AIED: raising awareness on risks of biases in sexism and discrimination

Other

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Innovative impact

AIED: raising awareness on risks of biases in sexism and discrimination

AIED is definitely an innovative technology with a high disruptive potential, which carries significant risks for individuals. AIED systems learn from humans because they are programmed by humans. Therefore, there's a good chance they'll also adopt the biases– gender, racial and socio-economic discrimination that exist in society.

Correcting the biases of technology and EdTech is essential to combat the gender gap and other risks of discrimination.

Learning data must be well-curated, privacy and security must also be ambitiously addressed to comply with regulations and all levels of education should stimulate and empower women roles in technology, and specifically in AI and AIED software and algorithms development. Research should act as a call to build ethics while developing AI and AIED technologies.

Introduction

While we may not see humanoid robots acting as educators within the next decade, there are many educational systems in place that use artificial intelligence (AI) to help learners and educators get the most out of the learning experience. One of the key ways of how AI will impact education is through the application of greater levels of individualised and personalised learning helping artificial intelligence in education (AIED) ecologies to be better adapted to learners and educators' needs, including those with special needs (Rodrigo & Tabuenca, 2020).

AIED: artificial intelligence in education

AI can automatize the administrative duties for educators and institutions. Educators are usually overloaded with repetitive tasks (marking exams, assessing homework), because continuous assessment processes contain dozens of assessment figures for each learner. In e-learning it is necessary to gather lots of data about learner progression, to avoid plagiarism and guarantee learners' identity.

AIED-based chatbots are a very powerful educational tool, they can be used for updating institutional information or improve learners' support and services (Singh, 2018; Iniesto et al., 2020). Chatbots can facilitate learners' requests, i.e. helping learners on the registration process, or other administrative duties. They can also collect information about learners' preferences and interaction. Chatbots curate answers on demand resolving issues fast and in a way that feels natural, therefore they can better instant feedback allowing richer interactions and learning in and outside of the classroom with 24x7 availability.

In that sense and regarding instant feedback, whether it is for the learner or educator, it is very important to improve the learning process: learners nowadays are already used to instant messaging software and social media. Educational institutions need to speed up their learner communication processes to draw the attention of this fast-paced and instant generation. Therefore, game-like, avatar simulations can also enhance learner's engagement (Curtin Univ., 2019). Educators spend lots of time providing valuable responses to their learners. In this area, intelligent tutoring systems can provide a personalised learning environment to the learners by analysing their responses and how they go through the learning content, even presenting real case situations through virtual environments, avatars and chats for textual or voice interaction.

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Aside from all the above systems, Data Science (DS) and Learning Analytics (LA) (Rienties et al., 2020) are used to tackle big data and include data cleansing, preparation and analysis. AIED systems can provide powerful support for educators in the iterative process of improving the effectiveness of their teaching and enhancing learners' performance. AIED systems can gather data from multiple sources and apply machine learning, predictive analytics, and sentiment analysis to extract critical information from the collected data sets, plotting them into nice-looking dashboards and graphical indicators. Both DS and LA enable educators to explore and correlate user preferences, behaviour and interactions with learning objects usage, accesses to platforms and repositories, learning activities and assessment results. LA helps to process large data sets in microseconds concerning individual data analysis interests of educators and assuring data privacy issues of learners, if it is well programmed, complying with specific privacy-by-design guidelines (e.g. the EUR GDPR – European General Data Protection Regulation).

Facts for risks

Scientists have researched to show that AI can have some discriminatory aspects along with making human life easier. Burnett (2017) developed the GenderMag method to help software developers and usability professionals find and fix software features with gender-inclusiveness "bugs". Nowadays, we have countless examples of female AI personas, i.e., personal assistants that can reinforce negative stereotypes of women as subservient (e.g. Siri and Alexa). Besides, if voice recognition technologies are trained and tested only by men, the systems will struggle to understand female voices.

Fact 1: AIED data are not correctly processed and algorithms may be biased

AI encompasses the broad fields of data capture, storage, preparation, and advanced analytics technologies. But data are never objective and usually are unclean (Munappy et al, 2019), that's the main reason why nowadays the current data challenge in most businesses, including educational institutions, is to struggle with poor data quality: the existence of data silos, bad data, data compliance, and mainly, lack of data experts and inadequate systems. This growing problem has significantly reduced business customers' (e.g. lecturers and educators) faith in data-driven decisions. Data quality-related problems surfaced in historical data, which may have been gathered from multiple sources with inconsistent standards and varying levels of accuracy.

AI-based systems, included those used in educational contexts, train their algorithms with a source of data moderated by mathematical weights (parameters). At this point, the biases appear simply because these databases may contain a greater amount of male than female sourced data simply due to historical reasons. Also, AI algorithms are trained, based on pre-fixed case studies to deliver predictions and build data categorisation (e.g. clustering types of learners). Machine learning is difficult to apply and often it involves making hypothetical corrections that require expertise using the system to act with fairness.

Fact 2. Who are programming the algorithms?

The technology and EdTech industries are gender diversity biased (Raré, 2020): a study observed that the number of US computer science jobs expected in 2020 is 1.4 million. However, only 29% of those jobs will be filled due to labour shortages in the industry, and worse still, estimates show that only 3% of the jobs will be filled by women. Self-reported diversity statistics from some of the largest technology companies in Silicon Valley show that men vastly outnumber women in programming jobs. At Google, women make up 17% of technical employees; at Facebook, it's just 15%; while worldwide 27.5% of developers are women (DAXX Report, 2020). In the Global North, female participation in computer science has plunged since the mid-80s, while female participation in medicine and other scientific fields has increased steadily. In the UK only 16% of computer science undergraduates –and a similar proportion in the US –are female. Fortunately, figures vary between continents and countries, the balance is different in India, Malaysia and Nigeria where more than 50% are women.

Conclusion

AIED is definitely an innovative technology with a high disruptive potential in education, which carries significant risks for individuals. If a computer system reaches a biased conclusion, it is because someone has programmed it to do so; AI systems learn from humans because they are programmed by humans. Therefore, there is a good chance they will also adopt biases that exist in society such as gender, racial and socio-economic discrimination (Rodrigo, 2019). The emergence of trace data from digital learning environments has sparked a controversial debate on how we measure learning (Tempelaar et al., 2020). To avoid deviations, data must be well-curated, privacy and security must also be ambitiously addressed to comply with legislations.

For many years young women have been kept away from STEM professions. Inside the male-dominated environments, women can often suffer isolation and a hostile environment; culturally male software engineers were like nerds (sometimes called the male computer geek stereotype). These aspects might lead to women' disengagement and lack of motivation. There is compelling evidence that unconscious biases have a powerful effect on what people expect from themselves to be good at, therefore, correcting the biases of technology are essential to combat the gender gap in digital skills. All levels of education should stimulate and empower women roles in technology, and specifically in AI and AIED software and algorithms development. Research should act as a call to build ethics while developing AI and AIED technologies (Holmes et al., 2019). As Karen Spärck Jones, a pioneering British computer scientist who campaigned to encourage more women into the field said: "computing is too important to be left to men" (Sparck-Jones & Runciman, 2007); therefore, why Siri and Alexa could not have a gender-neutral personality (Chin & Robison, 2020).

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