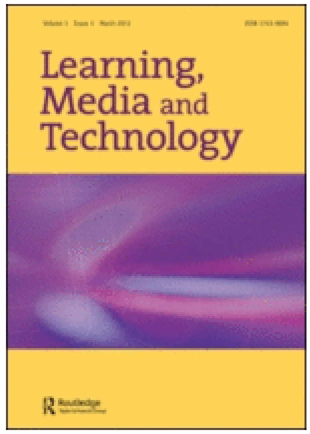

AI in Education: learner choice and fundamental rights

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Abstract

This article examines benefits and risks of Artificial Intelligence (AI) in education in relation to fundamental human rights. The article is based on an EU scoping study (Anonymous, 2017). The study takes into account ~~both~~ the potential for AI and 'Big Data' ~~big data~~ to provide more effective monitoring of the education system in real-time, but also considers the implications for fundamental human rights and freedoms of both teachers and learners. The analysis highlights a need to balance the benefits and risks as AI tools are developed, marketed and deployed. We conclude with a call to embed consideration of the benefits and risks of AI in education as technology tools into the development, marketing and deployment of these tools. There are questions around who - which body or organisation - should take responsibility for regulating AI in education, particularly since AI impacts not only data protection and privacy, but on fundamental rights in general. Given AI's global impact, it should be regulated at a trans-national level, with a global organisation such as the UN taking on this role.

Keywords: Artificial Intelligence; Big Data; Predictive analytics; Data protection; Fundamental rights, Education.

1 Introduction

"Artificial Intelligence" (AI) applied to the ~~increasing~~ proliferation of real-time data (Big Data~~big data~~) is ~~being~~ promoted as a way to~~–~~ improve education~~al systems~~ in ways that offer ~~learners experiences that are~~ more personalised, flexible, inclusive and engaging learning (UNESCO, 2017). To realise these benefits, governments, education sectors and technology organisations have been exploring ~~ways to introduce~~the introduction of AI ~~to provide~~ tools~~–~~ and platforms ~~in learning and~~ to ~~help~~ deliver educational system monitoring that is~~–~~ more ~~is more~~ efficient (with less administrative burden) and effective (~~more~~ with timely, accurate, and informative indicators) than in contemporary education~~al systems~~.

AI ~~can be~~is defined as "*the ability of a digital computer or computer-controlled robot to perform tasks commonly associated with intelligent beings*"[1]. ~~Within this broad area m~~Much of the current attention is on machine learning and data mining; techniques that use a range of statistical-analytic (algorithmic) methods to harvest, structure and analyse computationally large data sets to reveal patterns, trends, and associations and to derive predictions from these. ~~The~~ A system is considered 'intelligent' ~~because~~ when it 'learns' from the data it is fed[2]. In theory, n~~N~~ew data – if ~~truly~~ representative of what they are intended to represent - enable the system ~~(in theory)~~ to make more informed decisions about new, individual cases.

AI scientists have been ~~building~~ adapting ~~on techniques of~~ machine learning, computer modelling and statistics techniques used in the business sector to improve decision making in educational systems (Nistor et al, 201~~6~~5: HEC Report, 2016). ~~In education, t~~The patterns, trends, and associations identified by AI in educational systems tend to relate to complex human behaviour and interactions. These AI ~~systems~~ systems ~~used in education use~~capitalise on a range of modelling techniques~~approaches~~, such as 'early alert systems' that use predictive models to forecast the likelihood of a learner falling behind or dropping out of a course; 'visualisation systems' that illustrate learner progress in relation to pre-determined learning pathways; 'recommender systems' that endorse resources, people or future actions of the learner; and 'adaptive systems' that personalise content, presentation, recommendations and other design elements (Siemens & Long, 2011; Wolff et al, 2013; Nistor et al, 2016; Papamitsiou & Economides, 2014). Many of these systems have ~~also~~ been subsumed under the term "learning analytics", ~~defined by a key professional association as~~which represents "the measurement, collection, analysis and

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[1] https://www.britannica.com/technology/artificial-intelligence

[2] https://www.britannica.com/technology/machine-learning

reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs", with "analytics" referring to "~~e.g.~~ statistics, visualization, computer/data sciences, artificial intelligence"[3]. To emphasize the ~~manifold~~numerous connections to other fields in which AI is being deployed, and to ~~also~~ encompass AI systems that go beyond data and analytics, we will refer to 'uses of AI in education' and similar terms throughout this paper.

