It's getting personal:

The ethical and educational implications of personalised learning technology

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Abstract

Personalised learning systems—systems that predict learning needs to tailor education to the unique learning needs of individual students—are gaining rapid popularity. Praise for educational technology is often focused on how technology will benefit school systems, but there is a lack of understanding of how it will affect the student and the learning process. By uncovering what the meaning of 'personal' is in educational philosophy and as embodied in the technology, we illustrate that these two understandings are different regarding the autonomy of the student. Personalised learning technology, therefore, bears the risk of failing to achieve its educational ideal of what personalisation should be. We also illustrate how personalised learning technology effects student autonomy by requiring the intensive tracking of the learning process, exposing them to privacy and data protection risks. We do not claim that education does not need technology, but we want to illustrate the importance of values as drivers of innovation.

Key words

adaptive personalisation, autonomy, EdTech, personalised learning technology, privacy

Introduction

Personalised learning is an emerging paradigm in educational technology in which big data, learning analytics and adaptive learning systems are considered to hold the potential to fundamentally adapt education to 21st-century ideals through the customisation of education and personalisation of learning (Roberts-Mahoney, Means & Garrison 2016). Although the underlying idea of personalising education can be traced back to Dewey (1916), the current debate is heavily technology-driven. Advocates of personalised learning technology argue that, if technological platforms such as Google, Amazon, Netflix and Facebook have transformed the way we conduct business and work, seek entertainment, shop and communicate, it only makes sense to apply the logic of these platforms to educational systems for the sake of progress and innovation (Roberts-Mahoney et al. 2016). Personalised learning technology promises to overcome the deficits of the 'one size fits all' model of education, where one teacher teaches the same material with respect to media-type (e.g. linear text or visual content) and learning level (e.g. understanding, applying or evaluating) within a uniform time-span to a large group of students who are all individually unique in their learning styles, preferences and needs. In line with a deeply held cultural belief in the power of technology and data science as drivers for progress, personalised learning technology presents itself as a (cost-)effective solution for adjusting to 'the information age' (Selwyn, Gorard & Williams 2001).

Complaints about the sad state of education and the need to improve and innovate have a long history (Biesta 2009). The promise of educational technology attracts school

districts to invest in new tools and gadgets. However, the decisions to do so are often 'rash, misplaced and misconceived' (Salomon 2016). In this context, Evgeny Morozov (2013) points to the dangers of 'solutionism'—the idea that technology can solve complex social problems. This mind-set pushes us to see everything as a problem that can be solved with technology. In contrast, Sarewitz and Nelson (2008) remind us that not all problems yield to technology. and determining which will and which will not should be central to policymaking. The praise for personalised learning technology is largely focused on how promised improvements will benefit school systems, but there is a lack of a nuanced understanding of the impact of personalisation technology on students and their learning processes. The black box of personalisation needs to be opened to assess how effective personalised learning technology can be in achieving its pedagogic ideals.

Finally, personalised learning technology requires collecting large amounts of student data to achieve a tailored education. Tracking every aspect of how a student learns bears privacy and data protection risks that can, in turn, have consequences for the quality of the learning experience. In this context, questions arise about the legitimacy and boundaries of data-intensive technology and the protection of the student and the learning process.

In this paper, we will focus on the meaning of personalised learning technologies for the wellbeing of students. However, we need to be aware that such systems also collect data about others involved in the educational process and, at the very least, data about the performance of students can also be used to evaluate the performance of teachers. If personalised learning technology becomes the future of education and is widely adopted by schools, it is important to question its desirability in order to see to what extent it can be responsibly implemented in the 21st-century school. In the first section of this paper, we will map out the EdTech landscape to situate our specific case,

personalised learning technologies, in the larger context. After having provided more details on personalised learning technologies, we will inquire into their educational and ethical implications.

EdTech

To better contextualise personalised learning technology in a field where technological innovation takes many shapes, we will provide a brief overview of a rapidly evolving landscape of educational technology (EdTech).

One of the basic assumptions in the development in EdTech is that technology can enhance ~~the~~ learning experiences and, therefore, learning outcomes. The term technology-enhanced learning is used to describe the application of information and communication technologies to teaching and learning (Kirkwood & Price 2014). A similar educational vision is one that advocates blended learning. Blended learning entails that traditional education, the physical classroom, is combined with technological tools and applications. What these technological means include can be as broad as replacing hard copy books with digital books, using computers or tablets to complete assignments and using learning management systems (LMS), which are digital platforms, to share and discuss learning materials.

