IT'S GETTING PERSONAL:

An assessment of the desirability of personalised learning technology in schools

Philosophy of Science, Technology and Society

Name	I.C Huis in 't Veld
Supervisor	Michael Nagenborg
Examiner	Philip Brey
Date	11-10-2016

UNIVERSITY OF TWENTE

SUMMARY

Personalised learning is an emerging paradigm of educational organisation that aims to move away from the “one size fits all” model where every student – even though everyone is different – receives education in the same form. The ideology of personalised learning stems from the desire to recognize individual differences in learning and advocates that students ought to be taking on more active roles in making their own educational choices, enabling them to become co-authors of their educational script. Even though personalised learning does not necessarily include the use of technology, the two are often inseparably linked. This thesis is an assessment of the desirability of personalised technology as a tool to achieve the ideals of the ideology of personalised learning.

When the black box of personalised learning technology is opened, it can be divulged that these systems vary in the extent to which they are responsive to students’ needs: from customisation, where the action of the user is required, to data-driven systems that automatically adapt the material to the predicted individual needs. Critique of artificial intelligence entails that rule-based algorithms cannot make the complex decisions that teachers can because computational systems lack contextual knowledge. Even though this might be the case, technology might still be an improvement compared to a teacher who does not have the capacity to anticipate needs of many students and provide them with tailored approaches. However, even though data-driven personalised learning systems might do a decent job at tailoring, the ideology of personalised learning argues for tailored education only in the sense that the student becomes the agent of its educational decision-making. When personalised learning systems are providing tailored education automatically, they no longer require the users’ action for the personalisation which undermines their autonomy. Personalised learning technology does not only risk failing to achieve its own educational ideal, the data-intensive form of monitoring student learning poses a threat to student privacy. This might have negative consequences of the students but also for the quality of learning itself.

When personalised learning technology will be implemented as a fix for the traditional model of education, policy-making and technology design should aim to avoid automatic personalisation since it undermines student autonomy and also strive to protect student privacy and student data according to the contextual information sharing norms.

PREFACE & ACKNOWLEDGEMENTS

When I first met my current employer, she explained to me that she was in the business of 'Privacy by Disaster'. What she meant with this – besides making a clever reference to the design philosophy of Privacy by Design - is that the topic of privacy is often addressed because it was already infringed and therefore too late. A 'Privacy by Disaster' was also my trigger to study technology, education and privacy. The company InBloom provided a cloud-based storage system for student data including names and ages, what students ordered for lunch, family conditions and learning disabilities. InBloom promised to analyse the data and make the results accessible to anyone with a legitimate educational interest to teach students more effectively. Soon they turned into the hottest company in the emerging field of personalised learning until, in April 2014, they announced their shut down because they were heavily critiqued by parents and schools for infringing student privacy by, amongst others, having a lack of security, sharing data with third parties and not requiring parental consent[1]. This exposed me the vulnerability of technological trends in educational setting and raised questions about personalised learning and why privacy matters for learning.

This master thesis brought together my favourite topics of ethics and technology and this marks the end of my time at the University of Twente. First of all, I want to thank my University supervisors Michael Nagenborg and Philip Brey, with whom I had the pleasure to work with, not only for the 8 months of thesis writing but also during my internship at the 3TU.Ethics prior to it. I want to express how much I enjoyed having Michael as my supervisor: every progress meeting gave me a rush of new energy and inspiration and he always knew exactly how to keep me motivated. I want to thank Philip for the flexibility and the (extra) time he devoted to being my examiner. Furthermore, I want to thank my colleagues at Eticas because they have all been a great support in helping me deal with working full-time and writing my thesis at the same time. In particular, I want to mention the inspiration Gemma gives me by sharing her passion and showing faith in me. I am grateful to have found a great place to work and the plans we have make me look forward to continuing my future in the field of ethics and technology. Finally, I want to thank my parents for supporting me in every way possible. Not only during my time at the University, but also for supporting me in all my passions and dreams throughout life. I am extremely happy to see that my thesis subject is a perfect mix of my dad, who is a technical engineer, and my mom, who teaches primary school children.

[1] http://www.bloomberg.com/news/articles/2014-05-01/inbloom-shuts-down-amid-privacy-fears-over-student-data-tracking

INHOUDSOPGAVE

1. INTRODUCTION

Imagine Lily and Mira, two 14-year-old girls in the same school and in the same class. They are in a maths class together and today's course is about the Pythagoras' theorem. The teacher just explained the principle in front of the class and the students are now using their books to work on the assignments that match the instructions. Lily, who is a mathematics superstar, has already finished all the assignments which she considered to be way too easy. Now she is sitting with her hand in the air to attract the teacher's attention to tell him that she would like to do some additional assignments. Unfortunately, the teacher is very busy trying to answer to everyone and does not seem to notice her. Lily decides to drop her hand and starts looking outside of the window feeling bored and unmotivated. On the other side of the classroom is Mira who has always had difficulties keeping up with the pace of the class when it comes to maths. She did not understand the theorem explained by the teacher and therefore she does not know where to start with the assignments in front of her. Unfortunately, the teacher does not seem to notice Mira's struggles. Mira is left confused, insecure and stressed about the situation.

1.1 Personalised learning

Lily and Mira's classroom is an example of the "traditional" classroom as we know it. The traditional "one size fits all" model of education is criticized for not having the capacity to respond to individual learning needs of students causing a decline in student motivation. The traditional model has its roots in educational essentialism which is the philosophical school of thought that beliefs that students should receive education in the "essentials" of academic knowledge in order to safeguard the accumulated wisdom of our civilization (Howick, 1971). In this sense, school has to have a fixed curriculum with fixed courses, for example reading, literature, history, science, mathematics, art and music, that are supposed to teach students the fundamentals to function in society. Learning has a linear form because starts from the basics and gets more complex along the way and all the students can receive this knowledge in a fixed pace based on age-based cohorts. The state determines the disciplines that have to be taught and the teacher has a central role education as he or she is the source of knowledge and is responsible for transferring it to the students.

In 1916, John Dewey published his influential work "*Democracy and Education*," in which he advocated placing the student, instead of the curriculum, at the centre of the classroom. He argued that not two students are the same, and the pedagogical practice of treating them as if they are causes a decline in motivation.

