All Party Parliamentary Group on Artificial Intelligence

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Thank you for the opportunity to contribute to the important work of this All Party Parliamentary Group on Artificial Intelligence. I am Professor of Learning Informatics at the University of Technology Sydney, prior to which I was a professor at The Open University in the UK. Over the last decade I have been active in shaping the emerging field of Learning Analytics, co-founded the Society for Learning Analytics Research, and have published extensively on the human-centred design of educational technology powered by analytics and AI, with specific attention to the skills and dispositions learners need for lifelong learning.

In response to your questions:

What are the benefits and challenges of different types of AI-based assessment systems in education?

There is great interest in *adaptive AI tutors* that coach students at their own pace until they have mastered core skills and knowledge. The full automation of teaching, assessment and feedback works for certain modes of teaching and learning, and where the student's mastery of the curriculum can be modelled in detail. In STEM subjects, there's evidence that compared to conventional learning experiences, students in school and university can learn more quickly and in some cases to a higher standard, using AI tutors [1-4].

A different class of technology has no deep knowledge of the curriculum or students' expertise, but can still *predict if a student is going to struggle academically* [5, 6]. Student-support teams skilled in the use of predictive models are improving outcomes for struggling university students, by making more timely interventions [7-10].

I will flag two challenges for the way we introduce these tools.

A key factor is *teacher training.* When teachers are suitably trained they use the tools well, and value the insights they gain to make better use of their time [3, 10]. However, upskilling teachers is all too often neglected and under-funded.

Secondly, while AI tutors can enable impressive gains in the efficiency of learning core skills and facts — *what do we do with the time this releases in the curriculum?* Do we fill those free slots with more disciplinary knowledge and skills to master? A smarter strategy is to enrich the curriculum with activities to more fully develop the qualities that so many educationalists and employers are calling for: curiosity, collaboration, reflection, critical thinking, ethical thinking, systems thinking, holding perspectives in tension, and the readiness to step out of your comfort zone [11-15]. The frontier challenge is to *harness analytics and AI to build the knowledge, skills and dispositions* needed for lifelong learning, and a workforce better prepared for change and complexity. It is more challenging for AI to help build these higher order qualities, but progress is being made [15, 16].

How can it be guaranteed that AI assessment will deliver reliable and fair results?

Designing valid, reliable assessments is an established discipline, and AI should be held to the same standards. Some AI tutors are validated assessment tools, predictive of student performance in established exams [17-19]. Looking to the future, however, high stakes exams may become irrelevant as a yardstick, since they test students for just a few hours under artificial conditions [20]. Learning tools powered by analytics and AI can continuously assess students as they are learning over extended periods, under diverse and more authentic conditions, providing a more robust picture of their ability.

In the many contexts where full automation of teaching and assessment is not possible, AI can still give formative feedback. However, reliable and fair outcomes depend on greater human agency: both teachers and students must be equipped to question and over-rule an AI diagnosis [9, 21]. In fact, critiquing and teaching an AI tool is a powerful form of learning for students [22].

Finally, we must *listen to educators.* We know that when we give them a real voice in shaping AI tools, this builds trust in the system [23, 24]. They feel respected as professionals, and become champions to their peers [25].

How might AI-based assessment systems change the teacher-student relationship?

The skilled use of AI tutors shows teachers with much greater precision how their students are doing. They can focus attention on what is proving the most difficult material [3]. Predictive models can help teachers become more proactive, providing more timely support to students before they drift too far off course [9].

Students can now receive feedback that in certain contexts is more timely and detailed than any teacher can provide [26]. This pays off particularly in large classes [10, 27], and for student work that is time-consuming to grade and give good feedback on, examples of the latter being complex capabilities such as producing high quality academic writing [28-30], and face-to-face teamwork [31]. Chatbots are becoming increasingly common, and some people prefer to disclose more to an AI advisor than to a human, because it's perceived as less judgmental. Students from minority groups have preferred to receive support from a pedagogical agent, which they feel is less biased towards them than human staff [32].

AI also opens new possibilities for teacher professional development, to improve how they interact with students. For instance, movement sensors can reflect back to teachers how they are moving around the classroom as they teach, to provoke reflection [33].

So, while the teacher/student relationship will *change,* it remains *fundamental.* No AI is going to provide the warmth and support a student needs when they arrive on a Monday morning after a tough weekend in a broken home. There remains plenty for teachers and students to work on that will remain invisible to the machine.

How will these technologies affect students' motivation and trust in a fair evaluation of their performance?

We all know that we can be crushed or boosted by the way feedback is given to us. Designed and used well, AI can amplify all that we know about the provision of timely, actionable, personalised feedback, that both motivates and challenges [27]. For instance, students report a stronger sense of belonging when AI is used to expand the teacher's ability to give good personalised feedback to hundreds of students [10]. But in a dysfunctional teaching culture, tools powered by analytics and AI are dangerous because of the speed and scale at which they operate.

Concluding remarks

We are at a pivotal moment. There should be *no sense of inevitability* about the way that AI in education unfolds. It's not magic — it's conceived, funded and built by people — who as we speak are making design decisions about products that our schools, universities and businesses will soon buy. We need strategy and investment to ensure that AI shapes education in the most productive directions. This begs the fundamental question: *What kind of learners does society need, to tackle our most intractable challenges?* We cannot meaningfully discuss the future of AI in education, without discussing what kind of education we want.

Sources

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