The proponents of EdTech argue that because the younger generations are growing up with technology, its use for learning purposes in the classroom would fit students' expectations. Technology also offers the potential to make learning more fun, as digital applications allow for more interactive content. As gamification, the use of game design elements in non-game contexts, has been a successful approach in other domains, applying the same principles should also have the potential for engaging learners

(Dicheva 2017). A similar claim is made about the use of online content (Chen, Lambert & Guidry 2010).

A slightly different application of technology in education is the use of (big) data and learning analytics, that is, the use of large datasets to predict the preferences and behaviour of students. Big data applications can be found in many different fields; for example in marketing, where large data sets of consumer data are used to anticipate consumer's behaviour and marketing strategies are adjusted accordingly. With more and more sophisticated statistical techniques to analyse data and increasingly cheap data storage space, the future of big data seems to be bright. While conventional types of data are increasing in volume, we are also quantifying aspects of the world that had not been previously quantified. Cukier and Mayer-Schoenberger (2013) refer to this phenomenon as *datafication*. For example, location has been datafied with the invention of GPS ('longitude' and 'latitude'), and social media sites have led to the datafication of relational networks ('friends') and personal preferences ('likes'). Datafication of the learning process is a phenomenon increasingly applied by EdTech vendors and school administrations (Eynon 2015). Student data collection is not limited to proficiency assignments, learning styles and disabilities or demographic information provided from the school records, but is increasingly extending to other areas, transforming the classroom in a living laboratory of data points. Through learning management systems, teachers can keep track of log-ins, downloads and even the length of time it takes for a student to read a page or finish an assignment. GPS-trackers on appliances provided by the school can uncover where a student works and with whom. Eye-tracking software in cameras can monitor what it is about the content that draws a student's attention, and even heart rate monitors can be used to monitor excitement or nerves.

In January 2018, the European Commission published a report emphasising the potential of educational technology.[1] In this report, one of the priorities mentioned is improving education through better data analysis and foresight. As a concrete action, the Commission supports the launch of artificial intelligence and learning analytics pilots in education. Not only are governmental policies emphasising the potential of the cultivation of learning, philanthropic organisations and technology entrepreneurs like the Bill and Melinda Gates Foundation and Facebook's CEO Mark Zuckerberg are also investing in the development of educational technology. As a result, commercial companies offering innovative educational solutions are popping up everywhere. All over the world, the EdTech industry is booming and school administrations seem to have an undisputed belief in the potential of technology to change education.

Personalised Learning Technology

The next step in adopting big data approaches is the personalisation of the learning path. If the learning process can be predicted with big data and learning analytics, the learning content can also be tailored to the specific preferences and needs of the students. Descriptions and definitions of personalised learning include a broad range of explanations, causing expectations to run high. To assess the desirability of personalisation technology, it is important to map out what the technology can and cannot do and what 'personal' means in this context.

Regarding information technology, personalisation seems to be everywhere: personalised search results (Speretta & Gauch, 2005), personalised advertisements (Bilchev & Marston, 2003) and personalised website navigation (Graham, Bowerman & Bokma, 2004). Personalisation can be defined as follows. 'Whenever something is

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[1] https://ec.europa.eu/education/policy/strategic-framework/education-technology_en

modified in its configuration or behaviour by information about the user, we consider it to be personalized' (Searby 2003, p. 1). Personalisation has its roots in customisation, which is the modification of environments or objects to individual taste (Oulasvirta & Blom 2007). Initial internet-enabled personalisation was similar to customisation: users could select their preferences for their environment and content by changing the settings or by ticking check-boxes (Oulasvirta & Blom 2007). Advances in information technology have paved the way for more sophisticated forms of personalisation. With personalisation-as-customising, the personalisation originates from the decisions and actions of users themselves. Predictive analytics aims to personalise content without requiring any action from the user.

Data-driven personalisation can be a technological means to tailor education to individual students (Sampson & Karagiannidis 2002). To some extent, it is the teacher's role to 'tailor' mass education to individuals, for example, to provide extra explanation to students who were not able to fully understand the content of the lesson or to provide extra assignments to students with a higher level of understanding. However, providing this individual attention to students is a challenging task for the teacher. Understanding every student's needs and providing unique responses takes time and effort, especially in increasingly crowded classrooms. By using large databases containing data about how students learn, patterns in learning needs can be identified without direct input from the teacher.

