and learning administrative management that monitors student retention and drop-out issues (Lacave et al., 2018; Mah, 2016).

Machine Learning

The strength of machine learning is its ability to make accurate predictions based on the input data (Mannila, 1996). It is different from traditional statistics that is often used for making connections among the variables and making inferences in order to find possible explanations from the data provided. The essential function of machine learning is knowledge and insights discovery (Chen et al., 2020) since it creates models with various degrees of interpretation. Machine learning applied in education benefits include machine learning, data mining, statistics, and data modeling. It provides solutions to the problems learners encounter through learning patterns discovery, prediction, and decision-making based on the input data sets. Combining the computational and statistical perspectives of data analysis, data collected from the educational devices and software provide valuable information about learners and insights into their learning behaviors. Machine learning can reflect the more personalized nature of the data and form more customized insights and solutions to learners in their unique learning contexts. The four applications and products of machine learning in education include: (1) education administration that frees teachers from tedious teaching management tasks (Amigud et al., 2017); (2) monitor students' learning progress (Gray & Perkins, 2019); (3) analytics of content (Lan et al., 2014), and (4) instruction improvement (Zhou et al., 2018). The application and products of machine learning in education are shown in Fig. 3.

Two essential fundamental mechanisms of machine learning application in education include *educational data mining* and *deep learning* (Hernández-Blanco et al., 2019). Educational data mining is a process that analyzes the unique types of raw data generated from educational settings. It develops the methods to help understand students and the settings in which they learn, and provides useful insights that

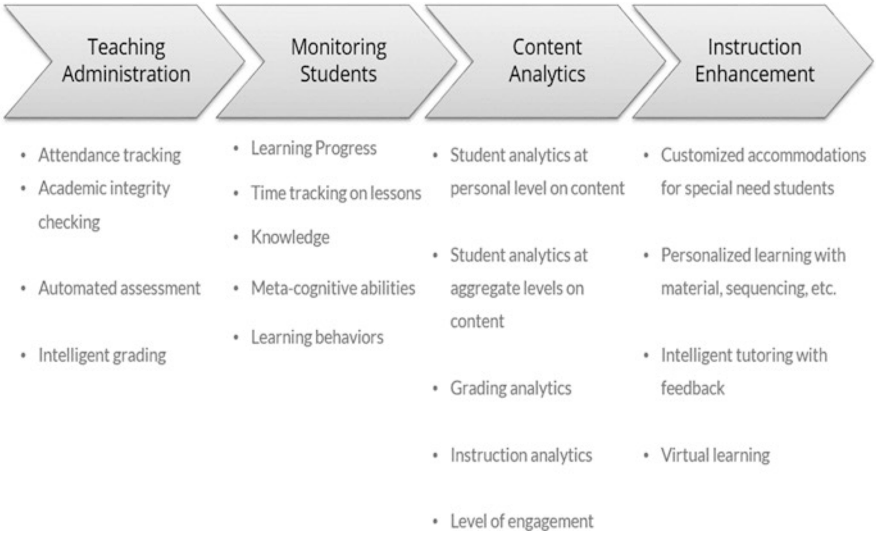

Fig. 3 Application and products of machine learning in education

could potentially be impactful on educational research and practice (Dutt et al., 2017; Romero & Ventura, 2010). In recent years, the trend of educational data mining applied as a new methodology to investigate educational research questions is observed widely (ElAtia et al., 2016).

Educational data mining is typically closely associated with specific learning objectives (Dutt et al., 2017). It is a powerful tool to improve the learning process and knowledge mastery for learners – learning pattern discovery and predictive modeling applied in extracting hidden knowledge in specific contexts. Educational data mining provides advantages such as laboratory experiments, in vivo experiments, and design research. The application and products of data mining in education include (1) analyzing student learning motivation, attitude, and behavior, i.e., performing erroneous actions, low motivation, cheating, and academic failure, (Mulwa et al., 2010); (2) understanding learning styles of students, i.e., student modeling (Sivakumar et al., 2016); (3) supporting diversified learning format and methods, i.e., personalized learning, e-learning, and collaborative learning (Dutt et al., 2017); and (4) learning outcome prediction (Mueen et al., 2016).