In educational psychology, motivation is understood to be a factor to determine the quality of the learning outcome as well as the enjoyment of learning (Pinch & de Groot, 1990; Vallerand, Gauvin & Halliwell, 1989). Theories of motivation distinguish between two types of motivation: intrinsic motivation and extrinsic motivation, where 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. In turn, extrinsic motivation is engaging in certain behaviour for external incentives rather than from intrinsic desire. When it comes to learning, extrinsic motivation can for example be studying with the goal to get a good grade, prize or to receive recognition from someone else. Intrinsic motivation is studying for your own sake, because you want to know more about what you are subject, without experiencing pressure from an outside source. According Ryan and Deci's (2000) self-determination theory point to the importance of self-determination, or autonomy, to determine the level of intrinsic motivation. Other influences of intrinsic motivation are relatedness and competence. The degree to which students feel related to others (for example the teacher) and the degree to which they consider themselves able to perform a task. In order to enhance student motivation pedagogical practice has to facilitate room for autonomy and choice in the learning process.

Dewey (1916) saw education not as an individualised process but rather as a social interaction between students and teachers. He believed that knowledge could not simply be given, but that a student must experience something and engage with it to learn. He argued that teachers should be guardians of high standards for students to learn the basics, yet create pathways that allow for the student to make his/her own choice. The role of the school should not be to impose fixed processes on students, but to guide students in their personal learning experience (Dewey, 1916). Teachers and students should work together in co-constructing education and to select curriculum content. These ideas, and other related authors that emphasized individual learning needs, gave rise to the ideology of personalised learning where the role of the student shifts from being a passive receivers of education to "active and responsible co-authors of their educational script" (Campbell, Robinson, Neelands, Hewston & Mazzoli, 2007, p.138).

1.2 Technology-enabled personalised learning

The educational paradigm of personalised learning advocates a re-thinking of the traditional model of education where the focus should shift from teacher-centred classroom to a studentcentred one where individual differences are recognised. Adapting teaching to individual competences, goals and needs has always been a component of teaching because the teachers use for example interpersonal cues and knowledge of the students to adjust their teaching style. However, as the scenario of Lily and Mira illustrates, it is highly challenging for teachers to facilitate everyone's personal learning path in a classroom with many students.

Personalisation technology is considered a cost-effective solution to accomplish a situation in which individual differences can be recognized and satisfied (Laurillard, 2007). The popularity of Massive Open Online courses (MOOCs), where everyone with access to the internet can participate in a course, shows how technology can enable students to learn what they personally regard as interesting in a self-directed way. While MOOCs are not institutionalised in the school as we know it, also within the school an effort is made to use technology in order to anticipate and adapt to personal learning preferences and styles. How does this work?

Imagine the same situation but this time Lily and Mira's school uses personalised learning technology. Lily and Mira are both working on their maths assignments on a computer or tablet with a personalised learning system that can follow every aspect of what they learn and how they do it. All the data is fed into a system that, based on this data and data of many more other students, is able to predict their individual learning needs and even adapt the learning materials to it to make the programme personally relevant. The system for example determines that Lily masters the concepts of today's class and automatically sends her additional assignments or let's her work on material for another course. This system detects that Mira has severe problems with understanding mathematical problems but recognizes that the problems are not with her mathematical skills but with reading comprehension, so instead of text, Mira learns the Pythagoras' theorem by watching videos and doing interactive assignments.

Governments and other funding sources see the potential of personalised learning and are investing high amounts of money in the development of personalised learning technology. For example, the European Union has invested €185 million for supporting technology-enhanced learning between 2007 and 2013[2] and the Bill and Melinda Gates Foundation invested 20 million dollars in the development education resources and innovative teaching approaches[3]. Recently, Facebook's CEO Mark Zuckerberg joined the movement by launching the Chan Zuckerberg Initiative, devoted to bring personalised learning to schools[4]. The pursuit of personalised learning drives a number of technological initiatives that use personalisation

[2] EU website technology-enhanced learning
[3] Gates Foundation website
[4] Mark Zuckerberg's Facebook announcement of the Chan Zuckerberg Initiative

methods and apply them to education (Siemens & Long, 2011). One company that offers a personalised learning platform is New-York based company Knewton. Knewton is a free adaptive platform that offers personalised lessons. The technical whitepaper on their website explains how they regard 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."*[5] Knewton founder José Feirrera elaborates on his company's philosophy in an interview with the website edtechreview[6]: *"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 exactly what kids know, and we know exactly how they learn it best. We can take the entire data base 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."*

1.3 Privacy implications

As becomes clear in the previous quote, personalisation requires the gathering of "so much data". Personalisation technology is often linked to privacy because personalisation is driven monitoring data about social behaviour, often including personal details (Riedl, 2001; Chellappa & Sin, 2005). The system that Lily and Mira are working on can monitor their proficiency level by assessing their performance, and in order to predict their needs it also tracks data that can contain clues on how they learn. For example, the system records how long it takes for them to read a page or answer a question. It detects key stroke patterns, time and location and records with whom they are working with. Data collection is thus not limited to proficiency assessments, learning styles or demographic information provided from the school records, but is increasingly extending to students' personal lives for example by including data from students' social media accounts (Singer, 2015). As these systems monitor and assess every step of the learning process, the room for privacy in the learning process decreases. What is the effect of this monitoring, or surveillance, of data that personalised learning technology brings to the school? In surveillance literature there tends to exist a negative understanding of surveillance focused on "the erosion of liberties" and describing society in terms of "dark and totalitarian forces" (Lianos, 2003, p.414). However, monitoring is an essential part in education because it is part of the role of the teacher to maintain class discipline and to be aware of a students' proficiency in order to adapt their approach to it. In order to determine the boundaries of legitimacy of surveillance in education, the phenomenon

[5] Knewton's technical whitepaper
[6] Interview with Knewton Founder Jose Feirrera

has to be assessed in the context of the changes personalised learning brings to the nature of student monitoring.

1.4 Problem statement

There seems to be a constant complaining about the sad state of education and the need to improve and innovate (Biesta, 2009). The promise of the potential of technology for education attracts school districts to invest in new gadgets, however, the decisions to do so are often rash, misplaced and misconceived (Salomon, 2016). The principle rationales for technology and education policies are often vague imaginaries of an ‘information age’ we should keep up with (Selwyn, Gorard & Williams, 2001). Personalised learning technology is seen as a promising and relatively cheap solution for the deficits of the “one size fits all” model of education. However, the black box of personalisation needs to be opened in order to assess how effective technology-enables personalisation can be in achieve the ideals of personalised learning. Not all problems yield to technology and determining which will and which will not should be central to policy-making (Sarewitz & Nelson, 2008). Also, the praise for personalised learning technology is focused on how promised improvements will benefit school systems, but there is a lack of understanding of the impact of personalisation technology on students and their learning process (Bulger, 2016). What are the legitimate boundaries of data-intensive surveillance to realise effective personalisation without harming the student and its learning process? If personalised 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 in order to see to what extend it can be responsibly implemented in the 21st century school. By opening the black box of technology and looking at what personalisation is in other context, this assessment will explain how personalisation works, what the impact is on privacy in this specific context and to what extent it can be effective in achieve the ideals of personalised learning. The answer is not binary, but will rather result in guidelines for maximising the benefits of technology and minimising the negative effects on student privacy.