In a recent working paper, Bulgur (2016) suggested distinguishing between two types of applications of personalised learning technology: responsive and adaptive systems. A responsive learning system embodies a kind of personalization comparable to customisation. Responsivity can range from students being able to choose their own avatar for learning activities to having their own personal, online learning environment on the school's LMS. Responsive systems can also take shape as recommender systems.

Recommender systems use data to recognise use patterns. Based on these patterns, user profiles can be created, and whenever a user matches a profile, the system can make recommendations for future actions. These systems work with predetermined decision trees, and the user is an active agent in deciding whether to follow up on the suggested actions or not. For example, if the student has shown a preference for multi-media content in the past, the system may recommend reading a longer linear text next because the data reveals that students who showed a similar learning behaviour in the past were more likely to meet the learning goals if they switched to a different content-type. Or the system may reveal that students with similar learning behaviour benefited from additional skills training.

Recommender systems can also be more advanced by implementing machine learning, which allows for self-learning algorithms. This is, for example, how Netflix works. Based on a large user data set, Netflix's algorithms offer a pre-selected choice of movies that the user is likely to enjoy. The user still makes an active decision whether or not to follow up on the recommendation; however, machine learning makes the process opaque and it is no longer self-explanatory why the system makes particular recommendations.

Responsive learning systems, whether based on pre-determined decision-trees or by using machine learning, are data-driven systems which are intended for either students or teachers to assist them in decision-making. The message to the student may have the following form: Students who showed a similar learning behaviour to you in the past seem to have taken the subsequent step in the learning path. Responsive systems can, therefore, be implemented to inform the teacher which students are struggling, which students excel and what actions can be taken as interventions.

Adaptive systems claim to be more advanced as they aim to not only recommend actions but to automatically adapt the content based on the predicted user behaviour and desired learning outcome. Adaptive learning systems are designed to dynamically adjust to the level or type of course content based on an individual student's abilities or skills. In adaptive learning, computers are interactive teaching devices that orchestrate the allocation of content on a very detailed level to each learner. One company that offers a personalised learning platform is the New York based company Knewton. Knewton's philosophy, as they argue in one of their marketing videos, is that 'teaching the young mind ought to be the most differentiated product there is'. The technical whitepaper on their website explains how they consider technology to play a role in personalising education. It states that 'if a human tutor can improve learning outcomes so radically, then many of the benefits might be captured by an automated system'.[2] Knewton founder, José Feirrera, elaborates on his company's philosophy in an interview with the website edtechreview.com[3]"

> We can figure out exactly what students are struggling with, down to the percentile and how proficient they are with each subject no matter how granular it is. Because we're gathering so much data, we know what kids know, and we know exactly how they learn it best. We can take the entire database of every kid who's ever learned through us and figure out who's really similar to this kid in terms of learning style, what they know and how they learn best.

Adaptive learning is often presented as the next step in technology-enhanced learning. We will argue that adaptive systems are not just the next step in the development of personalised learning, it is actually changing the nature of teaching and learning. The system no longer assists the student or the teacher in the decision-making process but

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[2] [Knewton's technical whitepaper](#)
[3] [Interview with Knewton founder Jose Feirrera](#)

rather takes control of this process. Adaptive systems give algorithms the agency to make the decisions in a student's learning path. This represents a fundamental shift from technology-enhanced learning towards technology-driven education. Even though critics claim that many of the self-proclaimed adaptive learning platforms remain more like recommender systems (Waters 2014), the desire of EdTech start-ups to move towards an adaptive form of education resounds. Thus, we will analyse the promises of adaptive learning in the next section.

Educational implications of Personalised Learning Technologies

As already pointed out in the introduction, personalised learning is not a new concept in educational theory. John Dewey (1916), for example, saw education not as an individualised process but rather as a social interaction between students and teachers. He argued that knowledge could not simply be given but that a student must experience something and engage with it to learn. Accordingly, teachers should be guardians of high standards for students to learn the basics, yet create pathways that allow the students to make their own choice. The role of the school should not be to impose fixed processes on students but to guide them in their personal learning experience (Dewey, 1916). To achieve this goal, teachers and students should work together in co-constructing education and selecting curriculum content. These ideas gave rise to the ideology of personalised learning where the role of the student shifts from being a passive receiver of education to 'active and responsible co-authors of their educational script' (Campbell, Robinson, Neelands, Hewston & Mazzoli 2007, p. 138).

