If personalised education and artificial intelligence are democratic problems, could pluralisation be the democratic solution?

Dr Natalia Kucirkova
Dr Sandra Leaton Gray
UCL Institute of Education, 20 Bedford Way, London WC1H 0AL

There is currently much debate about the 'dangers' of new artificial intelligence (AI) technologies as they start to impact on many familiar social systems. However, little is written regarding the broader educational sociology of AI. In its simplest form, AI merely represents a fairly incremental technological progression, through increasing personalisation of provision. However there is still significant work to be done, if AI is to reach its full potential in terms of human flourishing. We draw on Kucirkova's previous empirical work to outline the complexity of personalised learning that goes beyond algorithm-led learning models, and we argue that more attention needs to be paid to the democratic impact of such systems. Drawing on Bernstein's three 'conditions for democracy', we develop a new framework for conceptualising personalised education, assessment systems and AI. Finally we propose a set of best practice principles for AI use if they are to work sustainably.

Keywords: artificial intelligence, AI, personalised learning, algorithms, democracy, Bernstein.

Artificial intelligence is frequently talked about in terms of its impact on education systems (Luckin, Holmes, Griffiths and Forcier, 2016) but rarely is it properly considered in the wider context of personalised education. In this article, we discuss the assumptions behind the algorithms from a set of theorised perspectives, and we focus on the instructional implementation of these technologies in current school systems. As such, this represents the first paper of its type on critical algorithm studies in education, positioning algorithms as a social concern, and something that is key to locating educational personalisation in a social context.

The article begins by defining terms, addressing the current popular conceptualisation of personalised education, and making a case for developing a sociology of artificial intelligence as it relates to personalised learning. The article is structured according to two fundamental questions concerning the use of big data and artificial intelligence in education:

(1) What changes do there need to be to assessment systems of personalised education systems in order to align them more appropriately and rigorously to developments in the field of artificial intelligence?

(2) What consideration needs to be given to the community context of personalised learning in a society where the use of artificial intelligence is expanding?

The first question is answered by discussing our empirical data on personalisation and describing the basic function of artificial intelligence within current personalised educational settings. We lay out some of the primary problems associated with its undemocratic use. The second question is answered by drawing upon the social theory of Bernstein (1996/2000) to identify three conditions for democracy that need to be applied to the adoption and implementation of artificial intelligence systems in education, if they are to stand a good chance of encouraging human flourishing (as defined by Reiss and White, 2013) in a medium to long term sense. The article concludes by identifying a series of principles for best practice for personalised learning in an artificial intelligence context, examining the role of algorithms in determining how inclusive systems are, and arguing for greater use of pluralisation in new forms of technology-based education.

Balancing democracy and education

A central concern since the advent of universal primary education in the West in the 19^{th} century has been to see education in the context of cohorts of children, and seek to maximise the impact of group-based interventions. In 1984, Benjamin Bloom asked: 'Can researchers and teachers devise teaching-learning conditions that will enable the majority of students under group instruction attain levels of achievement that can at present be reached only under good tutoring conditions?' With his mastery learning model, Bloom (1984:5) urged researchers and instructors to seek 'more practical and realistic conditions than the one-to- one tutoring, which is too costly for most societies to bear on a large scale.' One recent potential mechanism for this over the last decade has been the introduction of increasing the availability of personal mobile technologies, such as smartphones and tablets, in public schools worldwide. It has contributed to a rapid evolution of large-scale data-based personalised learning in education. These systems can strategically collect, combine and archive students' data on a massive scale, and notionally adapt learning paths to maximise the rate of individual progress without the intervention of individual teachers (other than to create learning objects initially and to monitor pupil progress through the system remotely). In terms of design, these systems therefore represent a form of artificial intelligence for supporting learning, as well as potentially a form of democratising education, potentially providing the 'practical and realistic' solution that Bloom sought.