Many AI systems in education use data about the choices and behaviour of previous learners to support and enhance learning in a number of ways~~. For example, by~~: providing Intelligent Tutoring (~~see for example~~cf. Roll, Russell, & Gašević, 2018; Chou, Chan, & Lin, 2003); ~~to~~ predicting each student's grades, allowing the system to propose remedial action; ~~to~~ introduc~~e~~ing new forms of assessment (~~for example see~~e.g., ~~the~~ International Journal of Artificial Intelligence in Education, 28(1), 2018); or ~~to~~ linking academic performance predictions with university openings or job applications (Anonymous, 2017).

~~Although p~~Predictive systems offer benefits, ~~such as~~ alerting tutors about ~~which~~ students ~~are~~ 'at risk' of falling behind~~,~~. However, there are a number of ~~issues~~ drawbacks associated with the use of these systems. First, there are risks of amplifying the 'status quo' in education (West, 2017).~~–~~ Algorithms may be designed to conform to existing processes and to be trained on data ~~collected to address existing processes~~that includes existing biases (Custer et al, 2018).~~–~~ ~~Not only does the implementation of data-based~~Thus the use of these~~–~~ systems ~~make it more difficult to change educational approaches, but~~ amplifies existing prejudices, such as gender or ethnicity biases, making it more difficult to change educational approaches and systems~~may be amplified within the system~~.

Second, ~~although~~ using ~~new~~ tools continually ~~are promoted as being~~to ~~useful for~~ monitoring individual students~~, this form of observation~~ can ~~also amount to, or~~ grow into ~~,~~ aggressive tracking~~–~~ and potentially can be used for more sinister applications, such as state monitoring of citizens (Sellgren, 2018; Jack, 2018). ~~Although intensive surveillance has been used to identify 'cheating' behaviour, the technique potentially can be used for more sinister applications, such as state monitoring of citizens.~~

Third, AI systems can ~~be allowed to~~(inadvertently) exert influence and control through making decisions that have serious and ill-considered risks and drawbacks associated with them. For example, linking academic performance predictions with university or job applications will likely have a serious impact on an individual's future choices (Anonymous, 2017).

[3] https://www.solaresearch.org/about/what-is-learning-analytics/

These ~~sorts of~~ risks of AI in education are not always apparent because they are unseen, ~~may not be inherent in the technology itself, but sometimes arise as~~ unintended or unanticipated consequences of the use of AI systems in education (Pringle, Michael, & Michael, 2016). ~~Nevertheless, these wider risks are not always taken into consideration. Over the past few years there have been~~These issues are highlighted through a growing number of studies of the legal and ethical issues associated with embedding ~~the introduction of~~ AI systems in education (Prinsloo & Slade, 2016~~; Prinsloo & Slade~~, 2017). However, there have been ~~Yet, there are~~ few analyses of the ~~likely~~ impact of AI in education on individual freedoms and fundamental rights.

There are significant human rights concerns associated with the use of systems that gather large amounts of personal data about learners.[4] Large-scale collection and analysis of personal data are of concern to human-rights advocates, who ~~have called and~~ continue to call for strong(er) data protection legislation and implementation (~~see for example~~e.g., Watters, 2018, Williamson, 2015). Thus, the benefits of AI have to be considered alongside a proper assessment, critique and questioning ~~around~~ of ~~the risks. In particular it is important to question why AI systems are being used in education and~~ who~~se~~ are the beneficiaries whose goals are being met~~,~~ , whether educators, students, parents, policy makers or technology companies~~, all of whom potentially benefit from AI~~.~~-~~ ~~It is also important to consider the impact of the use of AI systems on fundamental rights and whether there are better alternatives.[5]~~

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[4] For our argument, the following three terms can and are used mostly interchangeably: *human rights* in the sense of the Universal Declaration of Human Rights, *fundamental rights* as legally protected human rights, in particular the *freedoms* such as privacy, protection of personal data, expression and education (see Charter of Fundamental Rights of the European Union).

