A short history, emerging challenges and co-operation structures for Artificial Intelligence in education

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Summary: To accompany the special issue in Artificial Intelligence and Education, this article presents a short history of research in the field and summarises emerging challenges. We highlight key paradigm shifts that are are becoming possible but also the need to pay attention to theory, implementation and pedagogy while adhering to ethical principles. We conclude by drawing attention to international co-operation structures in the field that can support the interdiscipniary perspectives and methods required to undertake research in the area.

Keywords: artificial intelligence, learning analytics

1. Introduction

Although Artificial Intelligence (AI) is a driving force of the transformation of our era, the public discourse around it tends to be focused on its promises on economic potential or revolves around ethical and other concerns from a socio-economic perspective, ignoring the applications and implications in Education and the long history in the field. It is hard to ignore that, at the time of this writing, the world is still battling with the ongoing Covid-19 pandemic. The pandemic brought to light many existing problems within society, such as the fact that many educational systems today follow the nineteenth-century "factory model" of education, where all students are forced to learn at the same pace, in the same way, and at the same place (Kai-Fu Lee, 2018). It also revealed that there are only very limited well-thought uses of educational technology let alone AI in education across the world. Many voices in the field were already pointing to several challenges that the field needs to address before the AI promises become a reality (UNESCO, 2019, Holmes, Bialik and Fadel, 2019).

AI properly applied in Education, promises to address challenges in many areas of education. The field typically points to the potential to recognise and recommend personalised content and learning activities to individual learners, save time for teachers, especially for activities like test correction, and therefore provide more space for more personal supervision of learners. With the increase in digital technologies for education, more process data is

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being collected, and there may be, for the first time, the chance to unfold the promises of the over 50 years old research on AIED (since Jaime Carbonell (1970)'s AI Approach to Computer-assisted Instruction) into mainstream education. We can group these promises in macro, meso and micro-opportunities (Greller & Drachsler, 2012). At the macro level (organisation), AI can be used to optimise evaluation and planning processes. At the meso level (classroom activities), new forms of assessment, grading, tutoring and classroom management are possible. But the main application so far revolves around individual support actions on the micro-level such as personalisation of learning and feedback systems as well as automated (usually formative) assessment.

We are seeing an increase in AI technologies across all areas of education, from kindergarten through primary and secondary education to higher education. However, this movement is mainly visible in Anglo-Saxon countries like in the US and Australia, as well as very strongly observed in China. AI in Education tools that are adopted at a larger scale seem to be on subjects that are logically sequential such as mathematics, science, and other technical subjects. Language education is also considered a logically sequential subject that can be supported by AI tools. On the other hand, support for topics that are more open-ended in nature and for children with mental and/or physical disabilities is gaining traction in research, yet is due to make a significant impact in real-world implementations.

As the German education system is less digitised so far (Bildungsbericht, 2020), also the adoption of AI technologies for teaching and learning is only done in early lighthouse projects (Holmes, Anastopoulou Schaumburg, & Mavrikis 2018) and it is not so established as in other countries. Therefore, Germany has the opportunity to critically review practices in other countries, while investigating the usefulness of AI application in education in Germany. As the field is therefore maturing, before introducing some challenges and drawing attention to German and other international co-operation structures, the next section goes briefly through the history of AIED and provides pointers to key review papers and books.

2. A brief history of AIED: definitions and related fields

Looking back into the history of the field provides a useful perspective to contextualise the contributions of this special issue. Of course, reflecting on 50 years of research would not be possible in this short article space provided here. For more detailed reviews, the reader is referred to (Holmes

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et al. 2019, Boulay, 2019, Mavrikis & Holmes, 2019, Roll & Wylie, 2016, Woolf, 2010) among others. Nevertheless, it is worth tracing the seeds of the field back to the 70s with well-known examples such as ELIZA, SCHOLAR and MYCIN and the emergence of an area later characterised as Intelligent Tutoring Systems (Sleeman & Brown, 1982; Shute & Psotka, 1994).

At this point, it is useful to pause and reflect on what we mean with intelligence and AI in Education. While there are multiple definitions and many attempts to identify AI in Education, they tend to be either visionary and technocentric about the potential of AI, or too specific to the technology of what each research or individual defines as AI. We will avoid the pitfall of trying to come up with a definition here, but posit that AI is best characterised both as a field of research (or in fact multiple fields c.f. Wang, 2019) and as the technology by its features and functions. In fact, a well-known conundrum in the field is what has been labelled as 'AI effect' i.e. that the definition changes over time because as soon as we know machines do something 'intelligent, it starts being computation' (c.f. McCorduck, 2004).

