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# Vision, challenges, roles and research issues of Artificial Intelligence in Education

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ABSTRACT

The rapid advancement of computing technologies has facilitated the implementation of AIED (Artificial Intelligence in Education) applications. AIED refers to the use of AI (Artificial Intelligence) technologies or application programs in educational settings to facilitate teaching, learning, or decision making. With the help of AI technologies, which simulate human intelligence to make inferences, judgments, or predictions, computer systems can provide personalized guidance, supports, or feedback to students as well as assisting teachers or policymakers in making decisions. Although AIED has been identified as the primary research focus in the field of computers and education, the interdisciplinary nature of AIED presents a unique challenge for researchers with different disciplinary backgrounds. In this paper, we present the definition and roles of AIED studies from the perspective of educational needs. We propose a framework to show the considerations of implementing AIED in different learning and teaching settings. The structure can help guide researchers with both computers and education backgrounds in conducting AIED studies. We outline 10 potential research topics in AIED that are of particular interest to this journal. Finally, we describe the type of articles we like to solicit and the management of the submissions.

## 1. Vision and challenges of AIED

The rapid advancement of computing and information processing techniques has sped up the progress and applications of artificial intelligence (AI), which aims to enable computers to perform tasks via simulating intelligent human behaviors, such as inferencing, analysis, and decision making (Duan, Edwards, & Dwivedi, 2019; Topol, 2019). In the past decades, significant progress has been reported by researchers who have conducted AI studies. Through techniques such as conventional machine learning or modern deep learning, an increasing number of products can provide "intelligent services" by inferring or behaving like humans. Nowadays, AI has been applied to various domains, such as visual and voice recognition, decision-making, and natural language processing and translation between languages, in multiple forms, such as computer programs, applications, embedded control systems in equipment, or robots. For example, some robots can interact with humans via visual and audio tracking technologies (Lathuilière, Massé, Mesejo, & Horaud, 2019; Okuno, Nakadai, & Kitano, 2002), and some medical systems can assist human experts in detecting potential diseases or making judgments by analyzing a large set of data (Li, Li, & Niu, 2020; Zhu, 2020).

With the field of AIED established for over 30 years now (O'Shea & Self, 1986), applications of AI in education have grown even the additional attention of researchers from the fields of both computer science and education in recent years with the rapid advancements in AI. It can be foreseen that a growing number of studies will be conducted which apply AI to educational settings as well as discuss the potential approaches of promoting and teaching AI knowledge at all educational levels. For example, will the use of robots in classrooms encourage students' learning motivation and engagement? Can EFL (English as Foreign Language) students produce better English writing outcomes when learning with an English article evaluation program than those learning with traditional instruction? How can AI technologies help policymakers address the open challenges in education and cope with the issues by making effective decisions?

One of the crucial objectives of AI in education is the provision of personalized learning guidance or supports to individual students based on their learning status, preferences, or personal characteristics (Hwang, 2014). From the perspective of precision education, which emphasizes the need to provide prevention and intervention practices to individual learners by analyzing their learning status or behaviors, enabling learning systems to serve as an intelligent tutor by incorporating experienced teachers' knowledge and intelligence into the decision-making process of the system is a crucial issue (Hart, 2016). In the early 1980s, the question regarding intelligent tutoring systems (ITSs) was raised by educational technology and computer science researchers (Larkin & Chabay, 1992; Van Seters, Ossevoort, Tramper, & Goedhart, 2012). Recently, a relevant term "adaptive learning system" gain much attention that emphasized the aim of facilitating individual students' learning by adapting several possible aspects of learning systems, such as user interfaces, learning content, or learning paths based on each learner's status (Essa, 2016; Xie et al., 2017, 2019).