~~[5] We use *human rights* in the sense of the individual rights affirmed by the Universal Declaration of Human Rights. The UDHR Declaration or its parts are not legally binding in themselves. They have however been influenced by, and have strongly influenced, many legally binding affirmations, including national Constitutions and the Charter of Fundamental Rights of the European Union. The term *Fundamental rights* is used, especially in Europe, to thus denote (human) rights thus protected by constitutions or the law. Most fundamental rights, including those to privacy and the protection of personal data, are also referred to as *freedoms* in this Charter, and thus the EU law GDPR refers to "fundamental rights and freedoms". In other contexts, "fundamental human rights" is used to denote the same concept. While we argue with specific references to the GDPR, the rights~~

Some scholars have argued that the ~~rise~~ main beneficiaries of AI in education ~~has been fuelled by~~are the so-called 'Tech Giants' - global technology companies such as Facebook, Google and Microsoft ~~– primarily for their own benefit~~ (Watters, 2018). These companies have been proposing and offering practical "AI solutions" that are infiltrating education systems globally. Industry initiatives ~~include~~ such as Facebook for Education (https://www.facebook.com/education), Google for Education (https://edu.google.com) and Microsoft education (https://www.microsoft.com/en-gb/education) have led to a 'creeping surveillance' embedded within education sectors. ~~The degree to which the systems these companies produce are implemented and used within education sectors in different countries depends on the national perspective and needs of each country. Governments that need to rapidly scale up educational opportunities, such as China, Kenya and Liberia, view technological systems as a way to support learning at scale. However, the way technologies are implemented within educational systems varies widely. On the one hand countries like China retain some control of how systems are used, for example by restricting the use of search technologies. On the other hand, countries such as Kenya and Liberia allow for-profit companies to integrate systems into their education systems in a (relatively) unrestricted way (Tyre, 2017). These government policy choices sit on a continuum from state jurisdiction to private enterprise. These choices often are positioned as education technology alternatives, which makes it difficult for students to appreciate the potential consequences of their decision to learn using a particular system. This leads to a power imbalance between citizens and those who control and process the data about them, whether governments or 'Tech' companies.~~

To ~~reduce this power imbalance~~make sure use of learners' personal data provides benefits for the learners, themselves some governments and supra-national entities (such as the European Union, EU) have ~~tried to~~ ma~~ke~~de explicit political choices in favour of protecting individual rights. One notable example is the EU General Data Protection Regulation (GDPR), one of the most ambitious and far-reaching attempts to regulate the use of Big Data, which came into effect as law across all EU countries in May 2018. The GDPR is based on the principle that all individuals should have control over how their personal data is used across different contexts, including AI-based decision making. Although GDPR focuses on data protection and privacy rights, its explicit purpose is to protect the fundamental rights and freedoms that underpin democracy. Thus, the GDPR is an important part of the narrative around examination of the risks to citizens associated with the use of AI.

~~we refer to, and the data protection principles designed to protect them, exist in similar form in many other jurisdictions. We therefore use all three terms.~~

This article considers the benefits and risks to citizens afforded by the use of AI in education systems. Its contribution is that of a critical review of empirical and theoretical literature, informed by our scholarly and professional expertise in educational technology and policy, AI, and data protection and privacy. The article is structured as follows: in Section 2 we examine the benefits and risks citizens face associated with the use of AI in education, by interrogating the choices learners may have about the use of their data. In Section 3, we describe how the risks identified in Section 2 are reflected in the GDPR framework, how these risks might be addressed, and what challenges remain. ~~We conclude i~~In Section 4 ~~by~~ we make ~~recommending~~ recommendations on how governments might protect their citizens against issues associated with the use of AI in education.