However, while there may have been a democratisation of provision, this may not necessarily apply to outcomes as well. Many of us understand a democratic classroom as a place where individuals act with a sensitivity to the needs of other community members, which involves managing the tension between individual needs and desires, and the requirements of the group (Kucirkova et al., 2017). Current personalised education models lack the social agency agenda initially envisaged by proponents of differentiated instruction: the learning process of current personalised education follows cognitive and neurobiological models of learning, which, similarly to the efforts of personalised medicine, aim to 'tailor decisions about which treatment or which dose is most appropriate' for each individual (Hutchison, 2010: 578). Yet, for holistic and sustainable learning outcomes, the process of instruction needs to provide students with content that is most optimal for the individual student within, not at the expense of, collective or group-based learning. This point is not one of a disciplinary difference or context of application, but a fundamental concern of political equality. We begin our discussion of this aspect of democracy by defining the key terms of significance to the debate.

Definitions of key terms

Personalised education

Personalisation refers to the process of collecting information about individual users in order to tailor generic products and content to the individual's characteristics. Personalisation is essential for processing digital content and widely used in information retrieval via search engines or voice recognition software, but it is also the source of ethical and social concerns, especially if uncritically adopted for e-learning (Ashman et al., 2014). Personalised education involves personalised learning and teaching. Personalised *teaching* is a type of differentiated instruction that not only determines the learning path for an individual student, but also adopts the learning content to individual students' needs, preferences and abilities. There are several distinct understandings of personalised learning. The Personalised Learning Foundation defines personalised learning as 'a 21st century approach to education' (PLF, 2012), while Paludan (2006) makes a helpful distinction between personalised learning content and personalised learning pathway. He argues that in public education, the former is more difficult to achieve than the latter. Leadbeater (2004) discusses personalisation from the perspective of policy and the balance between personal responsibility of citizens and government duty to care for those who cannot provide for themselves. This article focuses on the content that is being personalised for individual learners but also on the ways in which the provision of this content is enacted in the educational system. In particular, we discuss personalised *data-based* education, which is personalised learning and teaching informed by data, such as students' individual assessment and performance scores, rather than teachers' own perceptions. The context of our discussion is personalised education that is increasingly *driven* by technological providers in Western countries and used in Anglo-American primary and secondary schools.

Data-based education

Data-based education is often understood under the umbrella term of datafication of education and relates to the use of students' data such as their test scores to evaluate their performance. A significant critique of the use of performance scores in early and primary education is that narrow assessment targets imposed upon young children's learning limit children's learning pathways to specific directions, impeding creativity and spontaneous play (Roberts-Holmes, 2015). Another way of using children's data, such as their language or reading levels, is to suggest relevant content, such as for example the use of children's language scores to recommend specific apps in the iRead™ ecosystem. Students' data can be collected by teachers or national organisations with paper-and-pencil tests and entered into digital databases for comparison purposes, or they can be collected directly with digital tools. In the latter case, systems designed for data-based instruction comprise three main parts: a data acquisition, data evaluation and feedback generation section (Adams, 2005). Datafication thus involves three stages - data input, data evaluation and data output – that can be enhanced through personalisation via artificial intelligence systems.

Artificial intelligence

Artificial intelligence (AI) has been identified as one of the transforming forces of public education in the Pearson's Open Ideas series (Luckin & Holmes, Griffiths & Forcier 2016) and the Open University Innovation Reports (Sharples et al., 2015). The components of AI are rapidly changing, which impedes attempts at defining the AI field. Put simply, AI is a 'feature, function or characteristic of computer systems or machines that try to simulate human-thinking behaviour or human intelligence' (Kose, 2014, p.2). While many futuristic reports focus on systems that can think instead of humans, the current technology can classify and recognise patterns, but not truly 'think' (Ryan, 2014, p.3). Luckin, Holmes, Griffiths & Forcier (2016) discuss AI in terms of new teaching capabilities available to teachers with new technologies. Rather than using general-purpose technologies for a range of tasks, they argue for the need of specifying AI's particular strengths for specific tasks, such as, for example, collecting real-time assessment scores. A more critical discussion of AI's contribution to pedagogy is essential to ensure that lessons learnt from decades of research in learning sciences are incorporated in its design, and that teachers can deliver more efficient teaching rather than administration of learning (*ibid*).