1.5 Research question

This leads to the following research question and sub questions that will be answered in order to assess the desirability of personalised learning technology:

To what extent does technology-enabled personalised learning live up to its promise of enhancing student autonomy and what are the risks of an intensified monitoring of the learning process for student privacy?

- How is personalised learning technology situated in the current landscape of personalisation?
- To what extent can technology be an effective means to achieve the ideals personalised learning?
- What is the role of surveillance and privacy in education?
- To what extent is the impact personalised learning technology on student privacy desirable?
- How can the benefits of personalised learning technology be maximised while minimising the negative consequences?

1.6 Overview

Chapter two will focus the roots of personalisation technology and how effective personalisation technology can be in being responsive to student needs. Chapter three will answer the question to what extent personalisation technology is an effective fix of the perceived problems of the traditional model of education and achieve the educational ideals of personalised learning. In chapter four, the focus will be on the impact of personalised learning technology as data-intensive solution on surveillance in the school and the risks to poses privacy of students. Literature about the ethics of workplace surveillance will provide a starting point to look for the boundaries between legitimate and illegitimate monitoring. Chapter five will conclude all the findings in order to answer the question to what extent personalised learning technology can be a desirable direction for education and provide guidelines for the future of personalised learning.

2. PERSONALISATION AS TAILORING

Personalised learning technology, which has its roots in information technology, aims to be a tool to tailor education to individual learning needs (Sampson & Karagiannidis, 2010). In this chapter the black box of personalised learning technology will be opened by looking at the underlying processes that enable personalisation and by distinguishing between different levels of personalised learning in order to see what the spectrum of possibilities is and to what extend technology is able to tailor education to individual needs.

2.1 Personalisation technology

In times of 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 modified in its configuration or behaviour by information about the user, we consider it to be personalised” (Searby, 2003, p.1). Personalisation has its roots in customisation which is the modification of environments or objects to individual taste (Oulasvirta & Blom, 2007). For example, people customise their mobile phones by using a case they like or selecting a ringtone or background image that matches their preferences (Häkkilä & Chatfield, 2006). 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 (Mulvenna, Anand & Buchner, 2000).

Key to these more sophisticated personalisation approaches is the use of data about human behaviour in order to predict future behaviour. In today’s digital world we already create immense amounts of data. An IBM study states that every two days we create as much digital data as all the data (both digital and non-digital) that was created before 2003 (IBM, 2011). Not only data that was already collected is 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”). By means of using digital technology, people generate data about their use patterns. For example, click patterns, browser history or the device used to access are logged to serve as a basis for personalisation.

The availability accessibility of large and relatively cheap databases made it possible to work with large data sets, which is commonly referred to as *big data* (Cukier & Mayer-Schoenberger, 2013). Data about the past activity, together with past activity of many more others, is stored and processed in order to find structures in these large datasets. Big data sets cannot be processed by the tried-and-true methods and have forced us to look beyond these methods (Jacobs, 2009). The storing and analysing big data sets is called *data mining* (Hand, 2007, p.1). The underlying assumption of this approach is that data about what people did in the past include clues about what people will do in the future. If future desires can be predicted by finding patterns in data about past behaviour, information can be filtered and offered to the user without requiring the user to ask for it explicitly (Mulvenna et al., 2000).

2.2 The personalisation of everything

Big data is not only about the size of datasets, it embodies a new paradigm in how society processes information (Cukier et al., 2013). Big data thinking takes data as some kind of truth where decisions are made on which changes the way we think about the world (Van Dijck, 2014). Different domains of life have adapted the big data mind-set of using data as probability to base decision-making on. Take for example personalised marketing. Personalised marketing is the use of data in order to target advertisement to the right user. Not only does personalisation aim to identify target groups, but the content that someone is exposed to tailored to it. A web shop can for example aim to identify what a person is looking for based on search history or previous purchases and tailor the content of the website to offer a personal service and attract the client to make a purchase. An example outside information technology is personalised medicine where the goal is to tailor medical decision to the individual. Whole genome sequencing is the process of determining the complete DNA sequence of an organism and it is believed that this information can enable healthcare to 'tailor' medical advice and treatment to the individual (Burke & Psaty, 2007). It is believed that when medicine progresses, the whole genome can be linked to specific health care risks. For example, scientist found a relation between the BRCA mutation and an increased change of breast and ovarian cancer (Burke et al., 2007). Men and women that have the BRCA mutation can take into account to not take birth control as this effects their change of getting cancer, or individuals with this genetic mutation can take preventative surgical decisions to safeguard their health.

2.3 Personalised learning technology

Personalisation is also seen as a method to tailor education to needs of students. In traditional education, the teacher is for 'tailoring' the mass education to individuals to some extent, but this is a challenging task for the teacher because it takes time and effort to understand every student’s needs and provide unique responses to them. Data-driven personalisation can be a technological means do the tailoring for the teacher (Sampson & Karagiannidis, 2010). Descriptions and definitions of personalised learning include a broad range of explanations which causes expectations about its ability to revolutionise education to run high. Bulger (2016) distinguishes between five different types of personalised learning systems to provide a clearer idea of the spectrum of possibilities.

1. **Custom interfaces**

Custom interface allow students to adjust their online environment by modifying the interface in order to have them reflect personal taste. For example, students can choose an avatar to work with or apply their favourite colours. In this type of system personalisation is understood as customisation: the personalisation originates from the decisions and actions of the user itself.

2. **Learning management systems**

Learning management systems (LMS) are online platforms that automate a range of classroom management tasks like attendance, grades, homework records or communication. Moodle, Schoology and Blackboard are for example learning management systems. A student has its personal environment and teachers can provide information they regard suitable for the individual. For example, on Blackboard the teacher can assign homework to the entire class but also upload a grade for an individual student.

3. **Data-driven management systems**

Data management systems are management systems that aim to effectively determine a students’ proficiency level in order to provide recommendations for teaching. The determination of the proficiency level is based on data about what and how the student learns, but the purpose of the system is more to track and organise and inform the teacher than actively change content accordingly. For example, personalised tests can point to areas for individualised instructional focus, with or without actionable recommendations for the teacher. Data-driven systems are personalised in the sense that they recognize individual differences, the outcome is more of a recommendation than a decision. This is for example how Netflix works when it recommends a movie that might match your interests. Teachers and students remain the centre of decision-making.