2 The Paradox: learner choice

Education systems face a paradox. In formal education systems, such as schools~~, colleges and universities~~,[6] participation is compulsory. Even in colleges and universities, learners have to participate in ~~specific~~ learning activities and assessments that are considered (by teachers) to be beneficial for ~~learners~~them. Paradoxically, obligatory participation ~~in exercises~~ may be viewed as a ~~restricting~~ reduction of fundamental human rights, including the right to exercise autonomy and to make choices~~, which is a fundamental human right~~. This paradox comes into sharp focus where ~~Similarly, learner compulsory participation by~~ learners have to participate in in activities and assessments where their data ~~gathering~~ is gathered. Even in situations where data gathering could be beneficial for learners, if the choice is not made freely and in an informed way, it may restrict the learner's autonomy, choice and fundamental human rights. Learners could be given the right to opt out of data collection. However, ~~within AI educational systems~~ largescale data gathering may be regarded as critical for good data quality which may offer learner benefits~~,~~. Therefore, consideration of how to ~~which , on the one hand, is beneficial for learners, but, on the other hand, restricts autonomy, choice and fundamental human rights. Understanding how to~~ balance ~~these~~ fundamental human rights with data quality ~~requires a careful consideration~~and potential benefits for the learner is vital. This section presents a number of case examples of the use of AI in education and interrogates ~~the impact of~~ autonomy, choice and the ability to 'opt out' of data collection ~~on~~ as a fundamental human right.

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[6] E~~Of course, e~~ducation is not ~~a~~ monolithic ~~whole,~~ and children have ~~particular~~specific needs and rights (e.g., Livingstone & O'Neill, 2014; Lupton & Williamson, 2017; Anonymous, 2017). However, ~~here~~ we focus on issues and arguments that hold across different ages and educational contexts.

2.1 The ability to 'opt out'

Learners may wish to opt out of data collection (or not 'opt in') for ~~very different~~diverse reasons, including political objections to surveillance~~ or religious motives~~. However, students who are below the legal age of adulthood are (in many countries) not able to legally 'opt in' or 'out' of monitoring. These decisions usually are made on their behalf by parents or legal guardians who may not be aware of the implications of their choices.

The choice to opt in or out of data collection influences data quality~~: d~~. Data gathered may be biased ~~since these data could~~by over- or under-representing specific groups of learners. This problem is difficult to resolve, because it may not be obvious which groups are mis-represented ~~not~~ and ~~how~~ in what ways the representation of these groups is inaccurate. If datasets are non-representative and biased, the conclusions drawn from data analysis are not reliable. Analysis of these data may accentuate disadvantage by leading to conclusions that ~~disadvantage and~~ discriminate against under-represented ~~types of~~ learners (~~for example~~~~see, for example,~~cf. the relationships between Big Data~~big data~~, representation, and discrimination ~~are~~ discussed by Barocas and Selbst, 2016). ~~Therefore, o~~~~On the one hand it~~It is important that learners can 'opt out' of having their data collected, but the act of 'opting out' may ~~paradoxically~~ skew data representation, accentuating disadvantage.

One example of a system that allows students to opt in or out of data monitoring is *OU Analyse*, an AI system developed by The Open University (UK) to provide early prediction of 'at-risk' students (Kuzilek et al, 2015). If the student agrees to have their data collected, the system gathers demographic data, including age, gender, place of residence and prior qualifications, and combines these with observed activity within the university's Virtual Learning Environment (Moodle). Each individual's data is analysed in relation to data from prior cohorts of students to predict the likelihood of passing the next assessment. These predictions are visualised as a course overview dashboard where the tutor who will mark the assessment can view the progress of each student using a 'traffic light' system. The system uses the data to make a decision whether remedial action is needed and recommends to the learner what to study next. While this type of system can be useful in helping a student progress, the use of the system raises fundamental questions such as: ~~can the system be manipulated; what is the main rationale behind introducing~~who does the system benefit (the student or the organisation)? Is it intended to support learning or to enable the organisation to gain more revenue income? Can the data gathered be used to influence what type of staff are hired? D~~; d~~oes the system, which is based on the idea of regular, traditional assessment, ~~enhance or~~ impede innovation~~;~~? Does the system benefit the learners or systems designers who create the analytics to diagnose learning outcomes?

Can the system be manipulated?~~can the data gathered be used to influence what type of staff are hired?~~

Systems that focus on supporting students to pass an assessment can be manipulated for all kinds of reasons. For example, the system may make sure students achieve the grades they need to ensure sufficient income stream for the organisation; tutors might focus on preparing students for the exams, rather than on learning specific concepts. There is evidence (Daly et al, 2012) that this already happens in some UK schools in more advantaged areas, where teachers ~~may~~ sometimes focus on preparing pupils for university entrance exams, rather than on the broader goal of learning, a strategy sometimes termed 'teaching to the test'.