Deep learning is a machine learning method. Based on neural network architectures with multiple layers of processing units, it allows computational models to "learn representations of data with multiple levels of abstraction" (LeCun et al., 2015, p. 436). There are two key aspects of deep learning that allow it to outperform traditional machine learning with increased size of dataset: "(1) models consisting of multiple layers or stages of nonlinear information processing; and (2) methods for supervised or unsupervised learning of feature representation at successively higher, more abstract layers" (Deng & Yu, 2014, p. 201). Deep learning has made great progress in complex tasks like image recognition and natural language processing, and performing complete knowledge games like chess and "Go" (Fawaz et al., 2019; Nguyen et al., 2019).

With deep learning applied as the approach to educational data mining, Hernández-Blanco et al. (2019) summarized in total 13 tasks. In addition to the ones previously mentioned in the educational data mining subsection, deep learning enhanced data mining could also help with the following three aspects in education. First, it can be applied to social network analysis, which can show the various possible relationships among students and better understand their learning-related interactions. Second, it can provide feedback to students, which allows them to find and highlight the information related to course activities and student's usage information on course materials for instructors and course designers. Third, deep learning enhanced data mining can help develop concept maps of various aspects to help instructors define the process of education.

With a good understanding of the available techniques of AI in education, we present the applications and available products with the above-mentioned technologies as the foundation for three major agencies in education: education administration, teachers, and learners.

Agencies of AI in Education

Effective and appropriate application of AI offers opportunities to revolutionize education by assisting teachers with administrative tasks and teaching while subsequently impacting students' learning. In this section, we focus on specific applications of AI systems in the domains of education administration, instruction, and learning.

Education Administration

Traditionally, educational administrative tasks are primarily carried out by teachers at the classroom level, by educational administrators at the school and district level, and stakeholders at a wider and higher level. Introducing AI-enhanced education administration can free teachers from performing administrative work and allow more support and attention to go to the actual instruction. From the available AI-enhanced technology and applications, education administration can be facilitated at four different levels:

Level I: Substitution. At this level, AI applications free teachers from daily tedious manual/labor work by performing tasks like taking class attendance and grading objective questions. Substitution functions of AI are particularly beneficial for providing timely feedback and increase their effectiveness in classes with large numbers of students.

Level II: Intellectual augmentation. AI in this level collects and tracks students' learning data over an extended period of time, which provides comparable and more holistic information for teachers to see the learning development of students over a period of time, and reduces the impact of possible biases or subjective impressions the teacher formed based on individual learning performance. Examples could be seen in student profiling systems and learning performance-monitoring systems.

Level III: Revolution. Based on the AI characteristics of modeling and prediction, education administration systems nowadays can provide learning predictions and allow educational institutions to engage in student learning interventions. Representative examples are drop-out prevention systems and at-risk student identification systems.

Level IV: Holistic revolution. Some intellectual education administration systems have performed functions beyond learning management. The systems can support teaching in various formats and styles. Many educational establishments incorporate interactive learning environments (ILE), such as learning management systems (LMS), to assist teachers and professors with administrative tasks. ILE is a software system which sometimes includes specialized hardware designed to support teaching and learning in education (Psotka, 2012). It combines digital technologies, e-learning techniques, and interactive pedagogical approaches to maximize students' personalized learning (Chassignol, Khoroshavin, Klimova & Bilyatdinova Chassignol et al., 2018). The four levels are shown in Fig. 4. In the rest of this section, we introduce several representative education administration systems to help understand how AI supports teachers and administrators.

Artificially Intelligent Tutoring System (ITS) is a branch developed as a part of LMS evolution that uses AI systems to achieve the goal of interactive and personalized learning. ITSs are computer systems developed to improve teachers' effectiveness by offering instructions and guidance to and off-loading teachers' duties of providing assessments and feedback (Chassignol et al., 2018). As teachers are often guided by grading rubrics, similar techniques are used by automatized assessment technologies offered by the AI. A typical ITS includes four main components (Almasri et al., 2019):

1. The Domain Model
2. The Student Model
3. The Teaching Model
4. The Communication Model (Fig. 5).

The Knowledge Model represents the knowledge about the teaching material. The Student Model contains the knowledge about each student to respond to their individual skills and interests and promote effective learning. The Teaching Model helps select a suitable tutoring strategy and pedagogical actions (e.g., providing a hint, or feedback) based on the information from the Student Model and on student's interaction with the system (Almasri et al., 2019). The Teaching Model