Using AI in education (AIED) has created new opportunities for designing productive learning activities and developing better technology-enhanced learning applications or environments. However, it remains a challenge for most researchers and practitioners from the fields

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of both computers and education to implement relevant activities or systems (Kay, 2012). The challenges of developing intelligent tutoring systems and adaptive learning systems are not only computer programming skills, but also techniques of simulating the intelligence of human experts. The latter include the knowledge and experience of human tutors for making judgments and decisions based on the best available evidence to help solve individual learners' problems and help them learn better. These challenges occur because AIED is a highly technology-dependent and cross-disciplinary field. Without knowing the roles of AI in education as well as the functioning of AI technologies, researchers might fail to effectively implement AIED applications and activities, not to mention raising and investigating valuable AIED research issues.

For example, an AI application might play the role of a tutor who observes students' learning processes, analyzes their learning performance, and provides instant assistance to them based on their needs. Based on the potential needs of students, an interdisciplinary team (e.g., composed of computer and learning scientists) can develop an intelligent tutoring system that enables students to learn, practice, and interact with peers or teachers but also provides hints, guidance, and supports to individuals based on their status or needs. On the other hand, knowing the capabilities and features of AI technologies, school teachers could adopt suitable AI applications in their classes to promote students' learning performances, motivation, or engagement, while educational researchers can study the implications of the AI applications.

In the following sections, we propose a framework for clarifying the roles of AI in education as well as the definition and features of AI technology. We discuss 10 research topics in AIED on the area of articles that are of interest in this journal and to guide researchers and school teachers who intend to study, implement, or apply AIED applications in the future.

## 2. Roles and framework of AIED

From the perspective of educational applications, there are several roles of AI in education, that is, serving as an intelligent tutor, tutee, learning tool/partner, or policy-making advisor, as shown in Fig. 1.

In the past decades, many AIED studies have been reported by researchers. Those studies can generally be categorized into four roles:

(1) Intelligent tutor: This could be the largest category of AIED applications. Those intelligent tutoring systems, adaptive/personalized learning systems, or recommendation systems belong to this category. Several meta-analytic studies have demonstrated the effectiveness of intelligent tutoring systems to promote learning outcomes (Ma, Adesope, Nesbit, & Liu, 2014; Steenbergen-Hu & Cooper, 2014; VanLehn, 2011). Examples of seminal intelligent tutoring systems include Cognitive Tutors (Anderson, Corbett, Koedinger, & Pelletier, 1995) that are developed to support tutoring in mathematics and sciences and AutoTutor (Graesser et al., 2004) is a dialogue-based tutor that support learning of physics, computer literacy, and critical thinking. A more recent example is ASSISTments that combines the features of intelligent tutoring with assesstement to provide real-time feedback to students while woking on assignments and offers data-driven reports for teachers on each assignment (Heffernan & Heffernan, 2014).

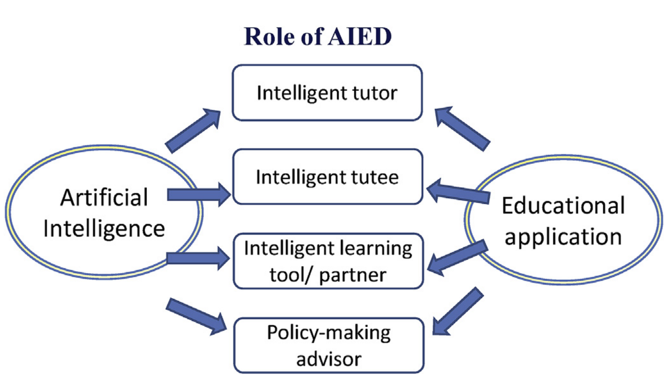


**Fig. 1.** Framework for the roles of AIED.

(2) Intelligent tutee: Studies in this category are rarely seen since most AI-based educational systems generally focus on helping learners rather than providing opportunities to encourage learners to serve as a tutor or advisor. Nevertheless, engaging learners in the contexts of helping others (i.e., AI tutees) understand complex concepts could be an excellent approach to promoting their higher-order thinking competences and knowledge levels. Although no studies have aimed to develop intelligent tutees intentionally and explicitly, many AI models and techniques are capable of learning the knowledge and experience from the interaction with humans. The learning ability of AI models and methods can facilitate the development of intelligent tutees in the future. For example, a smart tutee could be a chatbot such as Microsoft Tay (Wolf, Miller, & Grodzinsky, 2017) with a natural language processing interface and artificial neural networks. Members of the public made inappropriate comments about topics such as racisam and sexism while chatting with Tay. Tay imitated these comments and generated inappropriate expressions accordingly, and thus, Microsoft decided to shut it down. Ideally, if the ethics module can be embedded in the architecture of robots or chatbots (Arkin, 2008) and intelligent tutees can be developed, learners can interact with a well-developed chatbot or robot and "teach" it by providing training examples related to a particular topic. The chatbot or robot can then respond to the questions regarding the topic after the training process.