'Gaming the system' is not a new strategy in educational organisations.~~–~~ There is evidence that educational testing systems have be based on inherent bias. Advantaged students tend to have access to greater support to improve their grades, which means that grades are not a measure of ability, but a measure of what students have achieved with a high degree of supports they have access to.~~–~~ If improvement is rewarded, there is an incentive to downplay performance in the first measurement (Hargreaves and Shirley, 2009). These action-related inequities may exacerbate unfairness in educational testing, and this has been the subject of descriptive and remedial research for fifty years (Mitchell & Hutchinson, 2019).

Goodhart's Law states: "*When a measure becomes a target, it ceases to be a good measure*", and this general observation applies in educational settings as much as in the business field where it was conceptualised. The temptation ~~with Big Data~~ is to try to counter this phenomenon by measuring more, which creates a self-reinforcing dynamic of surveillance (Wright and Kreis, 2014, p.191). Systems that invite 'gaming' behaviour, where people to act in ways that they believe will offer them benefits, rather than behaving naturally, affects data quality. Poor quality data will negatively impact equity, which, in turn, may lead to ~~unwanted~~ unwarraented surveillance of 'poorly performing' students. Surveillance is ~~one of the key~~a major problem~~s~~ of large-scale data collection and analysis, and data protection laws ~~therefore~~ aim at ~~limiting~~ eliminating unnecessary data collection and processing.

Predictive modelling systems were originally developed to help companies with financial planning. ~~While these systems can be used to inform students about their likely progress, educational organisations also benefit.~~ Th~~is~~ese origins ~~nexus~~ raise~~s~~ fundamental questions about ~~t~~who benefits from the~~he~~ use of ~~these~~ AI systems in educations: learners, teachers, parents, institutions or the technical companies that create the systems. ~~One question is whether a teacher will be influenced by the data analysis received from the system. A teacher could unconsciously be biased by the data received from the system.~~

~~Another~~ There are question ~~is~~ around whether the data is used to alert education administrators a to potential reduction in the number of students who progress to the next stage, which could lead to a loss of ~~income~~ revenue for the organisation. ~~The more students progress through a course, the greater the income.~~

~~However, t~~To make accurate financial projections, it is also important for the organisation to predict the level ~~of~~ resources ~~they need~~needed to support each student. These data help organisations predict how many students ~~they~~ will progress, forecast their likely fee income and predict outlay costs for student support. In the future these data could be used to hire ~~and fire~~ teaching~~-~~ staff on a casual basis, depending on the numbers of students predicted for each cohort and the likely level of support they need. ~~To the best of our knowledge, there is currently no published evidence that predictive modelling is being used to regulate staff recruitment in education or that it biases tutor judgement.~~, ~~Hhowever~~Therefore, the introduction of ~~these~~ AI systems bring closer a consideration of economic concerns associated with the cost of education, the conditions under which teaching staff are employed and the ways students are supported.

~~There is a further problem in that, r~~Rather than supporting innovation, the use of AI systems can (inadvertently) reproduce and magnify traditional approaches to education. Algorithms that analyse and convert unstructured, institutional data into ~~meaningful~~ 'insights'~~,~~ are trained on ~~the basis of~~ near, real-time data~~, which may not be in a form needed to evidence learning progress. These underlying algorithms tend to be designed~~ used to support traditional approaches to teaching and learning, where students are guided through a sequential set of content, then engage in an assessment to mark the progress to the next stage (Knight et al, 2013).~~-~~ These data may not be in a form needed to evidence learning progress.