Current personalised education systems

The learning platform BYJU™ is an example of a personalised learning system that uses a simple artificial intelligence framework. It offers a range of adaptive learning modules that present students with learning content based on their previous performance. The content is presented in a series of animation-enhanced texts and with professionally edited, two-minute-long videos in which teachers present a topic in a highly engaging style. If students can't answer a question, the difficulty will be decreased until they answer the question correctly. Students' real-time progress can be shared with parents or teachers through a mentor app. According to the provider's website, the platform is currently used by 12 million students, predominantly based in India, and has 700k paid subscribers. BYJU is part of Think and Learn Private Ltd, India's largest education company, and has recently received significant financial backing from the Chan-Zuckerberg Foundation.

The BYJU's funder, Byju Raveendran, was quoted as saying that his main aim is to "Disney-fy education in India". This is a rather unfortunate analogy since Disney has been criticised for appropriating European folk tales and, through monetising them, monopolising aspects of the entertainment industry and promoting an American model of storytelling (Zipes, 1995). This reductive tendency to monetise human interactions at scale have clear parallels with BYJU, where the input of teachers is confined to a static contribution at the beginning and a report at the end. There is little evidence for the merits of such an approach in educational science. Instead, several erroneous justifications are provided on the BYJU's blogs, such as the argument that students belong to a younger generation who learn better if they are presented information in their preferred learning style, despite the widespread consensus in educational and psychological research that the idea of learning styles is a myth (Riener & Willingham, 2010; Howard-Jones, 2014; Coffield *et al*, 2004). It also invokes the erroneous assumption that all children are 'digital natives' (Prensky, 2001), which may be a popular concept, but again is not one supported by evidence (see for example Wilson & Grant, 2017).

From a broader critical perspective, systems like BYJU come with significant ethical challenges linked to the professional responsibilities of educators (Williamson, 2016). Given a significant political backing in Anglo-American countries for technology-mediated personalised learning (see Pane, Steiner, Baird & Hamilton, 2015; Pane, Steiner, Baird, Hamilton & Pane, 2017), these systems are often imposed on schools from outside as a result of a political mandate rather than a theoretical or educational one (Hartley, 2007). This leaves it unclear who is ultimately accountable for student achievement should the systems fail (Thompson, 2017). In addition, these systems often have their effectiveness tested through a trial-and-error approach more characteristic of business ventures and not always suitable in the complex environment of schools (Selwyn, 2016; Leaton Gray, 2017). As Kucirkova (2017a) has argued previously, current technology-driven personalised learning platforms of this kind do not personalise, but rather standardise children's learning according to a particular Western, commercialised model of education. They do this through an increased technological monopoly, clear commodification of knowledge, and a marketised approach to children's education. Even though this may ostensibly be achieved through the medium of social entrepreneurship, as in the case of BYJU, there are clearly a number of strong financial interests underpinning its dissemination given the fact it is a technology company. As such, this represents a clash with local democratic values, which we later explore and theorise in this paper in the context of Bernstein's three overarching 'conditions for democracy'. First, however, we assess the scale of personalisation and how this impacts on related assessment systems.

The scale of personalisation

Personal mobile technologies, such as iPads and tablets, have become widely available among all sections of the population, including young children in the UK (e.g., Ofcom, 2015, 2016 in the UK). These tools are designed for individual use and thus facilitate personalised engagement, potential of which has been explored from early on by software designers but less so by educationalists (Green, Facer, Rudd, Dillon & Humphreys, 2005). The 2010s has seen the rise in one-to-one tablet programmes in schools, financed by national governments or technology providers worldwide, for example in Turkey (The FATIH Project), in the United States (The LAUSD project in Los Angeles); in the United Kingdom (iPad Scotland), in Australia (department's iPads for learning trial), in Malta (Tablet Pilot Project) and in New Zealand (see for example the Tauranga's Te Akau ki Papamoa Primary School).