(3) Intelligent learning tool or partner: From the perspective of constructivism and student-centered learning, the provision of an intelligent learning tool or partner is an important issue. The device can help learners collect and analyze data in efficient and effective ways, enabling them to focus on critical points or higher-order thinking (e.g., inference and prediction), rather than low-level tasks (e.g., editing and calculation). Some tools can even analyze and present data in a "smart" way to help learners think in-depth and to find valuable implications underlying the data. For example, traditional Mindtools, such as concept mapping tools, help learners to organize knowledge by connecting the relationships between concepts in a passive manner. In contrast, an intelligent concept mapping tool could advise or provide hints to the learners as well as evaluating the developed concept maps during the concept mapping process (Hwang, Wu, & Ke, 2011). More recently, knowledge graphs, as a popular field in the recent AI, can construct the relationships among the different entities from the massive volume of linked data based on AI models (Wang, Mao, Wang, & Guo, 2017). There have been some knowledge graph projects for educational purposes (Chen, Lu, Zheng, Chen, & Yang, 2018; Chi, Qin, Song, & Xu, 2018), which will be a promising research sub-area for establishing intelligent learning tools or partners.

(4) Policy-making advisor: AI techniques have been employed in inform and guide development of policy or laws in the recent years (Gasser & Almeida, 2017). Therefore, it is possible and feasible to develop a policy-making advisor for policy building in education. With the help of AI technologies, policymakers can more precisely understand the trends and problems in educational settings from both macro and micro perspectives, which can help them build and evaluate effective educational policies (Macfadyen, Dawson, Pardo, & Gaševic, 2014; Siemens, Dawson, & Lynch, 2013; Tsai, Poquet, Gašević, Dawson, & Pardo, 2019).

## 3. Potential research topics of AIED of interest in this journal

As mentioned above, AI could play various roles in educational settings. The advancement of emerging computer technologies, such as quantum computing, wearable devices, robot control, and sensing devices, as well as the popularity of mobile and 5G wireless communication technologies, has provided new appearances and opportunities for applying AI to teaching and learning design. It is essential and exciting for researchers to consider how this can happen in practice. Therefore, many potential research issues of AIED are raised, including, but not limited to, the following:

(1) *Development of AI-based learning models or implementation frameworks.* There are various possibilities of implementing AI technologies (such as visual recognition, speech recognition, expert systems, and natural language processing) on different computer platforms or devices (including mobile devices, wearable devices, and robots) to fulfill the needs of educational purposes or learning design (such as problem-based learning, contextual learning, and inquiry-based learning) for different courses (including social studies, science, engineering, mathematics, art, design, medical and nursing courses). Therefore, it is an essential and vital issue to propose AI-based learning models or implementation frameworks by taking those emerging technologies as well as the educational theories and needs into account.

(2) *Evaluation of the performance and experience of the students learning with existing AI systems.* Implementation of AI-based systems offers much promise to enhance learning performance and experience of students and assist teachers to advance their teaching practice. An open research challenge here is on the evaluation of the impacts of the AI-supported learning design on students' performances and perceptions rather than the effectiveness of AI systems. Several aspects, such as students' learning performance, learning motivation, learning anxiety, self-efficacy, and cognitive load, can be taken into account. The researchers may also investigate the impacts of the AI-supported learning designs on and the performances and experience of the students with different personal characteristics, such as varying levels of learning motivation or self-efficacy.