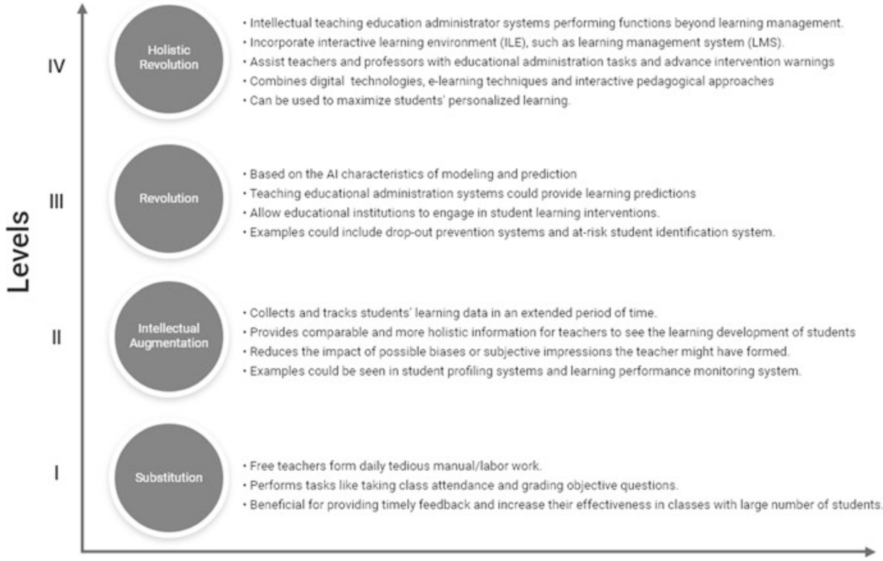

Fig. 4 Four levels of AI-enabled education administration

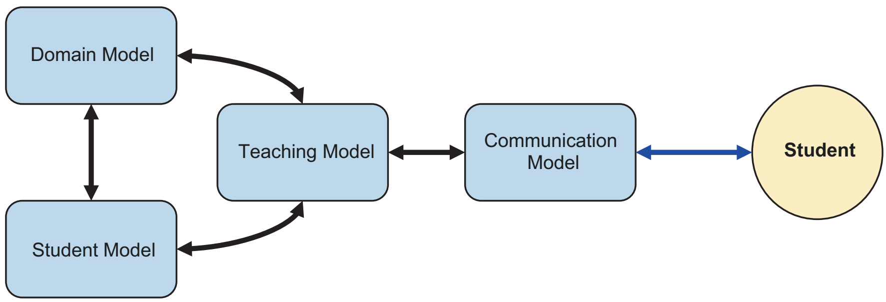

Fig. 5 Structure of a typical ITS. (Adapted from Almasri et al., 2019)

component can aid teachers in performing administrative tasks, and it has been used to assist teachers in providing feedback on mechanical rules. An important quality of ITS is that it receives information about students' intermediate steps of different tasks. Therefore, it can provide students feedback and hints on each step. The Communication Model ensures a successful interaction between the system and the user by means of graphic communication, speech recognition, and social intelligence.

Another important component in designing ITSs is *scaffolding*. Traditionally, scaffolding is defined as support offered by a teacher or a more competent peer which is adjusted to the student's level of understanding, and it is gradually removed when the necessary support is provided to transfer the responsibility back to the learner (van de Pol et al., 2010). By this definition, scaffolding strategies should be tailored to individual learners depending on their struggles and needs. In computer-based contexts, ITSs use students' prior knowledge to determine the level of fading needed to adapt to the individual learner (Booth et al., 2017). One example of an ITS called ASSISTment was developed to provide assessments on students' performance on a standardized state test preparation while providing them with instructional assistance when needed (Feng et al., 2006). Scaffolding helps break down problems by providing students with a brief tutoring session that gradually guides the student to the right answer. CAPIT is another ITS developed to teach students English grammar (Mayo et al., 2000). It provides students with short and specific feedback when their submitted solution contains errors and adds appropriate hints to scaffold student knowledge.

Teachers may take advantage of ITSs by using them as a tool for students to answer common questions about class assignments, course policies, or study schedules. In addition, ITSs may help identify gaps in students' knowledge (Chassignol et al., 2018). Based on a teacher's evaluations of students' past performance, the ITS can create a model which incorporates the same principles used by the teacher in their evaluations and implement this model to conduct assessments of other students.