As it stands, personalised education is a poorly defined concept with a significant potential to transform public education. Some US states are experimenting with alternative assessment methods (for example the 2017 initiative in the US state Michigan which offers students credits for mentoring other students), but most efforts are impeded by the state testing structures (Burnette, 2017). Even though students in Bring-Your-Own-Device classrooms receive individualized learning plans and can choose their own learning pathways, their learning achievements are assessed through standardised frameworks, national and international tests. As a result, personalised education is limited to initial stages of students' learning and its benefits reduced to students' motivation, something that is not necessarily always linked to learning gains (Son & Goldstone, 2009). As such, the role of personalisation is socially shaped and de-radicalised in the same way that the computer language LOGO was in the 1980s and 1990s (Agalianos, Whitty and Noss, 2006).

Therefore, clearly personalised learning exists within a messy, contested terrain. We have found this in our empirical research in the field. In Kucirkova et al. (2013), we emulated the design of commercially available personalised books and asked parents for some information about their children (such as their names, gender and what they like to eat) and used this information to create bespoke books for individual children. During our observations, all children taking part in the study were motivated to read their personalised books more than the non-personalised books. In follow-up interviews parents told us that the children cherished their personalised books long-term and for some, the books became their favourite books. Encouraged by these results, we examined children's spontaneous speech produced during adult-child shared reading of personalised books. We found a significant focus on self in children's spontaneous talk around the book, with a significantly higher use of personal pronouns and adjectives than reading non-personalised books (Kucirkova et al., 2015a). This is of concern given that reading books is supposed to expand children's horizons, foster empathy and focus their attention on other, typically fictional characters. At the same time, however, we found that children learn more new words when reading personalised books than non-personalised books (Kucirkova et al., 2015b). Personalised content can thus enhance certain learning outcomes, but if we measure additional effects of personalisation, we might find some limitations too. The complexity of using personalised learning soon becomes apparent, and for it to be transferable across domains, it needs to be about considerably more than immediate learner appeal and associated analytics.

Assessing personalised learning

This then raises the problem of how we move towards the idea of assessing personalised learning, which may vary greatly according to the needs of individual learners. Given the centrality of feedback to learning (Bandura, 1986; Suskie, 2010; Hattie, 2008), personalised assessment represents the logical next step. However, if assessment is to be aligned closely to content, we see a similar problem to that which applied to the introduction and use of the computer language LOGO in schools in the 1970s to 1990s, and which ended up being potentially responsible for its downfall (Agalianos, Whitty and Noss, 2006). Most systems of assessment simply represent a form of standardisation. Because it is impractical to assess everything, they measure a relatively narrow range of skills and knowledge, side-lining other aspects of students' learning. This creates systems where value is placed on what is easy to assess or evaluate, rather than deeper or more interconnected knowledge (Frede, Gilliam and Schweinhart, 2011). Crucially, from a democratic perspective, adaptive assessment developed by a technology provider is always going to be inadequate because of its vested interests in continuing to provide the product to the target market.

We see this fundamental assessment problem in the case of BYJU's intelligent system. While it claims to be solving the economic disparities in children's access to education in India, it deploys adaptive assessment systems, which favour those who have access to preferential circumstances, rather than those who don't. To change standardised assessments into truly personalised assessments would require the governments, educators and technology industry to work together and make structural changes to the way they operate - an effort that cannot happen at the fantastic pace at which technological innovation operates. In the meantime, the developers of personalised technologies have embedded adaptive assessments into their design, as a compromise. So, for example, the algorithms delivering BYJU's adaptive learning are based on students' performance on tests relevant for the BYJU content they have accessed previously. Students' progress on the test determines the difficulty level of the content they are provided with. When students pay for a premium package, they get access to a personal mentor, otherwise they need to work out the answer through trial and error. As such, the system indirectly tests social and economic status as well as knowledge and/or skills, and it is here that we see the strongest evidence for a failure in mutuality.

