It’s getting personal: The ethical and educational implications of personalized learning technology

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Abstract

Personalized 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 the 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. Personalized learning technology, therefore, bears the risk of failing to achieve its educational ideal of what personalization should be. We also illustrate how personalized 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.

Keywords: EdTech, personalized learning technology, adaptive personalization, privacy, autonomy

Introduction

Personalized 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 customization of education and personalization of learning (Roberts-Mahoney, Means & Garrison, 2016). Although the underlying idea of personalizing education can be traced back to Dewey (1916), the current debate is heavily technology-driven. Advocates of personalized learning technology argue that, if technological platforms such as Google, Amazon, Netflix, and Facebook have transformed the way we conduct business, 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). Personalized 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, personalized 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 mindset pushes us to see everything as a problem that can be solved with technology. In contrast, Sarewitz & 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 personalized 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 personalization technology on students and their learning process. The black box of personalization needs to be opened to assess how effective personalized learning technology can be in achieving its pedagogic ideals.

Finally, personalized learning technology requires collecting large amounts of student data to achieve a tailored education. Tracking every aspect of how a student learns is bearing 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 personalized 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 personalized learning technology will become the future of education and will be a widely adopted approach for schools, it is important to question the desirability of it 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, personalized learning technologies, in the larger context. After having provided more details on personalized learning technologies, we will inquire into their educational and ethical implications.

**EdTech**

To better contextualize personalized 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, the learning outcome. The term technology-enhanced learning is used to describe the application of information and communication technologies to teaching and learning (Kirkwoord & Price, 2013). 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 such technologies consider the use of technology in the classroom to be a logical step because the younger generations are growing up with technology and using technology for learning purposes would fit the expectations of students. 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 analyze data and increasingly cheap storage space, the future of big data seems to be bright. Not only is data that was already collected increasing in volume, we are also quantifying aspects of the world that had not been quantified before. Mayer-Schoenberger and Cukier (2013) refer to this phenomenon as *datafication*. 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 it is increasingly extending to other areas, transforming the classroom in a living lab of data points. Through Learning Management Systems (LMS), 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 emphasizing the potential of educational technology¹. In this report one of the priorities mentioned is improving education through better data analysis and foresight. As a concrete action, the Commission

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supports the launch of artificial intelligence and learning analytics pilots in education. Not only are governmental policies emphasizing the potential of cultivation learning data, philanthropic organizations 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.

**Personalized Learning Technology**

The next step in adopting big data approaches is the personalization 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 personalized learning include a broad range of explanations, which causes expectations to run high. To assess the desirability of personalization technology, it is important to map out what the technology can and cannot do and what “personal” means in this context.

Regarding information technology, personalization seems to be everywhere: personalized search results (Speretta & Gauch, 2005), personalized advertisements (Bilchev & Marston, 2003) and personalized website navigation (Graham, Bowerman & Bokma, 2004). Personalization can be defined as follows. “Whenever something is modified in its configuration or behaviour by information about the user, we consider it to be personalized” (Searby, 2003, p.1). Personalization has its roots in customization which is the modification of environments or objects to individual taste (Oulasvirta & Blom, 2007). Initial internet-enabled personalization was similar to customization: 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 personalization (Mulvenna, Anand & Buchner, 2000). With personalization-as-customizing, the personalization originates from the decisions and actions of the user itself. Predictive analytics aims to personalize content without requiring any action from the user.
Data-driven personalization can be a technological means to tailor education to individual students (Sampson & Karagiannidis, 2010). To some extent, it is the teacher’s role to ‘tailor’ the mass education to individuals, for example, to provide an extra explanation to students that 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 personalized learning technology: responsive and adaptive systems. A responsive learning system embodies a kind of personalization comparable to customization. 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 recognize 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 pre-determined 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 have shown a similar learning behaviour in the past were more likely to meet the learning goals if they were switching 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 data set of user data, Netflix’s algorithms offer a pre-selected choice of movies to the user, which the user is likely to enjoy. The user still makes an active decision whether to
follow-up on the recommendation or not; however, machine learning makes the process opaque and it is no longer self-explanatory why the system recommends something.