~~Yet, i~~There is general agreement~~t is widely agreed~~ that traditional assessment is not an effective means of measuring learning and ~~does not give a good indication of whether a student is learnin~~progress~~g~~ (Brown & Knight, 2012), yet assessment data are used ~~. The reliance of teachers on~~in many predictive analytics systems. This arguably makes it more difficult for schools, colleges and universities to change assessment models to more authentic and reliable forms of assessment (Hood & Littlejohn, 2018). This problem becomes even more acute where AI systems do not allow students to 'opt out' of data collection.~~.~~

2.2 Systems with limited 'opt out'

A number of systems are being trialled in schools to monitor children's progress through continual surveillance and data gathering. A system trialled in schools in China used robots located in ~~the~~ classrooms and data chips embedded in each child's uniform to gather facial recognition and locational data and analyse these to monitor engagement and interaction (Shelton & Xiao, 2018). ~~The system records each instance of the student being distracted or checking their mobile phone.~~ The parent ~~has~~ is given the option to opt out the monitoring on behalf of the child. However, as there is strong social pressure not to opt out~~. P~~, parents may ~~give~~ consent. Parents may ~~because they~~ believe it is in their child's best interest to focus at school and trust that ~~the~~ data ~~shared can~~will be used by the government to help improve education.

~~A similar~~Another system trialled in China deployed headsets to detect and monitor brain activity (Jing & Soo, 2019) - technology normally used for brain scans in hospitals. Each student ~~wore~~ wears a headband with small electrodes to measure the brain's electrical signals~~. These data were used to measure the~~ to monitor each student's level of concentration. A red light displayed on the headband when ~~a~~ the student ~~was~~ is focused ~~and this turned~~turns blue when the student became distracted. The information could be sent directly (in real time) to the teacher and ~~to the~~ parents. While students ~~engaged~~ engage ~~individually~~ in problem solving activities, the teacher ~~could use these data to~~can identify ~~any student who was~~those not 'paying attention'. At the end of each class the teacher ~~received~~ receives a report detailing the overall concentration ~~level of each student in the class. The report indicates~~ and variations in concentration levels of each student~~, but~~. However, ~~the~~ data quality ~~of these data~~ may be compromised if the headset is not positioned carefully or the student is moving.

~~There are a number of problems with this system.~~ These headbands are being used to force students to focus on their lessons and it is reported they achieve higher scores (Jing & Soo, 2019). However, the stress placed on children through this form of constant monitoring has not been measured. There is pressure on teachers too, since the reports generated could mistakenly be used as a measure of teaching quality.~~ -~~ The government receives non-anonymised data which it is free to use. Moreover, the use of these data may not be obvious to the students, parents or teachers (Wall Street Journal, 2019). ~~In sum,~~ AI systems ~~that data~~use that subjects cannot opt out of lead to ~~less control over one's data~~a reduction of human rights, especially ~~if the~~where data legally ~~or de facto~~ 'belongs' to the data controller and ~~if~~ where processing is not transparent.[7]

[7] A data controller is "*the natural or legal person, public authority, agency or other body which, alone or jointly with others, determines the purposes and means of the processing of personal data*" (GDPR Article 4, 7.). ~~Informally speaking, it is the entity that~~Thus, it is responsible for, and often also performs, data collection and processing tasks.

Data “ownership” and control are a form of power differential. Student data can be highly detailed and distributed across educational ~~both~~ administrative ~~sources,~~systems and commercial ~~IT~~ platforms, ~~leading to challenges~~ raising complex questions around ownership and control (House of Commons, 2014). Learning management systems increasingly store learners’ ~~big~~ data in systems that are outside ~~the~~ an ~~geographic location of an~~ educational institution. While ~~a~~ systems may be intuitively easy to use (for example, clear menus and effective user training), their software design and hardware configuration adds a high degree of complexity ~~to the system~~. Teaching staff may focus on the teaching and learning functions, rather than understanding the underlying data storage and security functionalities. This can lead to various problems, for example~~, there can be issues where schools use~~ use of a proprietary system such as Dropbox for student work~~, since this~~ may breach privacy rules, because it stores ~~on~~ data ‘in the cloud’ (Kelion, 2015). These platforms do not provide teachers and learners sufficient access to their own data, undermining the individual’s ability to self-determine how their data will be used and making teaching processes inscrutable (for an argument involving Coursera, see Dehaye, 2016).

~~Criminal justice systems have used AI systems where future criminal behaviour is predicted and parole decisions are recommended by big data systems that appear opaque to the users.~~ Transparency and accountability ~~may be~~often are reduced where algorithms and software are proprietary~~, and where, e~~. Even if these systems are open to inspection, the algorithms may be ‘non-interpretable’ (Lipton, 2018). Lack of transparency and non-interpretability can have specific effects, such as ‘undetected representation biases’ or ‘undetected algorithmic biases’ (Williamson, 2015), increasing the difficulty with which algorithmic systems and power structures can be challenged.