BYJU is only one example of how personalised education systems engender new forms of social exclusion, which might not be immediately apparent. For example, although Massive Open Online Courses (MOOCs) were initially heralded as opening up access to education, later evaluations show that they mostly attract students who are already in the education system and motivated to learn, with students' intrinsic motivation and engagement significantly influencing their completion of the course (Xiong, Kornhaber, Suen, Pursel, & Goins, 2015). With BYJU, those who succeed in the system get to the top of the pile by receiving more difficult and enhanced content. As such, this represents a self-selecting elite, despite appearing on the surface to be a meritocratic one.

How could this situation be remedied? There are different types and levels of feedback and we limit our discussion to those that are most immediately related to personalisation and AI.

Forms of assessment feedback

Centuries of educational research and practice have led to the development of diverse forms of assessment feedback, including quizzes, essays or defence and viva voce for more substantial piece of work. Different domains of learning involve different forms of assessment, with, for example, discrete-points, multiple points and task-based tests used for evaluating students' comprehension of a topic (Brown & Hudson, 1998) and essays used for evaluating analysis and synthesis skills (Huot, 2002). Different forms of assessment influence students' learning approaches (Scouller, 1998) and their strategic placement in the instructional process (often conceptualised as formative versus summative assessment) influences students' understanding of the subject matter (Harlen & James, 2006).

Most UK schools follow traditional assessment forms, dictated by the national assessment frameworks. Yet, there is scope for more innovative assessment practices, which could include authentic forms of writing (e.g., the use of story boards, blogs, e-journals or Wiki pages), documentation of the learning experience and reflective process (e.g., use of a reflective journal, portfolio and annotated bibliography) or adoption of alternative assessment methods (e.g., the production of exhibitions, leaflets and posters, videos and performances). Technologies can further diversify the assessment portfolio. For example, intelligent tutoring systems are in some contexts as effective as human tutors (vanLehn, 2011). Touchscreens can provide feedback based on verbal, written but also visual and haptic data, a suggestion made by Kili (2005) in relation to games design. Technology-based assessment forms could be enhanced with datafication for documenting and archiving the process of learning (see e.g., Cayton-Hodges et al., 2012) and with personalisation to accommodate students' preferred ways of expressing viewpoints, understandings and comprehension. If students choose their own method of assessment, they report greater satisfaction with the course (Garside, Nhemachena, Williams & Topping, 2009) and well-crated personalised data-based assessment methods could positively influence student motivation and inclusiveness of assessment methods (O'Neill, 2017). However, as O'Neill (2017) points out, achieving equity and inclusivity is a complex matter as students' choices are often limited by their own familiarity with certain assessment methods, varied assessment workloads and development of different skills associated with different assessment methods.

Some of these difficulties could be addressed with AI methods. AI could enhance personalised data-based assessments by generating exact and specific descriptions of specific assessment methods and facilitate students' and teachers' choices in their selection. AI-enhanced data mining techniques in healthcare may be slower once human data-entry is factored in (New Scientist, 2017) but they can be more effective than humans in diagnosing medical problems (e.g., Tomar & Agarval, 2013) and AI could facilitate the choice of personalised assessments in well-defined learning situations with fixed outcomes.

However, while AI could generate simple feedback, teachers will need to provide elaborated feedback in order for it to be sufficiently useful. Van der Kleij, Feskens & Eggen (2015) showed that elaborated feedback is more effective than providing the correct answer, particularly for higher order learning outcomes (such as, for example using new vocabulary in context rather than just knowing the meaning of the new vocabulary). Elaborated feedback is resource-intensive, but it can be highly effective and it is here where AI could add value to learning, particularly for underprivileged groups.