4. **Adaptive learning**

Adaptive learning is data-driven learning that adapts the learning content according the prediction. In adaptive learning, computers are interactive teaching devices that orchestrate the allocation of content to the unique needs of each learner. These systems predict the needs of students from data and automate the decision-making about the next step by personalising the content for the individual. This resembles the example of Lily and Mira's personalised learning system which detected individual learning needs and automatically adapted the content accordingly.

5. Intelligent learning

Intelligent learning is currently more of a promise than a reality, takes personalisation another step further on the spectrum of possibilities. Intelligent learning is not focused on merely providing answers and modular guidance, but it is envisioned to inspire questions, interact conversationally and has enough options to move beyond a limited decision-tree. It extends past the realm of assistant and becomes a proactive learning guide. This type of personalisation is envisioned to become a reality when facial recognition software is developed enough to recognize and respond to emotions of students. Designers of intelligent tutoring systems hope that one day their systems will perform as well as – or possibly better – than a human tutor (Ainsworth & Fleming, 2006).

2.4 Tailoring needs

Different types of personalisation technology vary in the extent to which they can tailor to students' needs. Chadwick (2014) notes that personalisation is often explained with the analogy of tailoring. Within clothing, 'tailoring' entails a distinction between 'bespoke' and 'made to measure'. Whereas 'bespoke' clothes are created without the use of a pre-existing pattern, 'made to measure' alters a standard pattern to fit the customer.

In personalisation technology this difference also exists: mass personalisation and more individual forms of personalisation. In mass personalisation, the personalisation is not tailored to the individual, but rather to the group they belong to. The individual's behaviour is matched with a pre-determined classification of users, and the personalisation is tailored at one's 'profile' rather than at the specific individual. Individual personalisation aims to move away from profiling and filters content according to what is relevant for the specific individual, rather than for the group of people the individual is classified in. Bulger (2016) divides personalisation technology in a classification that highlights the different between made to measure and bespoke tailoring. Made to measure tailoring, which she refers to as *responsive systems* essentially offer an interface to pre-determined steps and content. Students are profiled and decision-making is tailored to the classification of students. These systems have pre-determined paths, were the next step is based on a decision-tree. More intelligent systems, *adaptive systems,* aim to mirror and guide the learning process, which is individual, unique and does not necessarily have a single end-goal.

Is data-driven personalisation of education as bespoke tailoring possible? Dreyfus (1979) is critical of the ability of computers to make these complex calculations. He argued that human problem solving is highly depended on the background sense of the context: in human problem solving, it is important to determine what is and relevant given the situation. Human intelligence and expertise depend primarily on unconscious instincts and Dreyfus (1979) argues that these unconscious skills can never be captured in formal rules that personalisation systems require. Computers rather make decisions on the process of searching through combinations of possibilities to find what we need. It is likely that a teacher cannot pick up on things that a teacher can take into account in their decisions. For example, imagine that the Pythagoras theorem class started on Monday and ends on Friday. During this week Lily, who usually does not experience problems with understanding math, severely fails to achieve good results. The platform she uses will not pick up on that this is due to the tragic event of her dog´s sudden passing. The teacher, however, knows Lily and can pick up on her body language or he/she might have spoken with Lily's parents about this. The teacher can put Lily's results in perspective where the system cannot.

Current technological options for personalisation cannot tailor education to the needs of students as 'bespoke', as they are rule-based and use pre-determined decision-trees. Intelligent learning, as Bulger (2016) describes, is envisioned to one day move away from a rule-based personalisation. Intelligent learning aims to move away from rules and pre-determined decision-trees by aiming for self-learning systems that are so smart that they can recognize contextual factors like human being can. Current studies are aiming to explore for example how emotion evolved during learning and how emotions can be detected by biometric sensors in order to improve the learning experience (Shen., Wang & Shen, 2009). These biometric sensors might be able to correlate Lily's sadness with her lack of understanding of the Pythagoras theorem. Developments like these could enhance the contextual understanding of learning and do a better job in tailoring but until then, tailoring in personalised learning technology can rather be understood as 'made to measure'.

2.5 Second-best

The meaning of 'personal' in the context of personalisation technology is 'to tailor' to one's needs. We have seen how personalisation methods use data in order to predict one's needs and how different personalised learning technologies vary in the extent to which they aim to predict student. Where responsive systems, like customisation or learning management, are environments where human beings do the actual tailoring themselves and the system allows the organisation of it. Adaptive systems are data-driven and use data in order to predict the needs of students. This results in data-driven systems where data analysis aims to predict the needs of the student and a recommendation for the educational decision-making can be tailored. Adaptive systems use data to automatically personalise the educational materials to the prediction. These systems are based on a rule-based system where students are classified in groups and content is personalised for the individual as a part of that group. Personalisation is therefore not for the specific individual like the term ‘personalised learning’ might suggest. Dreyfus (1991) illustrated the shortcomings of technology to truly understand needs because they lack a contextual understanding that the teacher has which a rule-based system lacks. Considering that the technological capacities of personalised learning systems cannot truly understand the learning process or tailor education to the individual needs of the students on the basis of data, should technology as a means to personalise be rejected? This would be a narrow conclusion, because even though a computer might currently not be able to do a better job in understanding students’ needs than a teacher, considering the problem of the teacher not being able to provide this for a class of many different students, personalisation technology can be considered a second best option. It might be desirable to keep the teacher in the loop to add the contextual understanding, but technology can be a supportive tool in tailoring education.

3. THE TECHNOLOGICAL FIX

In the previous chapter technology-enabled personalisation was regarded in its capacity to tailor education to individual needs, however, tailoring does not cover the ideology of personalised learning to the full extent. An important component of personalised learning is the idea that tailoring is valuable because the student has the autonomy to have a choice in what he or she regards personally relevant. Can personalised learning technology also fit this goal? In this chapter the legitimacy of personalised learning technology as a fix to this problem will be assessed using three rules for technological fixes as put forward by Sarewitz et al. (2008).

3.1 Technological fix

Personalisation is often mentioned in one breath with technology, however, it has a background in debates that do not necessarily imply the use of technology. In her analysis of the meaning of tailoring, Chadwick (2014) illustrates that it might be helpful to remember that there is a longer history to personalisation outside the use of technology. In health care, the history of personalisation includes the debate over that the patient should be treated *as a person* with beliefs and wishes and to respect this, patients' autonomy should be respected and they should have a choice and voice in their medical decisions. The ideology of personalised learning is also about treating students as a person and respecting their autonomy because it serves the purpose of enabling intrinsic motivation and therefore the quality of educational results.