Regardless, it is important for the community to characterise what we mean by AI in education, if not collectively at least each research endeavour should be making clear its working definition. Especially when dealing with matters of public discourse and terms such as intelligence, learning and training will help us avoid otherwise inevitable public confusion (c.f. Monett and Lewis, 2018).

The rest of the section focuses on what is more central to this issue at the meso and micro opportunities and particularly on two areas of research. The first can be referred to as 'learner-facing AIED' (Baker, Smith, 2019) and the second relates to the use of data and falls under the cognate areas of educational data mining (EDM) and Learning Analytics (LA).

2.1 Learner-facing AIED

With learner-facing AIED, the field characterises the application of AI in systems that are used by students to learn specific topics. These systems respond to the students' individual needs (Baker, Smith, 2019) e.g., by adapting learning content based on each student's interaction and background knowledge and skills. While there are several terms and ways to refer to this technology, Mavrikis and Holmes (2019) refer to Intelligent Learning Environments (ILE) as a broad category of digital educational interactive applications equipped either with means of task selection or adaptation, or dynamic assistance while students are undertaking a task (c.f.

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Doroudi, Aleven, Brunskill, 2019). This expands on older definitions that centre on student assistance during problem-solving (Dillenbourg et al., 1994) or student-driven learning (Brusilovsky, 2004). Depending on the subject matter that these systems are designed to target, and the type of learning that they are promoting, the system-student interaction is characterized differently. For example, the system-student interaction may be referred to as tutoring (hence Intelligent Tutoring Systems), when the interaction is designed around the steps that students take when solving a problem (Van Lehn, 2011). At other times, it may be referred to as intelligent support when the interaction is more open-ended or exploratory (Gutierrez-Santos et al., 2012).

2.2 Educational Data Mining and Learning Analytics

Educational Data Mining emerged mostly from the realisation that traditional statistics have limitations for analysing large quantities of data. Work in this area revolves around methods for exploring the unique types of data that come from educational settings and using those methods to better understand students and the settings in which they learn. Learning Analytics is similarly concerned with measurement, collection of data and analysis (Siemens & Baker, 2012). Both communities have the goal of improving the analysis of educational data to support practise and education. Siemens and Baker (2012) present these differences in detail. In brief, the most important one for our purposes here is that data mining tends to focus on automated discovery and improving techniques e.g., for modelling student affect (Baker, Ocumpaugh, 2014) whereas the same work in Learning Analytics would pay greater attention in empirical testing in the classroom (e.g. Grawemeyer et al., 2016) or putting the human in the loop to help understand the knowledge that is derived by analytics often to support teaching e.g. (Mavrikis et al. 2019). Apart from the techniques and methods, a key difference is that the Learning Analytics field puts a strong emphasis on understanding systems as a whole. As Siemens and Baker (2012) emphasise, these distinctions are oversimplifications and call for collaboration between the two fields to promote this work and better articulate it to policymakers, instructors, and educators in general.

3. Challenges in the field

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There is a lot of discussion of technical challenges in the associated conferences in the field. For example, from the perspective of EDM and LA, the reader should refer to Baker (2019). In relation to the application and adoption of the AIED more broadly, there is still a long way to go both in terms of carefully defining the field and its terminology, as mentioned earlier, and considering practical issues that matter to practitioners, such as whole classroom implementations and of course any ethical implications around this work. Within the AIED and related research communities, several challenges are currently known and actively addressed to increase the adoption of AI for education. We identified the following challenges that are relevant especially for Germany.