Possible approaches to assessment feedback

Students can evaluate their own work through a self-review process (see Defeyter and McPartlin 2007), or they can receive feedback from the teacher (expert-based feedback), from fellow students (pair-based feedback) or national and international evaluations (generic feedback). Rather than having a contingent (special arrangements for specific students) or alternative approach (different arrangements for specific students), effective and equitable assessments are inclusive for all groups of students (Waterfield, West & Parker, 2006). However, self-assessments can be unreliable (e.g., Schlossberger, Turner & Irwin, 1992) and other evaluation biases impede inclusive quality assessments. For example, peer-marked evaluations can be biased because of the desire to reciprocate (e.g., Magin, 2001) and teacher-marked assessments can be biased against specific groups of students such as race, gender and ability groups (e.g., Sullivan, 2009).

It follows that a major concern in assessment feedback is transparency and the imperative to ensure equity of assessment for all students. Personalised data-based education enhanced with AI methods could significantly mitigate against bias risks and improve transparency of assessments. For example, the HireVue technology, which is an AI-enhanced assessment system used for video-based recruitment interviews, records candidates' verbal response, intonation, and nonverbal communication and analyses them together with the candidates' answers to job-related questions, past education and work experience and social media activity. The developers claim that 'By linking to each job's unique performance measures, these AI-driven assessments use custom algorithms to connect the dots between assessment information and job success. Since they are built for specific roles, they can also be vetted for adverse impact - ensuring that the assessment is treating all groups fairly' (https://www.hirevue.com/blog/ai-in-recruiting-what-it-means-for-talent-acquisition).
HireVue is the first AI-enhanced assessment technology on the market and the concept is very much in infancy. However, if the technological affordances are applied to students' data, personalised to the abilities of individual students *and* informed by

teachers' and students' reflection, they could be used to inform schools' assessment procedures.

However, we first need to understand why the current assessment of personalised education systems confine enhanced assessment forms to those who are able to pay premiums. In order to understand what the current commercially-driven models mean for the future of personalised learning and intelligent systems, we need to take a step back and reflect on the wider issues impelled by AI-enhanced personalised education. We see the fundamental issue to be that of the systems' misalignment with democratic values in education.

Democratic values in education

The educational systems in Western countries that are supposedly being scaled up by such initiatives as the BYJU model notionally follow democratic principles that have at their core the somewhat difficult and rather complex 'notion of egalitarianism' (Perry, 2005, p.686). In some ways, the advent of accessible and affordable Internet-connected devices (such as smartphones and tablets) has visibly expanded the opportunities for democratic engagement of previously marginalized groups (see Shirazi, Ngwenyama, & Morawczynski, 2010). A further consequence however has been to open up new educational agendas for technology developers and providers. While access to information might address important digital divides across the world, the idea of technology simplistically bringing democracy to the world may be seductive but it is not unproblematic and needs to be considered in relation to global identity and global citizenship (Keohane, 2015), as well as any relationship with individual, social and political power structures.

Towards the end of Bernstein's seminal work *Pedagogy, Symbolic Control and Identity: Theory, Research, Critique* (1996/2000) he lays out a framework of what he calls 'conditions for democracy'. The framework provides a mechanism for understanding the issue of mutuality in education (who gives and who receives), as well as how and when we should contest any shortcomings in mutuality, for example when there isn't a good reason given other than it is too difficult or expensive to operationalise. Bernstein consequently suggests three pedagogic rights based on this mutuality. As discussed in Leaton Gray (2017) in relation to national infrastructure reform, these rights are the right of enhancement, the right of inclusion and the right of participation. **Enhancement** refers to the idea of seeing past and possible futures for pupils. **Inclusion** refers to the idea of social, cultural, intellectual and personal inclusion operating individually (as well as groups). Finally, **participation** refers to the idea of the right to participate in civic practice, through procedures whereby order is constructed, maintained and changed. To what extent are these three rights respected in the context of personalised learning and the artificial intelligence systems that underpin its provision?