Why is the recognition of the students' agency such an important indicator of quality education? In educational psychology, motivation is understood to be a factor in determining the quality of the learning outcome as well as the enjoyment of learning

(Pintrich & de Groot, 1990; Vallerand, Gauvin & Halliwell 1986). Intrinsic motivation is considered the most desired form of motivation for predicting the likelihood that an individual will engage in certain behaviours (Ryan & Deci, 2000). *Intrinsic* motivation refers to behaviour that is driven by internal satisfaction or fulfilment. Conversely, *extrinsic* motivation is engaging in certain behaviour for external incentives rather than from intrinsic desire. When it comes to learning, extrinsic motivation entails studying with the purpose of getting a good grade, winning a prize or receiving recognition from someone else. Intrinsic motivation is studying for your own sake, because you want to know more about the subject, and without experiencing pressure from an outside source. Ryan and Deci's (2000) self-determination theory points to the importance of self-determination or autonomy to evaluate the level of intrinsic motivation. When students can self-determine or self-regulate their learning processes, they should also be able to reflect on *why* something is personally relevant. This enables students to have a relationship with their own educational path, which is believed to increase educational outcomes and enhance the enjoyability of learning (Deci et al. 1991). Personalised learning from this perspective is about making education more 'personal' and giving students a voice in their own learning process. This understanding has paved the way for educational research to focus on student-centred learning methodologies. In a student-centred approach to learning, students are encouraged to have more responsibility for their learning; it is a process that requires different approaches to teaching (McCabe & O'Connor 2014).

To pin-point the difference between the ideal of personalised learning (as rooted in Dewey's philosophy) and the current technology-driven approach, the original idea in personalised learning was to make room for students to make education fit their personal needs, while the technological-driven visions aim at personalising the learning process *for* students. Adaptive systems, hence, come with the promise of offering tailor-

made content based on the recorded and analysed behaviour of the student but also with the risk of taking away the students' voice and ownership. The ideal of personalised learning is based on a dialogue between teachers and students to enable them to co-author the learning process. Responsive learning systems—especially if they take the form of recommendation systems—follow a similar logic while lowering the workload of the teacher. While it can be debated whether such a system can emulate the flexibility of teachers, a recommendation-based approach still asks the student to take active choices. Adaptive systems, in contrast, make the decisions for students based on their past learning behaviour, which effectively undermines students' sense of ownership and the possibility of reflecting on their role in co-authoring the educational process.

Technology-driven learning sparks questions about which educational values are implemented in personalised learning technology. Technologies, such as adaptive learning systems, are not neutral. The tools we choose to use in education shape how we teach and how we learn. Technology embodies certain values of what 'good education' is. When algorithms are determining how students learn, it is important to understand the definition of success that is implicit in the technology. It is easy to misunderstand algorithms as technical and objective, but algorithms are designed by humans and are built on their values and understandings of teaching. To put it pointedly, if computer systems take over educational decision-making, what are these systems optimising for? Which educational values do they embody and whom will they benefit? Is the purpose to minimise drop-out rates, to improve the completion rates or grades, or perhaps to simply maximise profits (Slade & Prinsloo, 2013). And precisely how will the students' learning behaviour be analysed and used by the system? If we leave these important decisions up to for-profit tech start-ups, we might be risking more than educational ideals of autonomy. Hall and Stahl (2012), for example, point to the

risk of the commodification of education, and Selwyn and Facer (2014) warns about the tendency for schools to take on 'evidence-based' approach, bearing the risk of managerialism.

When data-intensive technology progresses to become increasingly complex and opaque, it is increasingly difficult to lay bare the values that are implicit in them. The development of educational technology should be an inclusive process in which experts in software programming and educational experts work together, and this process should be fuelled by discussions about what constitutes good education rather than what is technologically possible. Educational technologists should be striving for transparency in terms of which values and beliefs are the drivers on which learning algorithms are built. We do not argue that technology should not be part of the school of the future; we maintain that stakeholders such as school administrations and teachers should have a critical mindset when considering technological approaches. Change in education should not be technology-driven, but change should be driven by values and ideals. Before the procurement of technological tools and gadgets, schools should have a pedagogical discussion of what drives the change, and those outcomes should guide the choice of technology.