Do methods of personalisation technology effectively fix the larger social problem of education? Schools are often attracted to implement technological innovations while these decisions can turn out rash, misplaced and misconceived (Salomon, 2016). The application of technology as a 'quick fix' is part of a broader societal trend, which Evgeny Morozov (2014) refers to as "technological solutionism". Morozov is critical of this tendency of modern society to turn to technology to solve problems, regardless of whether technology is able to solve more than just the symptoms of the problem. Part of the problem is the societal trust in technology, which is well established. In his book "to save everything, click here", Morozov (2014) criticizes the way society regards complex social problems as if they are definite, computable, transparent and self-evident processes that can be easily optimised by technology. Can technology-enabled personalisation be an effective fix for the larger problem of the mass educational system? The three rules of the technological fix can provide guidelines in making this assessment (Sarewitz et al., 2008). The following three rules will be applied to personalised learning technology, which will lead to a conclusion about its legitimacy to fix the larger problem of education:

1. The technology must largely embody the cause-effect relationship connecting problem to solution
2. The effects of the technological fix must be assessable using relatively unambiguous or uncontroversial criteria
3. Research and development is most likely to contribute decisively to solving a social problem when it focusses on improving a standardized technical core that already exists.

3.2 Cause-effect relationship of personalised learning

As described in the introduction, the ideology of personalised learning is about treating students as persons with their own beliefs and desires by allowing them to have autonomy in the learning process. Instead of being receivers of tailored education, they should be the co-constructors of their personal learning path. Autonomy is considered to be an important aspect because it is associated with the philosophical ideal of having the freedom to create a life that is experiences as meaningful and fulfilling (Dworkin, 1988). Educational psychology showed that it is not only philosophical ideal, it also has a positive effect on a student's intrinsic motivation (Deci et al., 1991). Intrinsic motivation to engage in certain behaviour is determined by autonomy, competence and relatedness. When a student is able to self-regulate learning, education will not only be matching to individual needs, the student is also able to reflect on why something is personally relevant. This enables the student to have a relationship with its own educational path, which is believed to increase educational outcomes and enhance the enjoyment of students to learn (Deci et al., 1991).

Does personalised learning technology allow for the control of students over their learning process? According to Oulasvirta et al. (2008) personalisation as customisation, where the user the agent of personalisation, can enhance autonomy, relatedness and competence. But can personalised learning systems that automatically adapt the educational content also enhance autonomy, relatedness and competence or do these systems fail to achieve their educational ideal? The question whether automated adaptation is likely to enhance control or not is part of a broader discussion. Brey (2006) asks the same question about control in ambient intelligence (AmI). He describes AmI as a new paradigm in information technology that envisions a future in which people will live in environments that recognize and respond to them in intelligent ways. Microprocessors and sensors are embedded in everyday objects and environments that track the users and aim to infer patterns from it which can be anticipated in the future. This creates environments that respond to user needs. Personalised learning technologies operate under the same philosophy: data about a students' learning behaviour is collected and analysed in order to make education more responsive to the individual students' needs. Proponents of AmI claim that it can help people to gain more control over the environment because it is more responsive to their needs, but paradoxically the control is gained by delegating it to technology (Brey, 2006). In personalised learning, the degree of control a student has is especially important since it determines the quality of learning. In adaptive personalised learning systems, the information is filtered before reaching the user, this is a silent process without actions of the user (Bozdag & Timmermans, 2001). This automatic process undermines the possibility of self-governance decreasing student autonomy which is problematic for the learning process because with the loss of control, the student loses sense of competence because he/she is not able to meta-reflect on why something is the next step for him/her. With this approach, the student nor the teacher is the source of personalisation but instead the system is the active agent of personalisation. As Deci, Vallerand, Pelletier and Ryan (1991) have argued, the lack of experience of autonomy, relatedness and competence decreases students' intrinsic motivation and therefore their results and enjoyment of learning.

Can personalised learning systems be effective in both being responsive to student needs as respecting their autonomy? Brey (2006) argues that this is very complicated: in order to enhance control, systems have to meet high criteria: they should be correct about the needs of users and they have to perform actions that can easily be modified or corrected by users. Making correct estimations of student needs by the use of rule-based systems is difficult. But even if intelligent learning becomes a reality, and student needs can be anticipated correctly, the algorithms become so complex that the inferences can no longer be accounted for: understanding and changing the pathway becomes impossible. The more intelligent the systems become, the better they will be in being responsive to student needs. However, these more intelligent systems will increasingly undermine student autonomy, as these complex algorithms do not allow for capacity for students or teachers to assess and influence the mechanisms that do the filtering (Bozdag et al., 2001). The aim to find optimized paths to student learning seems to necessarily be bound to erase choice options (Winne & Perry, 2000).

In order to assess whether personalised learning technology meets the first rule for technological fix, we need to answer whether personalised learning technology largely embodies the cause-effect relationship connecting problem to solution. From the analysis above, it follows that this cause-effect relationship is absent between personalised learning technology and the problem of realising the ideal of increasing student autonomy through personalisation, as it seems that personalised learning technology requires autonomy to be delegated to the technology which undermines the possibility of self-governance.

3.3 Assessment of the effects of personalised learning technology

Personalisation technology is enabled by complex algorithms that interpret data and connect consequences to these interpretations. Algorithms can be understood as pre-written step-by-step operations that a computer programme follows in the execution its tasks. In developing algorithms for personalisation, developers need to define “rules” for the system to follow. However, learning has a highly contextual character and therefore pedagogy is difficult, if not impossible, to describe in set-in-stone machine readable rules such as those that adaptive learning systems are looking for (Verpoorten, 2009). One example of a rule is that reading time is often taken as an indicator for reading comprehension even though there is a lack of prove for it and it is believed to be highly dependent on the learning style of the specific student (Bulger, 2016). Also, considering that algorithms are determining consequences for the next learning steps, they are not value-free (Introna & Nissenbaum; Kraemer, van Overveld & Peterson, 2011). Embedding values in these systems is problematic because there is no general consensus of what ‘good’ education is. Questions such as the following examples go unanswered: Is there an end-goal of learning and, if so, what could it be? Is the goal of education the mere transfer of knowledge or does it include the development of character through social interaction? Is school supposed to prepare students for future employment? When personalisation technology does rely on algorithms, which specific rules and values will be embedded in their design and how explicitly will this be communicated to the user of the system? These questions can become increasingly complex when the algorithms are developed by commercial companies that either are not adequately informed about educational theory or prioritise their own, commercial values in the development of personalisation systems.

Analogous to assess the first rule of technological fix, an answer needs to be provided to the question of whether the effects of the technological fix are assessable using relatively unambiguous or uncontroversial criteria. Even though no reasons were provided to assume that none of the effects of personalised learning technology can be assessed by relatively unambiguous or uncontroversial criteria, it is argued that there is a great amount of ambiguity and controversy with regard to the values, like ‘end-goals’, of learning. Subsequently, if the goal of personalised learning technology is to contribute to educational values like achieve end-goals, it is not possible to assess its successfulness in relatively unambiguous and uncontroversial criteria. In other words: If it is not known what personalised learning systems are optimising for, how can success be determined?