3.1. Attention to implementation and pedagogy

So far, most advancements in the field are done from a more technical perspective. There are only very few studies that have investigated the effects of AIED systems at scale with methods from empirical education research (Jivet et al., 2018; Jivet et al., 2019, Rummel et al., 2016) Thus although, we see new opportunities arising, and soon a critical mass of people will technically have access to a personal agent in their pocket to train certain skills, very little is known about the actual quality and effect of this AI-driven education. The challenge requires advancing the methodological state-of-the-art in both design (Mavrikis et al., 2013) and evaluation methods (Cukurova & Luckin, 2018).
One of the criticisms of the field is that intelligent tutoring systems follow a particular pedagogical method where the learner passively accepts the information from the system similar to the idea of Skinner Box from the 60s (e.g. Watters, 2015, Wilson and Scott, 2017). While valid concerns, these criticisms are mostly applicable to much earlier work in the field. A response and measured discussion including related empirical evidence was published in the 50th year anniversary of the British Journal of Educational Technology (Boulay, 2019) who makes clearly the case that in contemporary work the field has been paying attention to student agency and involving the teacher in the loop (e.g., Holstein, 2019; Mavrikis et al., 2019).

3.2. The promise and challenges of multimodal data

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Traditionally, the AI-based systems designed for education, typically Intelligent Tutoring Systems (ITS), relied on classic desktop computer interaction with mouse and keyboard (also known as click-stream data). Recently there is an increasing interest in the data-driven educational research communities in using multimodal interaction data and methods (Blikstein & Worsley, 2016). Cukurova, Giannakos, Martinez-Maldonado (2020) provide a detailed review of a special issue in the British Journal of Educational Technology with recent work in the field. In brief, the variety of interactions, multi-sensor devices and multimodal data can provide a more detailed representation of the learner in the computer (Di Mitri et al., 2018; Sharma et al., 2021). This can range from voice recognition technology (Mavrikis et al., 2014) to physiological sensors that can provide a wealth of information to further contextualise students' performance (Di Mitri 2019; Giannakos et al., 2019) and also opens up ways to support more complex pedagogical approaches such as collaborative and project-based learning (Cukurova et al. 2017, Spikol et al., 2018). The multimodal approach however poses significant challenges on multiple dimensions including logistical (i.e the organisation and planning of multimodal data collection; implementations of MMLA tools in real-world settings); methodological (i.e technical improvements to model and analyse multimodal data; cleaning and fusion of high-frequency heterogenic data); pedagogical (i.e the integration of MMLA tools in existing educational practice; evaluation of their impact on learning outcomes; human factors and adoption of MMLA); and ethical (i.e the moral principles and aspects of the MMLA; fairness, inclusion, transparency, accountability of MMLA models; surveillance aversion) (c.f. Cukurova et al. 2020).

3.3. Co-teaching and learning of humans and AI

As AI is becoming mainstream in all walks of life, imagining a future where AIED displaces teachers misses its potential. As AI-based tools are starting to make valuable contributions to education, it is becoming increasingly clear that teachers and AI have complementary strengths. As such, the real challenge of the application of AI in Education lies in augmenting teaching and learning i.e. supporting teachers, learners or other individuals such as parents and carers to policymakers to undertake tasks that would otherwise be impossible. But to what extent human–AI interaction will take place is largely underexplored (Holmes, Bialik, Fadel, 2019). Examples of such interest in the field are beginning to emerge (An et al., 2020). For example,

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setting meaningful collaboration groups based on student interaction with a tool would be impossible for a teacher especially in real-time. Gutierrez et al. (2017) present a tool for suggesting classroom groups for discussion based on characteristics of the problem-solving actions of the students (in this case different solutions for the same problem to encourage discussion). What tasks the human will focus on and which tasks an AI can act on autonomously, as well as where humans and AI can learn from each other is unclear so far. Developing and implementing such human-AI hybrid systems requires new scientific, technical, and design knowledge about how human and AI judgment can be brought together in a loop of iterative, bi-directional learning & teaching.

3.4. Ethics and trust in AI systems

The use of AI in education requires comprehensive ethical guidelines that each field and society as a whole must set for itself. The ethics and the ultimate success of the AI systems are dependent on the data used as input and on the design decisions. In the field of education, minorities such as learners with disabilities are often not sufficiently represented in data sets and are thus considered outliers in the AI algorithms. Consequently, these individuals will probably not be able to benefit from the adaptive and personalised learning or even might be disadvantaged. To mitigate, the AI research community is starting to advocate for Fair, Accountable, Transparent and Explainable (FATE) AI systems (Dignum, 2019). These new trend in AI research is often accounted as Explainable and Responsible AI and is particularly relevant when AI is interacting with humans or is using human data, such as in the case of AIED systems. As summarised in (Holmes et al., 2019, p157) "the constant monitoring of student behaviors and achievements raises significant and far-reaching ethical questions that must first be properly investigated and addressed".
In the Learning Analytics community, there are various setups towards the sustainable usage of learning analytics. The most prominent examples for this are various code of practices on learning analytics that have matured over the years, particularly in the UK (Open University UK, 2014, University of Edinburgh, 2018) but also more recently in Germany (Herrmann et al., 2020; Engelfriet, Manderveld, Jeunink, 2017). In the AIED community, these issues are beginning to be addressed, with a series of workshops, "Ethics in AIED: Who Cares?" (Holmes et al., 2018). The suggestion, further developed in (Holmes et al., 2021), is that a practical framework needs to be developed