This focus on algorithms obscures another problem: the availability and integration of ~~other~~ multiple sources of data.

~~In principle, algorithms can be developed in-house, which alleviates the problem of proprietary algorithms. Software can, in principle, be deployed in-house, which alleviates problems of data leakage. However, c~~Current trends in computing towards service-oriented architectures (McLellan, 2016) and industry concentration (Lynn, 2017) make it more likely that large vendors (~~the~~ so-called “Tech Giants”) control both the algorithmic software and ~~the~~ data, opening up opportunities for further linkage and profiling.[8] This

[8] For example, two common platforms integrate Microsoft Office 365 (EUFolio) resp. Microsoft Office Online (Smartschool).

increases the risks of large-scale security breaches[9] and power differentials and reduces the likelihood of transparency for the user, and of their trust in the data system (Gürses & Hoboken, 2017).

In theory each individual's right to data protection can reduce the power imbalance between the individual and those who control the data (Gutwirth & De Hert, 2006), and this form of individual empowerment is one of the main goals of the GDPR (Tsormpatzoudi et al., 2016). However, ~~introducing~~ embedding AI ~~into~~ systems into– educational~~al systems~~ may exacerbate power imbalances and create new, unforeseen disparities. AI s~~S~~ystems may ~~inadvertently~~ shift the locus of expertise and power from teachers and school administrators towards programmers or systems designers who create the analytics to diagnose learning outcomes, predict future educational achievement and to determine who gets recommended for what. These shifts in decision-making pose a range of risks including de-skilling (known from other domains; see Condliffe, 2016, Economist, 2014~~7~~) and transfers of public responsibilities and powers to private actors not subject to democratic control (Taekke, 2011).

Data-related challenges ~~are not only about~~extend beyond data 'ownership'~~, but focused on~~ to embrace effective data control and usage rights. The spirit of the EU GDPR data protection is not concerned with who owns personal data, but focuses on how these data are being protected (no matter who owns them) by enabling individuals to exert control of data about them. Treating personal data as a property allows people to sell their data and data rights, an option that is likely to be chosen by poorer or less well educated people. Thus, the possibility ~~for each individual~~ for ~~of~~ individuals to sell~~ing~~ their own personal data could increase social divides (see De Wolf et al., 2017).

2.3 Lifelong data measurement

Having a lifelong 'record of achievement' has been viewed by governments, education ~~al~~ policy makers, teachers and learners themselves as a valuable way to demonstrate their ability to enter educational programmes or gain employment. One problem is that the record may only include formal assessment records. In ~~some~~ domains~~,~~ such as computer programming or the design disciplines, achievement is better demonstrated through analysis of day-to-day activity and outcomes, rather than through assessment *per se*~~.~~ (Deno, 1985). These activities often are distributed over different sites, ~~for example at~~such as

[9] Cf. the purchase of Lynda.com by LinkedIn ~~(Owsinski, 2015, Kapko, 2016)~~ and the subsequent data ~~breach (Hacket, 2016).~~(Barbaschow, 2016).

work, ~~in~~ an online forum and ~~on~~ social media, rather than in one educational institution or learning system. Therefore, there is a need to gather and analyse data related to achievement distributed across different sites.

~~Different~~ There are different ~~computational concepts have been considered for~~techniques for collecting and storing ~~these types of~~ lifelong learner profiles. A common example is the e-Portfolio, where students “*document their learning, deposit and share collections of work, reflect on their learning and showcase their learning and achievements*”.[10] These e-portfolios allow an audit trail of activity that is useful for documenting learning progress (Kamentez, 201~~4~~5). Blockchain technologies have been proposed as a way to ensure ~~the~~ ‘authenticity of ~~the~~ data’ stored ~~with~~in ~~these~~ e-portfolios. A blockchain is a distributed record of online activities, or digital events, which has a consensus method to agree whether a new ‘block’ is legitimate (Sharples and Domingue, 2016). This system allows formation of a permanent, distributed record of intellectual effort and reputational reward. A central claim is that blockchain ‘democratises’ education by opening up records of achievement beyond traditional forms of certification in ways that allow employers to view a wide range of achievements (e.g. Kaplan & Garcia, 2019). In reality, blockchain is probably just ‘less insecure’ tha~~e~~n existing data security methodologies (Orcutt, 2018), and by requiring a shift of trust from institutions to technology (Schneier, 2018), it may actually undermine attitudes that are necessary for a democracy to function~~.~~