(3) *Investigation of the effectiveness of AI-based learning systems from various perspectives.* Examples of several promising topics of research include the studies of the impact of AIED on students' higher-order thinking, interactive or behavioral patterns, and cognitive load) have been investigated in the literature (Mussack, Flemming, Schrater, & Cardoso-Leite, 2019; Pu, Wu, & Jiang, 2019). It would also be interesting to consider applying AI to those seldom-applied domains, such as arts, design, medical and nursing courses. By employing AI technologies in new fields while considering different issues, researchers might be able to find opportunities to cope with the problems that cannot be resolved using the conventional technology-enhanced learning approach.

(4) *Reexamining and redefining the existing educational theories by considering different roles of AI in education.* Distinct classes of educational technologies often imply different pedagogical perspectives. The diverse functions of AIED (namely, tutor, tutee, learning tool/partner, and policy-making advisor) suggest distinct concepts of teaching and learning. Based on existing educational theories, researchers can derive new interpretations or ideas on the pedagogy and the learning sciences steaming from AIED applications.

(5) *Proposing innovative AI-supported learning or assessing strategies.* Incorporating new technologies into educational settings implies new concepts of learning design. Consequently, it is a promising time to reconsider and revise existing learning and assessment strategies. A problematic example is that, if competition-based learning (Burguillo, 2010) is employed for classroom writing, the teacher needs to review manually papers submitted by students. This approach implies that the teacher would announce the winner after all the students have submitted their reports. In an AI-supported learning design, an AI system could serve as an intelligent article reviewer in such a competition-based activity, implying that the learning design or competition guidelines could be quite different. One new rule could be that the students can revise and resubmit their articles after receiving the review results and feedback from the AI reviewer before the time is up.

(6) *Reexamining and reconsidering the way of using existing learning tools in AI-supported learning content.* Like most technology-enhanced learning contexts, employing effective learning tools or strategies. Many existing learning tools (e.g., concept mapping tools or mind mapping tools) or strategies (e.g., problem-posing, gamification, peer-assessment, progressive prompts, and voting) could be the right choice in this regard.

(7) *Big data analytics for large-scale data sources in learning systems and educational contexts.* Learning analytics is a well-known field focused on the collection, measurement, analysis, reporting of educational data (Gašević, Dawson, & Siemens, 2015; Lang, Siemens, Wise, & Gašević, 2017). Learning analytics received much attention over the last decade as a field that sits between data science/AI, learning sciences, and design (Gašević, Kovanović, & Joksimović, 2017). Meanwhile, data sources from various learning systems and educational contexts become increasingly vast, complex, and multi-modal in the current big-data era (Azevedo, R., & Gašević, 2019; Jin, Wah, Cheng, & Wang, 2015; Macfadyen et al., 2014). Learning analytics can provide a data-oriented perspective in AIED that complements existing AI techniques. For instance, new patterns mined in large-scale data sources in learning and educational systems can provide useful domain knowledge to AI systems. Secondly, big data can help improve the performance of AI techniques as the quality, quantity, and format of the big data can help enhance the learning of parameters in various AI models. In the last few days, big data has become increasingly popular and critical not only in Massive Online Open Course (MOOC) platforms, such as EdX, Coursera, and Udacity, but also in various AI-related systems, including computer-assisted testing systems, online proctoring systems, and game-based learning systems.

(8) *Developing large-scale learning systems*: The large-scale learning systems aim to facilitate the quality learning experience for millions of learners with scalable technologies (Li et al., 2009). To achieve this goal, AI-based software modules like classroom chatbots can provide instant feedback and support to inquiries from thousands of students. Hardware devices, such as smart glasses, wearable devices, mobile tablets, and VR glasses, can further streamline the collection, integration, support, and analysis of data in learning platforms. These research issues are open and challenging for large large-scale learning systems, as different devices involve the challenging integration of a multitude of data sources acquired, different learning needs from learners, and diverse deployments of learning strategies and pedagogies from instructors.