ITSs are becoming frequently used to identify potential at-risk students and ways that can help them increase their performance using academic failure monitoring systems. Arnold and Pistilli (2012) describe Course Signals, a tool designed at Purdue University, which incorporated learning analytics to track students' progress and predict their academic success. Using the trace data collected by the LMS and the data from the institutional Student Information System, Course Signals implemented a data-mining algorithm to identify students at risk of academic failure in a course. In addition to identifying these students, the system also provided them with resources and recommendations that would help set students on the right track and improve their performance. The incorporation of this early alert algorithm and the student support system showed high levels of predictive accuracy and positively affected student retention and course pass rate when compared to students in courses where the Course Signals tool was not implemented (Fig. 6).

Feng et al. (2006) also investigated the predictive model of AI-based ITS. In their study, the ITS logged the number of assistance requests sent by students to perform different tasks and complete course assignments, such as the number of hints requested and the number of attempts made. The ITS was able to successfully predict students' test scores by taking into account the information on students' assistance requests.

Personalized learning ensures that the educational process is centered round students' needs and includes content sequencing, scaffolding, feedback, and assessment (Canales et al., 2007). The incorporation of Web-Based Educational Systems (WBES) requires not only meeting individual students' needs, but also creating solutions that include reusable content components for different communities of teachers and students (Wang & Qian, 2005).

Brusilovsky and Peylo (2003) emphasize the importance of WBES to be both intelligent and adaptive to students' needs. WBES supported by AI can provide high-quality support for its users by providing individual responses to specific students based on the information accumulated about them such as their goals and preferences.

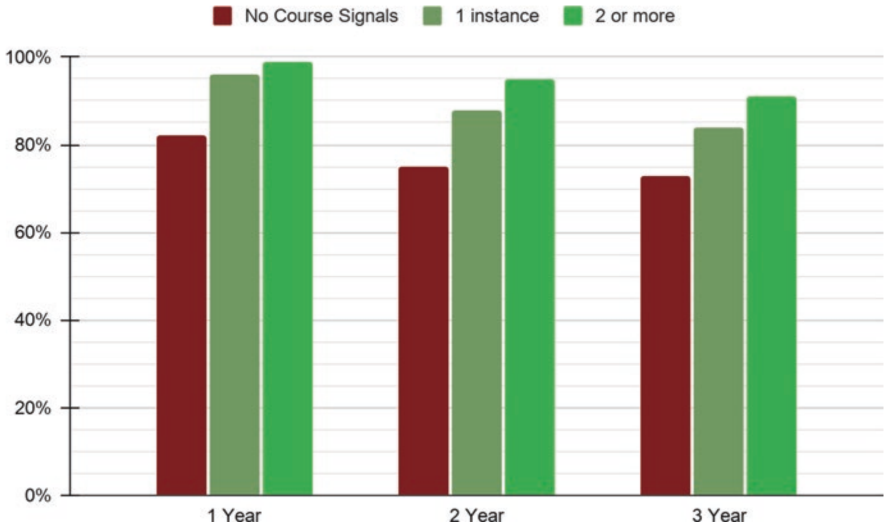

Fig. 6 Retention rates from the 2008 entering cohort among students who used and did not use Course Signals. (Created based on Arnold & Pistilli, 2012)

Additionally, AI enhanced education administration not only restricted its application in the interactions between the instructors, teaching management agencies, and the learners, it also extensively employed in monitoring the interactions between the learning environment and the learners. In some Chinese elementary schools, AI facial recognition is used to help capture the student attendance information. Classroom robots are used to collect and analyze the data of students' health and engagement level; the students' uniforms are designed with chips embedded to track the students' physical location and provide safety protection for students' in school and commuting (Panchal & Shaikh Mohammad, 2020).

Instruction

AI has facilitated the creation and deployment of systems, and these systems provide powerful pedagogical tools that can improve the quality of the instruction (Chen et al., 2020). The integration of AI in education combined with other technologies resulted in the development of advanced instructional tools. The adoption of AI systems in robotics for education leads to the development of robot teaching assistants that can help teachers during a class without disrupting the lesson. They can undertake tasks of different complexities that can foster effective instruction, such as providing assistance in reading and pronouncing certain words (Timms, 2016) as well as answering questions students commonly have about assignment requirements, policies, and information about instructional materials (Pokrivcakova, 2019; Sharma et al., 2019). These robot teaching assistants may constitute the ITSs that are equipped with abilities to have a conversation with students and have been able to foster the effectiveness of instruction (Rus et al., 2013).