Ethical implications for student privacy

Another problematic aspect of the emerging paradigm of personalised learning technology is that it is increasingly data-intensive, which sparks questions about surveillance and privacy. Personalisation involves collecting and analysing different types of data about the learning process of a student. Although most of the data collected for learning analytics are aimed at proficiency assessments, more elaborate forms of analytics are emerging. An example is the use of 'emotional learning analytics',

which is focussed on automatic detection, assessment, analysis and prediction of the emotional state of a student (Lupton & Williamson 2017). Lupton and Williamson (2017) point out that increasing datafication of the lives of young people will lead to the reality of the 'datafied child' who will be subjected to privacy risks throughout his or her life. Monitoring the learning process will, therefore, create a 'datafied student' who will be subject to an intensive form of surveillance in the school. With the emergence of digital technology, surveillance of students is extending to the digital realm of 'dataveillance' (Raley 2013).

Monitoring students in school is not a new phenomenon (Monahan 2006). The role of teachers has always been to keep an eye on students to enforce classroom rules, to maintain discipline and keep the students safe. In a sense, to be young is to be under surveillance; teachers, as well as parents, watch young people to keep them safe and correct their behaviour (Steeves & Jones 2010). The monitoring of the learning process also is not a new phenomenon since the same is done when standardised assessments and examinations determine proficiency. Surveillance is, therefore, an important component of education and is not undesirable by definition. However, this does not mean that surveillance does not have an effect on students or that there are no boundaries for its legitimacy. The students' experience of 'being-looked-at-ness' is marked by a lack of autonomy (Steeves et al. 2010). Lepper and Greene (1975) found that children placed under surveillance exhibited lower intrinsic motivation than those who were not monitored. So a degree of privacy is necessary for children to play and be themselves, but privacy is also important for the learning process itself as it is an important condition for intrinsic motivation. There is value in the ability to get away from adult power and control to experience freedom. Students need their own space physically, imaginatively and emotionally to become effective and satisfied learners. Control can be a danger to motivation, as it is linked to extrinsic rather than intrinsic

motivation. A degree of privacy where autonomy is safeguarded is a condition for the learning enabled by intrinsic motivation. Delivering tailored education using data-driven methodologies presents range of privacy risks. Personalisation becomes more effective by using bigger data sets including a large variety of data points. In an imagined future, adaptive learning technology might consist of intelligent digital tutors who deeply 'know' students and their learning styles and preferences. For intelligent tutors to truly know a person and his or her learning style and preferences, the student's behaviour and qualities should be rendered in data completely. When so much is tracked about a person, one might experience this as surveillance, a form of control, which can limit their experience of autonomy and freedom in the learning process.

Conclusion

Personalised learning technology is one of the many data-driven applications brought forward as a promising tool to 'fix' education. In this paper we have argued that schools should avoid falling for 'solutionism' by using technology to change education without understanding the problem first. As we have demonstrated, there is a clear difference between 'personalised learning' as an educational ideal and 'personalisation' in a technological sense. Whereas 'personal' in educational theory signifies the ability of students to have agency in their own learning process, 'personal' in adaptive learning technology is understood as education tailored to a student's needs by using predictive analytics. Adaptive learning eradicates the choice and agency of student and teacher, bearing the risk of making education *less* personal by undermining the student's sense of ownership.

We have also argued that personalised learning technology demands a shift in education towards an increasingly data-intensive practice for the datafication of learning. The intensive tracking and surveillance necessary to offer tailored education is a risk to students' privacy. The effects of personalisation on privacy can undermine educational aims and ideals. This constant tracking of students can cause a feeling of being monitored which, again, can lead to the experience of less autonomy. School administrations adopting technology should, therefore, always ask the proportionality question: how does the infringement of privacy weigh up against the potential benefits of the technology for students?

Rather than blindly distribute power to technology start-ups, schools should be critical of how technological applications influence the role of the student and the teacher. We are not arguing against technological innovation, neither are we claiming that schools do not need to use data. Technology, if implemented properly by respecting educational values and the rights and freedoms of students, can bring a valuable change for schools. Schools and educational policy-makers need to think more carefully about what the problem is that we want the technology to fix, and whether technology can effectively achieve educational ideals. It is, therefore, important to see the use of digital technology in education as a matter of values, preferences and politics rather than neutral tools to improve education.

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