3.4 Solving the social problem

The last rule that Sawewitz et al. (2008) bring forward, which sounds more like a requirement, entails that research and development should be likely to contribute decisively to solving a social problem when it focusses on improving a standardized technical core that already exists. What is the larger social problem? Personalised learning is an answer to the problem of the deficits of the traditional educational model of mass education. Mass education is regarded to not contribute to quality learning so the larger social problem is the quality of educational organisation.

Sarewitz et al. (2008) argue that a technological solution is most effective when the scientific understanding is embodied into the technological solution. This embodiment should allow the technology to achieve the desired results without depending on the understanding of the users of the understanding that is embodied into technology. At first sight it seems clear that personalised learning technologies do indeed embody an understanding of pedagogical processes into the algorithms as they find patterns in student learning that can point to correlations that contribute to an understanding of how one learns.

However, Sarewitz et al. seem to presuppose that this ‘scientific understanding’ needs to be established as empirically adequate and uncontroversial. This presupposition, as shown both in this as well as the previous section, does not apply to the understanding that is currently being implemented in personalised learning technologies. Personalised learning technologies might build on an understanding of what factors correlate with enjoyment of learning the Pythagoras theorem, and they might be used to facilitate the teaching of the theorem. However, this ought to be done without understanding the inferences made and without knowledge of its rationale or effectiveness.

3.5 Legitimacy of the fix

This chapter contained an analyses of personalised learning technologies in their ability to provide a technological fix to the problems posed by mass education. This analysis illustrated that, following Sarewitz’s three criteria for technological fixes, because of a multitude of reasons, personalised learning technologies have the risk to not qualify as a legitimate fix.

The analysis has shown that there are a number of controversial values at stake. First of all the fact that the more complex and effective adaptive personalisation algorithms get, the less understandable and accountable the algorithms become. It has furthermore been shown that the values of what learning ought to be are ambiguous, which makes it hard to assess the desirability of personalised learning technologies in general.

Personalised learning is essentially about allowing space for the student to make choices about its learning pathways in order to make it individually relevant. Responsive forms of personalisation that are more in line with functionalities of customisation can be can be a fix to enlarging control and therefore competence and relatedness (Oulasvirta & Blom, 2008). However, automated adaptivity is a progressed form of technological possibilities for personalised learning, but it is not contributing to solving the problem of education and therefore adaptive learning technology cannot be considered a legitimate fix of the problem of current educational organisation.

4. PRIVACY IMPLICATIONS

While advocates have put forward arguments about the benefits of personalised learning systems for the organisation of education, the perspective of the impact on the students remains under addressed (Bulger, 2016). Many technologies developed or implemented to solve certain perceived problems, can create other problems in the process for example problems with regard to privacy. This chapter will assess surveillance and privacy in the context of education to explore the boundaries of the desirability of personalised learning technologies.

4.1 Surveillance and privacy

Lyon (2007) defined surveillance as “any focused attention to personal details for the purposes of influence, management, or control”. Surveillance thus extends past the realm of mere people-watching and involved a dimension of control. Surveillance can take physical shape, but surveillance practice has also been shaped by the possibilities of modern information technology (Marx, 2002). Information technology build on the generation and use of data about human behaviour. In today’s digital world we create immense amounts of data, which can be used to track human behaviour. This shifts the monitoring from the physical to the digital domain, which some refer to as dataveillance (Clark, 1988; van Dijck, 2014).

We easily relate monitoring, or surveillance, to the debate about Edward Snowden and his revelations of government surveillance programmes (Lyon, 2015). This framed debates about surveillance as activity that infringes human rights like the right to privacy. However, not all situations wherein surveillance plays a role are in essence unacceptable. The legitimacy of surveillance should be considered from the specific institutional context, and the fundamental importance of surveillance – for example in enhancing institutional efficiency - should be taken into account (Lianos, 2003). In other words: instead of a value-laden activity that is necessarily about control with negative intent or necessarily about harming human rights, surveillance can be understood as “a generic process characteristic of living systems with information borders” (Marx, 2015, p.734).

Surveillance is linked to privacy because the monitoring can involve personal details about the individuals involved. Privacy is a value of having private space free from outside interference and it is also a right, often framed as “the right to be let alone” (Warren & Brandeis, 1890). Because of the “new surveillance” that Marx (2002) describes, a type of “new privacy” came into existence: informational privacy. Privacy scholars have different ideas on when informational privacy is infringed. Some say privacy involves the control of undocumented information about oneself and that privacy risked when the individual is lacking the control (Parent, 1983; Boyd, 2010). Others hold that privacy relates more to who has access over the information about the individual (Tavani & Moor, 2001). Nissenbaum (2011) argues that when it comes to privacy, the distinction between offline and online does not benefit the understanding and the ability to find effective solutions because online life is thickly integrated with social life. Therefore, informational privacy should not be understood as fundamentally different phenomenon. Also, the term dataveillance implies it is significantly different from surveillance. If online privacy is thickly related to privacy outside the digital realm, privacy should not be regarded as information privacy and the term dataveillance does not do justice to understanding the social impact from the surveillance of data. What are the boundaries of legitimacy of surveillance? Nissenbaum (2004) understands online privacy as contextual integrity: the acceptability of information sharing is context-specific and the degree of privacy we are willing to sacrifice depends on whether the surveillance is in line with the norms we set for that specific context. So in order to determine whether surveillance is an infringement of privacy and to what extent that is desirable, the information sharing norms of the specific context can provide an answer. One might for example be comfortable with a doctor knowing about one's specific medical conditions and sharing them with a specialist in the hospital, but one might consider privacy to be infringed if this information is also shared with future employers.

4.2 Workplace surveillance

One context where control and management are essential is in the workplace where employers manage their employees. Surveillance is used as a management method and therefore monitoring and organisations often go hand in hand (Ball, 2010). Traditionally workplace surveillance was done by supervisors walking around the workplace to physically monitor employees. Nowadays, the workplace is increasingly filled with information technologies with surveillance capabilities like workflow management systems and e-mail and phone tapping enabling electronic monitoring. Ball (2010, p.93) describes three of reasons for monitoring employees: maintaining productivity and monitoring resources used by employees, to protect corporate interests and trade secrets and to protect the company from legal liabilities. Also the quality and productivity of work can be assessed through surveillance technologies, which is referred to as performance surveillance. Performance surveillance is defined as "the observation, examination, and or recording of employee work-related behaviours" (Stanton, 2000). Employee monitoring has obvious benefits for employers since it is a relatively easy way to be informed about the productivity of workers, but the consequences for employees can be as bad as losing one's job. Managers can also use to encourage employees by rewarding systems, which is used as the logical to legitimise its use of monitoring systems (Rosenblat & Kneese, 2014).