AI technologies can also effectively integrate in web-based instruction. AI has the ability to incorporate teacher-like functions in a web-based platform that allows a more comprehensive support for all students, which is demonstrated by the use of adaptive and intelligent web-based educational systems (AIWBES) (Kahraman et al., 2010; Peredo et al., 2011). Assistance with teaching responsibilities using AIWBES is achieved through providing instructions and directions to teachers and students in order to utilize technology in an efficient and systematic way to maximize students' learning (Chen et al., 2020).

In addition, AI and machine learning are widely studied to be applied in mobile devices to facilitate learning and training. These advancements create opportunities to incorporate natural language processing, speech recognition, and virtual reality spaces, thus taking mobile learning to a new level by allowing students to receive personalized and interactive learning (Ignatov et al., 2018). Examples include the developments of virtual reality simulation platforms, which open opportunities to create global classrooms by using AI to connect students to virtual classrooms. 3D technologies have fostered the use of these tools as an effective way to demonstrate learning concepts allowing students to gain practical experience in the subject, such as participating in surgeries for medical students, among other subjects (Mikropoulos & Natsis, 2011; Timms, 2016; Wartman & Combs, 2018). In addition, AI-based chatbots can offer personalized instruction by turning instructors into conversational agents, which are capable of effectively catering to students' learning needs.

Besides helping with the teaching, AI also provides informational data to help teachers better understand their students and their learning states. AI facial recognition is applied to obtain the students' concentration level in class. Additionally, a headband that can monitor students' concentration levels also provides good biological feedback to the classroom teacher (Panchal & Shaikh Mohammad, 2020). Feedback data like these can provide classroom teachers reference to adjust their teaching pace and make teaching and learning more effective according to student learning states.

Learning

AI technologies can be adopted and leveraged to improve students' learning. Adaptive learning technologies react to learner's data and align instructional materials in accordance with students' capabilities and needs (Mikropoulos & Natsis, 2011). AI can also be incorporated in order to offer students a more enjoyable learning experience, which results in increasing their motivation, engagement, and learning outcomes (Wartman & Combs, 2018). Therefore, smart technologies that incorporate AI and machine learning open new ways to achieve learning goals.

Curriculum sequencing technology is one of the major intelligent tutoring solutions that provides students with an individualized sequence of topics and learning tasks most suitable for their learning goals and needs (Brusilovsky & Peylo, 2003). An example of an adaptive learning system is *Duolingo*, a popular adaptive system for learning languages. AI allows Duolingo to personalize learning which incorporates a responsive placement test that automatically adjusts question difficulty depending on the test takers' responses. It also tracks progress and analyzes this data to determine next steps in the learning process. This technology identifies when the learner is ready to move on to the higher levels of difficulty of the instructional materials, including more advanced grammar and vocabulary. Similarly, if the system detects that the learner struggles with the current level, it will re-adjust the difficulty and provide more scaffolding to help learners master the current level before moving forward (Zheng et al., 2017). This example demonstrates how AI-based technologies can provide enhanced opportunities for learning that are specifically tailored to each learner's abilities and skill levels.

AI also takes a prominent place in the development of adaptive hypermedia systems or e-learning systems. To be effective, an educational course or a lesson needs to be designed with the goal to match learners' objectives and needs as closely as possible. This level of truly personalized learning is harder to be realized in a computer-free classroom with dozens of students and only one teacher (Melis et al., 2001), or be achieved using static hypermedia content. Adaptive hypermedia systems can adjust instruction according to students' achievements during the course progression. It adjusts educational tools and content in each hypermedia page in accordance with the learner's data acquired throughout the course (Brusilovsky & Peylo, 2003).

In adaptive hypermedia systems, electronic pages are not static, but dynamically generated specifically for each learner. One example of such a system is an open-source, web-based learning platform called ActiveMath (Melis et al., 2001). ActiveMath is programmed to dynamically assemble interactive math lessons and courses tailored to students' desired learning outcomes, abilities, proficiencies, and preferences. Each course is generated following a set of pedagogical rules.

Another type of advanced AI-based technology that can improve the quality of learning is educational robots. According to Mubin et al. (2013), AI-based robot teaching assistants are most frequently used for *language* and *science* education, while taking on a role of a tool, a tutor, or a peer learner in different learning activities.