(9) *Developing ethical principles and practices for employing AI technologies and applications in education*: Us'e of AI in education can not only promote the learning effectiveness and augment the human intelligence during the learning process, but may also raise potential ethical issues (Buckingham Shum & Luckin, 2019), such as digital hegemony in education, power relationships among learners, teachers, and AI systems, and digital divide. It is essential for AIED researchers and practitioners to take these issues seriously and to seek possible solutions from various aspects, including technological solutions (e.g., setting a constraint module in AI) and policy solutions (e.g., setting the principles and ethical codes for the use of AI in education).

(10) *Human-AI collaboration*: AIED has traditionally proposed and evaluated the ways to tutor and support students. Concepts of fading scaffolds and zone of proximal development are used to guide the extend to which AI-driven support should be offered to the learners. However, with the rapid growth of the use of AI in many parts of human lifes, many questions about the role of human and the relation between human and AI are posed. There is an opend debate to extent robots can support teachers and even more radical proposals to replace teachers completely (Selwyn, 2019). In this sense, it is also reasonable to examine how education should prepare learners for the work and life of the future in light of predictions that AI will automate many jobs. Topics related to human-artificial congition such as machine behavior (Rahwan et al., 2019), cognitive offloading (Risko & Gilbert, 2016), and new definitions of cognition (Bayne et al., 2019) are particularly relevat to study as the role of AI in education is growing in significance.

## 4. Conclusions

The advancement of AI has brought computer-supported education to a new era. By incorporating human intelligence, a computer system could serve as an intelligent tutor, tool, or tutee as well as facilitating decision making in educational settings. The integration of AI and education will open up new opportunities to vastly improve the quality of teaching and learning. Teachers can benefit from intelligent systems that aid in assessments, data collection, enhancing learning progress, and developing new strategies. Students can benefit from smart tutors and asynchronous learning in advancing learning outcomes. Additionally, the integration of AI and Education is not only a transformation of education but also a transformation of human knowledge, cognition, and cultures. As such, AI in Education is becoming a primary research focus in the field of computers and education.

This new open-assess journal, Computers & Education: Artificial Intelligence, aims to serve as a bridge to connect educators, students, computer scientists, and practitioners to advance the state-of-the-art in this emerging area. Our goal is to facilitate the interaction and collaboration among researchers from different fields and to encourage the development of innovative new ideas and promote the inclusive and transparent use of AI in education.

This journal publishes three categories of articles: *research paper*, *review papers, and position papers*. *Research papers* aim to publish full reports of methodology and data from original research about AI algorithms and applications in education, educational data mining methods, intelligent educational applications, AI education, AI-related ethical issues, and other areas related to this journal. *Review papers* aim to provide a comprehensive overview of a specific research topic and a perspective on potential challenges, opportunities, research trends, and future directions in the field. A review paper submitted should be within the scope of the journal. *Position papers* aim to present an arguable opinion, a new idea, an innovative pedagogical/system model, or a new conceptual framework about the research topics of this journal. Although a position paper does have to include data that supports the proposed opinion, its arguments and ideas must be logically valid and convincing.

Currently, Computers & Education: Artificial Intelligence has an editorial team, including four editors-in-chief, one assistant editor, and several editorial board members. These members are renowned experts and scholars in areas including AI, education, learning analytics, and educational technologies from various countries. In reviewing papers, this journal employs a double-blind review model. For each submission, the editorial team will have an initial screening and assign it to the most suitable editor-in-chief for handling. The handling editor-in-chief will then assign the paper to at least two editorial members or external reviewers for judging the quality of submission in terms of its significance, originality, and innovation. Each round of review is around one month, with another month allowed for each round of revision. The number of rounds of revisions and reviews depends on whether the authors can adequately address the problems raised by the editors and the reviewers. The review process of each submission will be very rigorous and competitive, as the journal aims to publish high-quality papers on AIED.

As a final remark, there is no doubt that AIED research is becoming one of the hottest topics in the field of computer science and education. In this editorial, we have proposed the roles and 10 research topics important in AIED. We hope that researchers with both computer science and educational backgrounds can use this paper as a guide to starting their AIED studies. In particular, we encourage researchers to use this new open-assess journal, *Computers & Education: Artificial Intelligence*, as a forum to share their up-to-date and quality research outcomes.

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