Responsive learning systems, whether based on pre-determined decision-trees or by using machine learning, are data-driven systems and 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 than 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 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 personalized 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 regard technology to play a role in personalizing 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.”

Knewton founder José Feirrera elaborates on his company’s philosophy in an interview with the website edtechreview.com. “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.”

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2 Knewton’s technical whitepaper
3 Interview with Knewton founder Jose Feirrera
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 personalized learning, it is rather changing the nature of teaching and learning. The system no longer assists the student or the teacher in the decision-making process but rather takes over power in 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 to be more like recommender systems (Waters, 2014), the desire of EdTech start-ups to move towards an adaptive form of education resounds. Thus, we will analyze the promises of adaptive learning in the next section.

**Educational implications of Personalized Learning Technologies**

As already pointed out in the introduction, personalized learning is not a new concept in educational theory. John Dewey (1916), for example, saw education not as an individualized 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 personalized 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, 1989). Intrinsic motivation is considered the most
desired form of motivation for predicting a human being's likeliness to engage in certain behaviours (Ryan & Deci, 2000). *Intrinsic* motivation is when behaviour originates from one's intrinsic desires to engage in it. Oppositely, *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 a student can self-determine or self-regulate his learning process, the student should also be able to reflect on why something is personally relevant. This enables the student to have a relationship with her own educational path, which is believed to increase educational outcomes and enhance the enjoyability of learning (Deci et al., 1991). Personalized learning from this perspective is about making education more ‘personal’ and giving students a voice in their own learning process. This understanding 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, and it is a process that requires different approaches to teaching (McCabe & O'Connor, 2014).

To pin-point the difference between the ideal of personalized learning (as rooted in Dewey's philosophy) and the current technology-driven approach, the original idea in personalized learning was to make room for the student to make education fit his personal needs, while the technological-driven visions aim at personalizing the learning process for the student. Adaptive systems, hence, come with the promise of offering tailor-made content based on the recorded and analyzed behaviour of the student but also with the risk of taking away the students' voice and ownership. The ideal of personalized learning is based on a dialogue between the teacher and the student to make her the co-author of 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 if such a system will show similar flexibility as teachers, a recommendation-based
approach still asks the student to take active choices. Adaptive systems, in contrast, will take the decisions for the student based on her past learning behaviour, which effectively undermines the students’ sense of ownership and the possibility of reflecting on her role in co-authoring the educational process.

Technology-driven learning sparks questions about which educational values are implemented in personalized learning technology. Technologies, such as adaptive learning systems, are not neutral. The tools we choose to use in education are shaping 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 understanding of teaching. To put it pointedly, if computer systems will take over educational decision-making, what are these systems optimizing for? Which educational values do they embody and whom will they benefit? Is the purpose to minimize drop-out rates, to improve the completion rates or grades, or perhaps to simply maximize profits (Slade & Prinsloo, 2013)? And how precisely will the students’ learning behaviour be analyzed 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 (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 good education ought to be like instead of what is technologically possible. In their effort they should be striving to be transparent, in 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
means. 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 personalized learning technology is that it is increasingly data-intensive, which sparks questions about surveillance and privacy. Personalization is done by collecting and analyzing 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 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 standardized 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 good and satisfied learners. Control can be a danger to motivation, as it is linked to extrinsic motivation rather than intrinsic. Keeping a degree of privacy where autonomy is safeguarded is a condition for the learning from intrinsic motivation. Delivering tailored education using data-driven methodologies presents a rat race for privacy risks. Personalization becomes more effective 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 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 cause a limitation in their experience of autonomy and freedom in the learning process.

**Conclusion**

Personalized 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 “personalized learning” as an educational ideal and “personalization” in a technical understanding. 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 choice and agency of student and teacher, bearing the risk of making education less personal by undermining the student’s sense of ownership.

What we have also argued is that personalized learning technology demands shifting 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 personalization on privacy can undermine educational aims and ideals. This constant tracking of students can cause a feeling of being looked at which, again, can lead to the experience of less autonomy. School administrations adopting technology should, therefore, always ask the proportionality question: does the infringement of privacy weigh up to the potential benefits of the technology for students?

To not 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 respecting educational values and the rights and freedoms of students, can bring a valuable change for schools. Schools and educational policy-making 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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