However, as Weckert (2004) argues, the experience of coercive control can have negative effects on the workers. For example, surveillance can create distrust and suspicion between employers and employees. Furthermore, the effects of surveillance in the workplace are linked to increased levels of stress, a limitation of individual creativity and a decrease in self-esteem (Oldham & Cummings, 1996; Weckert, 2004). Privacy, a space away from external control, grants the employee a level of autonomy where negative consequences can be prevented. As self-determination theory (Ryan et al., 2000) showed, a person is more likely to have high levels of intrinsic motivation when he or she experiences relatedness and competence, supported by autonomy. When an employee experiences the ability to self-determined action away from external control of the employer, he or she might deliver more creative work and enjoy the work more. So while performance monitoring seems like an effective monitoring method to manage employees, both the employees and the employers benefit from safeguarding privacy of the employer. Privacy boundaries are established when surveillance is described as coercive control, as benefiting the company and not the employee itself (Allen, Coopman, Hart & Walker, 2007). Finally, the information sharing norm of the workplace can to maintain a distinction between work and privacy. However, debates about the legitimate boundaries of surveillance are being negotiated in the context of a larger debate between what is 'public' and what is private. The boundaries of what constitutes a workplace are becoming increasingly blurred, especially since technology mediates much of our work content and communications both remotely and on at the workplace itself. Electronic monitoring can occur directly at work or as a function of employees' accessibility to employers through their devices outside the walls of the office.

4.3 Learning surveillance

Monitoring students in the school is not a new phenomenon (Monahan & Torres, 2009). 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 youngster to keep them save and correct their behaviour (Steeves & Owen, 2010). The monitoring of the learning process also is not a new phenomenon since the same is done when proficiency is determined by standardised assessments and examinations. 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. Like in workplace surveillance, the students' experience of monitoring is not without complications.

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 away from adult power and control to experience freedom. Students need their own spaces, physically, imaginatively and emotionally to become good and satisfied learnings. 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.

4.4 Technology, surveillance and learning

How does personalised learning technology shape surveillance and privacy in the school? Schooling is moving towards the 'more data is better' approach of technology initiatives (Bulger, 2016). Not only does the monitoring shift to the monitoring of data, the monitoring also gets intensified as aspects of learning that were not quantified before are now datafied. When everything is recorded, the surface of what can and will be assessed extends beyond assessment in fixed examination moments. The intensified monitoring of students might lead to lead to a similar situation as in workplace surveillance where the experience of control undermines autonomy and increases levels of stress, a limitation of individual creativity and a decrease in self-esteem. This can negative consequences for the quality of learning as autonomy is considered key for determining the quality and enjoyment of learning. The intensified surveillance, even though it is meant as a means to provide better education, can have negative consequences for the quality of learning.

Where without technology, a student could cover its notebook with his/her hands or decide to not tell their parents about their bad grades, with data-intensive monitoring everything is recorded and mistakes cannot go unnoticed anymore. But what can be considered legitmate surveillance in education and what extends beyond the boundaries of legitimacy? If Nissenbaum's (2004) understanding of privacy as contextual integrity is followed, the kind of privacy needed depends on the context the information flows to. One alarming change to the context is that where the school used to be the data controller of student data, but when services are outsourced to commercial companies, student data will end up in corporate hands. Depending on what their interests are in this data and whether this has consequences for the student, the legitimacy can be assessed. For example, when student data is compiled in 'learning profiles' and sold to future employers, one could argue the privacy of the student is infringed. Also, who has access to the data? In schools without data-intensive monitoring of students, the parents cannot have access to what their children are doing, if personalisation systems do allow for this functionality, one could argue contextual integrity is harmed. Finally, what are the boundaries of what can be monitored? While monitoring proficiency levels might be deemed to fit in the context of the school, monitoring social media profiles can be an infringement of privacy.

5. CONCLUSION

5.1 Conclusion

The traditional model of education maintains a “one size fits all” model that is criticised for lacking the ability to respond to individual learning differences. Personalisation technology promises to be a time-effective solution for achieving the goal of being responsive to personal preferences, skills and goals and tailor education to the individual. When the learning process is datafied and patterns in the data are found, personalised learning systems can predict students’ learning needs and serve as the basis of educational decision-making or the educational materials are automatically adapted. Even though, according Dreyfus (1991) computerised systems based on algorithms cannot have the full capacity of human decision-making and contextual understanding, personalisation can be responsive to the needs of students. The more data is collected the more accurate the tailoring can be. However, as Chadwick (2014) hinted with her exploration of historical debates about personalisation, the ideology of personalised learning is not only about receiving tailored education, an important factor in the treatment of students as persons with their own desires that should be given a voice. Personalised learning systems that allow for personal relevance by requesting action of the student can enhance both the control and the personal relevance of the material. However, data-driven adaptive learning platforms and the future ideal of intelligent tutors automatically adapt the learning materials to the needs of the students, undermining autonomy and therefore the intrinsic motivation of students to engage in learning. Another threat to student autonomy is posed by the intensification of the monitoring, or surveillance, of student progress. When every step of the learning process is recorded and students experience that everything they do is evaluated, they might experience their actions are being controlled and perform school work under extrinsic motivation. Students need privacy to feel like they can make mistakes and discover their creativity away from the control of others. The recording of data about the learning process is also challenging for data protection issues as a lack of protection will have negative consequences for the students. An answer to this question whether personalised learning technology is desirable for education cannot be binary since there are different types of personalisation. What are the boundaries of desirable implementation of personalised learning technology based on this assessment? Desirable technologies are technologies that can achieve the ideal of personalisation where the student has the control to follow his/her personal path of learning and do not risk privacy.

However, this assessment has showed that there are two controversial values at stake:

1. The better the prediction algorithms are, the less accountable these algorithms become. The rationale of these algorithmic decisions cannot easily be understood, let alone bring changes to them.
2. The better the prediction algorithms are, the more data is collected, the more students are exposed to privacy risks which undermines autonomy again.