As we have explained, big data and artificial intelligence technologies are routinely promoted under the auspices of adaptive or personalised learning, as well as democratic reach. However, if we test them against Bernstein's 'conditions for democracy', we start to see that there are problems. Firstly, we need to consider whether these new systems provide the opportunity for **enhancement**. The various funding bodies and organisations involved would no doubt strongly argue that they did. However enhancement to what purpose, and in relation to which educational model? If it is a primarily Western model, this might represent little more than the colonialization of education. Secondly we need to consider **inclusion**. If engagement in the educational model is predicated on financial transactions, even if they are rooted in the American tradition of philanthropic enterprise, as in the case of BYJU this may not be as inclusive as it appears. This is because the model has been imposed from outside, and without local investment and mediation it may not be sufficiently relevant or sustainable. Thirdly, we need to consider **participation**. As the local community is not sufficiently involved in commissioning, designing, implementing and evaluating these educational models, it means they are effectively excluded from civic practice in relation to the teaching of their children. Therefore in terms of Bernstein's model of democracy, even though they may spread various forms of knowledge and instruction, these systems can be said to have failed their users in terms of promoting their deeper pedagogic rights.

Future recommendations

There are three important principles for best practice that need to be observed, if artificial intelligence systems are going to be able to optimise personalised learning in order to allow for human flourishing: the principle of economic equality, social equality and political equality.

(1) The first principle is that systems need to encourage the achievement of economic equality. Personalised data-based education needs to be implemented together with assessment systems that enable the growth of *all* children, not only those who have the access to or possess resources and knowledge.

(2) The design of personalised learning technologies needs to be more community-oriented, to ensure that personalisation does not happen at the expense of pluralisation.

(3) Personalised learning systems need to follow a more participatory approach towards its innovative outputs, in which children are positioned as makers and active citizens, and educators as those who determine content and its assessment.

By following these principles, new systems in education (and not just personalised learning systems that draw on artificial intelligence mechanisms) can achieve the degree of mutuality that Bernstein argues is necessary if pedagogic rights are to be ensured. We suggest that the combination of pluralisation with personalisation, rather than personalisation on its own, could give rise to enhanced outcomes.

The importance of pluralisation in education

Bernstein's work on pedagogic rights is echoed by that of Hartley (2012), who describes the tension between democracy and capitalism and cautions that the purposes of personalised education are economic and political. Personalisation, unlike customisation, should be about collaboration as much as about personal development. One solution to this is pluralisation, in which the collaboration and communal aspects of learning are made visible. As such, this relates to all three principles.

This approach has been successfully used in an experimental context. In studying effective deployment of mobile technologies in UK classrooms, Kucirkova et al. (2017) developed a model that combined personalisation with pluralisation in predicting highest students' outcomes. Nested within Vygotsky's and neo-Vygotskian socio-cultural theories of learning, the model suggests that for optimal learning benefits, educators need to aim for individualising and diversifying children's learning and extending children's zone of proximal development (ZPD) to an 'intramental development zone' (IDZ, see Mercer, 2008). While with ZPD students learn from the more knowledgeable others in a vertical relationship of novice and teacher, in IDZ students and teachers are all learners, who learn from each other by mutually extending the 'zone' of what they know and don't know. Personalised pluralisation is therefore a learning space where the communal and individual aspects of learning merge and where the content tailored to individuals' aspirations and abilities becomes diversified with communal concerns.

The current adaptive learning algorithms (developed to support personalised data-based education) follow the logic of commercial or defence strategies where more data about an individual user can be used to produce more targeted offers/actions by the provider. The implicit assumption in these models is that increased personalisation results in better outcomes. However, these outcomes are better for the provider, not necessarily for the recipient of personalisation. This is because in education, content that the learner finds difficult or uninteresting creates the so-called cognitive challenge or cognitive conflict, which in constructivist learning theories, is the essence of creating knowledge and transforming thinking (Piaget, 1976).