Language learning is a common application of educational robots, and they are often used for general language learning, foreign language learning, and bilingual education (Cheng et al., 2018). Students who learn languages in robot-assisted classrooms show high levels of motivation and engagement, and they learn faster and retain more than students in the traditional classes (van den Berghe et al., 2019). In addition, the presence of a non-living educational robot reduces learners' anxiety and self-consciousness about making mistakes, which are common when performing in front of a human teacher. For example, Lee et al. (2011) developed robot educational assistants, Mero and Engkey, who have expressive faces that can represent different emotions like happiness, sadness, fear, joy, pride, shame, and many others. Because emotional expressions play an important role in human–robot interactions, vivid emotional expressions help students feel at ease when interacting with these robots. Mero and Engkey also have an automatic speech recognition that allows them to assist learners in developing their speaking and listening skills in their target language. In addition, learning with a robot companion has also shown to improve students' confidence, interest, and satisfaction from learning as shown by Wang et al. (2013). In their study, the researchers used learning companions shaped like cartoon figures who could perform actions while interacting with language learners, singing songs, and moving around, in addition to practicing conversations in English. Learners who interacted with robot companions demonstrated high levels of concentration and engagement, as well as motivation to practice English. They were also more encouraged to ask questions about correct pronunciations of words and sentences.

Integrating AI-based educational robots in science curriculum provides promising opportunities to engage and motivate learners, as well as increase their learning outcomes. For example, Janssen et al. (2011) describe an adaptive robot game that can motivate children to learn arithmetic. In their study, the researchers used NAO, a programmable humanoid robot developed by Aldebaran Robotics. NAO was able to interpret children's movements and speech, initiate dialogues while interacting with them, and control the screen that showed the educational assignments. The robot was able to adapt the level of the assignments to learners' arithmetic performance and track if it goes beyond the expected level. The results indicated that most students performed significantly higher than their expected levels and were ahead of their arithmetic education due to their interactions with NAO.

AI in Future Education

AI started reshaping the education realm by providing more education administration systems to teachers and administrative staff, and extending its impact on teachers, learners, and the extended practitioners. Hence, the merging of AI also requires new literacy and competence on teaching and learning.

For instructors, the use of AI-enhanced education not only redefined the role of instructors, but also empowered instructors with their decision-making. Instructors are no longer the sole source of knowledge and the only medium of teaching; they are required to become the learning coach for students (Waters & Leong, 2011). Data enhanced teacher decision making has received an increasing amount of attention from educational researchers. Mandinach and Gummer (2016) have noticed that the influx of data and data-powered tools available necessitate new teachers to construct their data literacy, more specifically, AI literacy and AI thinking (Vazhayil et al., 2019).

Additionally, various educational standards also point out the urgency of cultivating students' AI competency to competencies that enable individuals to "critically evaluate AI technologies; communicate and collaborate effectively with AI, and use AI as a tool online, at home, and in the workplace" (Long & Magerko, 2020, p. 2) in the AI era.

Concerns of AI Educational Application

With AI being the powerful and influential tool and its spreading usage in various scenarios in education, two concerns are particularly worth noting to educational researchers and practitioners with regard to the application of available AI products and applications in today's classroom – the potential issue with data collection privacy and transparency, and the equality of AI decision-making. In regard to the wearable technologies like the headband applied in some Chinese schools as mentioned by Panchal and Shaikh Mohammad (2020), although students' biological data is collected to better serve the improvement of their learning achievement, some parents still voiced their concern of the data collection, storage, and accessibility. With no guarantee of the data security, students' digital privacy might be exposed to insecure parties, which might cause unforeseen damage in the future. Hence, digital privacy and data security should both raise the attention of the researchers and promote the research developed along with the machine learning application in education.

Flaws in the AI grading systems are another concern observed from the actual AI application. With the popularity of grading systems implemented in many AI systems, two benefits are observed: relieving teachers from the grading labor and avoiding subjective grading bias. However, since the AI-featured grading system requires training data to establish the baseline for grading criteria, teachers should look out for the potential flaws before implementing the grading system in their own classroom without customizing the grading with data. An example of such a system could be seen used in Graduate Record Examinations (GRE) grading. The grading system enhanced with machine learning is susceptible to human bias. Further improvement and system training is required before serving teachers and learners in regular classrooms.

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