The threshold is defined in the table below:

Table 1: personalised learning desirability threshold

Type	Ability to enhance control	Low level of privacy risk
1. Customisation	✓	✓
2. LMS	✓	✓
3. Data-driven	✓	✗
4. Adaptive learning	✗	✗
5. Intelligent tutor	✗	✗

Following from these criteria, customisation functions and learning management systems are desirable personalisation applications for education. Their use requires actions from the student and the teachers themselves and their lack of being data-driven safeguards them from high level privacy risks. However, their functions are limited in causing real change in how personal desires effectively acknowledged on a large scale. On the other side of the scale are adaptive learning and intelligent learning. This assessment illustrated that these personalisation types move beyond the purpose of respecting the component of autonomy in tailoring needs because they automatically make decisions about the learning path by providing tailored content. The most interesting question about desirability is then about data-driven applications that use data to predict student needs and provide recommendations about the tailoring. So instead of automatically adapting, data-driven applications still require human action for the actual decision-making. However, data-driven learning still suffers from the problem of value-laden of algorithms that are lacking transparency and effective data-driven recommendations require the monitoring of data about the student learning process. Should data-driven personalisation be rejected? No necessarily. Data-driven education might have some implications in its effectiveness, but it can be considered better than mass education where individual differences receive very little consideration.

The aim of this assessment was to provide an answer to the following question: to what extent does technology-enabled personalised learning live up to its promise of enhancing student autonomy and what are the risks of an intensified monitoring of the learning process for student privacy? In providing an answer to this question, this thesis has shown that technological possibilities of information technologies have shaped the meaning of personalisation into tailoring. The distinction of tailoring as made to measure and bespoke also applies to personalisation: current personalisation technologies are not able to bring bespoke personalisation for the individual, but personalisation should rather be seen as made to measure where personalisation is based on one's classification to a group. However, as Chadwick (2014) noted, personalisation has its origins in debates prior to technology, for example, personalisation in the sense of to treat one as a person. Considering that the ideology of personalised learning is built on the idea that students should be co-authors of their own educational script, 'personal' in personalisation is not necessarily about tailoring, but rather about providing the student autonomy. When personalisation methods are applied to education, they risk to undermine student autonomy by automating decision-making to the predicted needs. Besides, what is needed for personalisation is a data-intensive monitoring of how students learn. Monitoring is not a new phenomenon in education, it is also an essential component of teaching, but the recording of every step in the learning process poses a threat to student privacy. Following Nissenbaum's (2011) account of privacy, student privacy is infringed when the technological monitoring invades the information sharing norms we regard important. Approaching a responsible future of technology-enabled personalisation, policy-makers and technology designers should take into account the importance of student autonomy and privacy as determining factors of quality education.

5.2 Recommendations

How can data-driven systems be implemented maintaining their benefits, while minimising their risks to privacy? This paragraph will entail an exploration of recommendations to achieve a responsible implementation of data-driven learning.

Policy recommendations

First of all, policy-makers should avoid personalised learning systems that automatically adapt education since this undermines both the autonomy of the users as the capacity of the teacher to understand the personalisation decision. Even though personalisation technology does not allow for tailoring purely to the individual, it can support the teacher in helping to make their decision. Technologies should not replace teachers because their contextual knowledge is desirable in the organisation of education, but personalisation technologies can rather serve as a supporting tool. When data-driven personalisation technologies are adopted to support educational decision-making, teacher should be able to understand the recommendations to act upon them. Therefor it will be highly recommended to train teachers in how these systems work and how they can interpret the data.

Furthermore, to ensure the protection of student data, the schools should aim to be the data controller in order to safeguard fair use. This could keep commercial interest out the door and could enhance the trust people have in technology-enabled learning. Hospitals work like this in the sense that they own electronic health records. When the school is the data-controller, they should implement data management policies that match the contextual norm and protect privacy where desired. School data management policy could include privacy-enhancing principles like parental consent, sharing policies and deletion protocols.

Design recommendations

Value Sensitive Design (Van der Hoven, 2009) is a design philosophy that advocates thinking, in an early stage of the development process or application of new technology or infrastructure, about relevant social and moral values and the integration of those in the project. Value sensitive design requires looking beyond technological possibilities and embed contextual norms by default. These contextual norms would include the dimension of control and transparency and the protection of privacy. Even though data protection cannot cover the the impact of “cradle to grave” surveillance on the development of young people (Steeves, 2006), data protection can also be protected by the design, avoiding many of the consequences that have to be faced if privacy decisions had to be taken by the individual response agent. Focus should be on identifying the ways in which students’ personal information is collected and evaluating regulatory responses in design that incorporate fair information practices (Lewandowski, 2003). This can for example include anonymization, data minimization and opt-in mechanisms.

5.3 Discussion

The previous recommendations for a responsible future of technology-enabled education are rooted in a theoretical analysis of desirability, however the actual design decisions are made by the technology designers. The developers of personalisation services are most of the time commercial companies that have financial interests in offering their services. However, they will not directly benefit from protecting privacy, as data is what they need to optimise their products of services. Change has to come from legislation or resistance from the education community. Personalised learning companies must understand that doing the right thing for students and for learning, but also from a financial perspective as teacher acceptance, and therefore use, will increase when the contextual norms are met (Verpoorten, 2009). Finally, in this assessment the ideology of personalised learning was tested with the technological possibilities to determine whether the technology can live up to their promises and how desirable the implementation would be. However, the desirability of personalised learning as an ideology itself was not the purpose of this thesis considering, there might be alternative educational theories or technological applications that provide solutions for mass education's deficits.

Further research

This assessment only contained the pre-conditions for desirability of the system but a complete desirability analysis should also include other components. One direction for future research could be a study of the *state-of-the-art*. There are relatively few examples known of adaptive educational systems in practical use (Verpoorten & Logan, 2006). What kind of personalised learning applications are currently being used in schools and how is it implemented in the curriculum? Are they used as supportive tools or as active decision-makers? The state-of-the art also includes current data management policies in schools. How sensitive are school managements for student privacy and how are they doing with regards to data protection? This desirability analysis was a high-level approach of the question that assessed the ethical conditions of the situation. What the legitimate boundaries of surveillance are can also have an answer from the stakeholders themselves. The factor of *acceptability* can be taken into account by engaging in conversations with stakeholders. Further research could for example study the experiences of students. McCahill and Finn (2010), for example, conducted interviews with children to see what their experience was of being monitored in the school and they found that experiences of surveillance differed accordingly to socio-economic status. The research was about CCTV cameras and not specifically about the learning process, but it is a reminder that surveillance is a social experience and differences in experiences should be taken into account. Another important factor in the implementation of personalised learning technology is the acceptance of teachers. Baker (2000) hints at that personalised learning technology might face an acceptability problem with teachers as working with these systems requires the complex understanding of software. Also, adaptive learning poses a threat to their jobs because some envision personalised learning technology to replace teachers. It could be interesting to see what the social impact of the datafication of education on the privacy of teachers is. What are the risks of intensified surveillance of the teachers? Finally, the stakes of companies offering personalisation services could be researched to see to what extent they conflict with other stakeholders' values.

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