Kucirkova (forthcoming) and Kucirkova et al. (2017) investigated the algorithms embedded in three reading recommendation systems for primary school-aged children: RM Books, MLS and Oxford Owl. Based on a features-analysis, it was argued that the current design of these systems misses the potential to leverage community reading recommendations and crowdsourcing content. Instead of focusing on individual reading recommendations and positioning teachers as absent librarians, teachers could be positioned as listeners and empowered to co-create the reading space together with the children, through a community-oriented dialogue around books.

In this respect, current reading recommendation systems illustrate the problematic conceptualisation of personalised education that is focused on an individual and maximising the personalisation process in any context and for any content. Based on personalised pluralisation we argue that for AI-enhanced systems to deliver sustainable learning outcomes, the learning content needs to be not only adapted to the current needs and capabilities of individual learners but also extend these beyond to the intramental developmental zone (Mercer, 2008), in which teachers become learners and learners become teachers and vice-versa, depending on the learning content and task.

According to the personalised pluralisation model, the real focus of personalised learning should be on when to apply *and when to restrict* personalisation, and combine it with pluralisation. In other words, the assumption that more personalisation equals higher learning outcomes needs to be challenged before the development of pedagogical tasks and resources. Based on the theoretical concept of personalised pluralisation, we argue that current conceptualisation of personalisation is incomplete and needs further theoretical underpinning before it can be enhanced with AI.

Personalised pluralisation and AI

Chattopadhyay, Shankar, Gangadhar & Kasinathan (2018) considered AI-enhanced solutions for assessing students' learning outcomes, including parents' and peer involvement in contributing data and enhancing the feedback loop. They developed a generic model of AI-based learner interface, which consists of three sub-models: a pedagogy model that incorporates teacher's expertise, assessment and feedback, as well as parental involvement in the assessment process; domain model that incorporates subject matter, facts, figures and procedures and a learner model that stores previous learning facts and can be used for peer-based learning (p.195). The three models process data through algorithms that feed the learning content to individual students, adapted to the students' needs and capabilities. AI is used for data analysis in the form of machine learning and pattern recognition and its results feed into an open learner model that makes the learning explicit to all involved in the system, that is students as well as teachers.

For the model suggested by Chattopadhyay et al. (2018) to offer sustainable learning benefits, the algorithms processing learners' previous knowledge and teachers' expertise need to be pluralised (diversified) as well as personalised. This means that the algorithm needs to use the information not only to select matching data from the domain model of what the student knows or likes, but also from other domains to expand and challenge students' thinking. Information from both the personalisation and diversification pathways needs to be extracted during data analysis and pattern recognition by AI systems and used to feed into the open learner model. [insert figure] It is clear, therefore, that greater transparency may be one of the solutions to more effective deployment of personalised learning systems.

Conclusion

The personalisation field needs to emerge from its infancy to capitalise on the technological capabilities of AI within the framework of an inclusive democratic process. Far from being a threat, artificial intelligence has the potential for supporting powerful forms of learning if, and only if, sufficient attention is given to the three conditions for democracy laid out by Bernstein as representing pedagogic rights: enhancement, inclusion and participation. We have considered some basic questions about personalisation to help explain the potential of AI in enhancing current models in this regard through the medium of pluralisation. We agree with those who prophesise that AI-enhanced personalisation can revolutionise children's education and our lives more broadly. However, we caution against jumping on the AI bandwagon without the essential theorisation that is necessary for bridging the gaps between the rhetoric and reality of personalisation. Personalisation is a complex nexus of practices, products and processes that need to be disentangled in the data-based education context before the AI frontier becomes its largest component. To this end, we have therefore proposed three principles for best practice, which are inclusive assessment processes, respect for the wider community context of personalised systems through increased used of pluralisation, and an increasing emphasis on participatory processes, as a means of ensuring maximum civic participation and agency. If innovative personalisation systems respect these principles, then learning stands a better chance of being optimised and human flourishing is more likely to prevail.

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