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to inform ongoing research, specific to the application of AI in educational contexts, rather than relying on more general guidelines from other AI subfields. The same point is emphasised by Smuha, in a forthcoming article (Smuha, in press), who points to the EU's Ethics Guidelines for Trustworthy AI which specify "the implementation of [the horizontal framework proposed in] these Guidelines needs to be adapted to the particular AI-application" (European Union, 2019)

3.5. Paradigm shifts

From a long-term perspective, the availability of AI and its application could challenge the overall structure of education. For example, utilising feedback on demand might instigate a paradigm shift in assessment. Societies that will adopt solid, accurate and ethical AI systems in their education systems might move *from an assessment-based education model to more continuous formative feedback educational model.* Summative assessments might be increasingly replaced by continuous smaller formative assessments and feedback given by an AI (Drachsler & Goldhammer, 2020; Shute et al., 2021). The competence development may become a much more personal activity that is based on individual time and preferences of desired competences to learn.

A possible second paradigm shift relates to the privatisation of education made even more visible during the covid-19 pandemic (Williamson & Hogan, 2020). We see this happening already with more generic AI companies aiming to support learners individually. Examples of that are grammatic spell and writing checker, multi-language translations, automatic summary agents like literature reviews, search engines, speech recognition and synthesis, and since many years also book and product recommendations. These products can be acquired privately, and although most of them come with a free service, in order to receive all their features, a subscription model is demanded.

The change from 'the public institutions offer the learning material and resources' for a certain degree to 'private companies offer content and smart services' to achieve a certain degree will increase. This paradigm shift may *displace public educational offers and advantage private educational offers.* Next to the third-party educational offers that exists already, there will be intelligent agents that support learners at each age group to achieve a degree. This runs the risk of increasing the so called 'disadvantage gap' especially in a country like Germany, where equal chances in education are not given in

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the current system already (Bildungsbericht, 2020). It would be very unfortunate if AI actually exacerbated the equality of opportunity for a good education. After all, AI systems could also be a means of targeting disadvantaged pupils and being able to call up an intelligent tutor regardless of their location or socio-economic status.

4. What next? International co-operations

AIED is a truly interdisciplinary field that requires a variety of perspectives and methods to undertake research. Researchers and practitioners working or simply interested in these topics should follow the community of the International AI in Education Society[1] (IAIED) that has a very active conference and publishes the "International Journal of Artificial Intelligence in Education" since the early nineties. IAIED is an interdisciplinary community of computer scientist, educators, and psychologists across the globe interested broadly in research and development of interactive and adaptive learning environments. The society and the conference in particular offers opportunity for forming international collaborations in this field to address the multidisciplinary challenges that emerge. Related societies include the Educational Data Mining[2] society, the Society for Learning Analytics Research[3] and the International Society of Learning Sciences[4] all of which have common points of contacts and a remit to build bridges with other societies. This effort has led to the International Alliance to Advance Learning in the Digital Era (IAALDE)[5] with the goal of fostering the diversity among these areas and facilitating productive partnerships between the societies and their members. In Europe, researchers in the European Association for Technology Enhanced Learning[6] are also actively engaged in research in Artificial Intelligence, as evidenced by the fact that the corresponding conference includes related themes.

Finally, in Germany in particular, the use of AI-systems for learning and education is becoming a strong focus in research with various national programs that facilitate the use of AI not only in industry but also in

[1] https://iaied.org/about
[2] https://educationaldatamining.org/
[3] https://www.solaresearch.org/
[4] https://www.isls.org/
[5] http://www.alliancelss.com
[6] https://ea-tel.eu/

education. The first projects are about to start in March 2020[7], while new once are proposed mainly in the area of HE by the German community to their funding bodies.

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