Despite the potential benefits of e-portfolios and blockchain, there are a range of associated risks. The first ~~problem~~ is the validity of the data and how records of achievement are interpreted by employers. There are many reasons why an individual may demonstrate a sudden dip in performance~~. B~~, but how might ~~this~~ periods of low performance be interpreted by ~~the~~ future employers? Ideally, when all records of achievement at every point of a student’s journey are recorded, data have to be interpreted in context. However, most analytics systems do not harvest data that takes into consideration the learner’s context and consequences for their learning decisions (Morozov, 2014). These systems tend to use quantitative data but there are fundamental questions around the assumptions that make it inevitable to use data that can be quantified, rather than qualitative, contextual data. These contextual data – learner motivations, goals, self-regulation and agency – are difficult to measure but are, nevertheless, critically important to learning (Littlejohn & Hood, 2018, p.82).

[10] Cited from http://eufolio.eu/,~~–~~ see~~–~~ also~~–~~ projects~~–~~ such~~–~~ as http://europortfolio.org/.

~~These c~~Concerns about context and agency illustrate a further problem associated with data ~~“~~ownership ~~” and control~~: students need to be able to control their own data and decide whether or not they wish ~~their~~ all records of achievement at ~~specific~~ every point~~s~~ in their lives to be included. Ensuring students are able to ~~actively~~ make choices about when and how their data is used is an important ~~aspect of social mobility~~consideration, to ensure individuals are not disadvantaged. However, the least advantaged are less likely to have access to support and advice ~~around~~ to help them decide how to include their ~~own~~ data in the system in ways that advantage them~~ compare~~. ~~Advantaged~~ Those learners who already are advantaged ~~students~~ are more likely to have support networks ~~they can draw upon~~ to help them manage their own data.

There also ~~are issues of~~questions surrounding who ~~takes any decision~~decides to retain or delete data~~, or to keep it stored~~. ~~If data of our~~If data about learning ‘follow’ ~~us~~ learners~~–~~ throughout their lives~~fe~~, who ~~will~~ stores it, who ~~will be~~is the data ‘steward’, can ~~we~~ data be selectively deleted~~ data that we regard as negatively impacting on us at present~~ – the internet is a massive archive, but often ~~with no~~does not support and allow agency of those the data represent (Lynch, 2017). ~~(LYNCH, C. 2017. Stewardship in the "Age of Algorithms". First Monday, 22, 12, online. Available: http://dx.doi.org/10.5210/fm.v22i12.8097.)~~

Educational e-portfolios ~~are more~~provide more information-~~rich~~ about achievement than traditional educational certificates. ~~This~~ They offers the convenience of having all ~~one’s certificates~~certification ~~and qualifications~~ in one place ~~and opportunity to add more~~alongside supplementary information~~. Opportunity is also related to the reasons,~~ which allows for more detailed data ~~in~~ analysis~~tics~~ . ~~contexts: Big data is often collected opportunistically following availability, speed and cost. If their processing of such data that does not lead to useful predictions and conclusions, there is always the promise that with more~~However, long-term data, ~~collected~~ collection ~~over a longer time, analyses and outcomes will become better. However, this~~ can ~~lead to long-term~~morph into unhelpful surveillance~~, with~~ capitalising on the association of learners with ~~carrying~~ ever-more detailed life-long data dossiers ~~with them~~. ~~At the same time, the same~~Another issue is that these data, aggregated differently, ~~also~~ form detailed life-long data ~~dossiers of~~trails that can be associated with teachers and others involved in ~~teaching and learning processes~~education. These longitudinal data collections pose challenges ~~over and above their level of detail,~~ which we will address next.

Lifelong, aggregated data ~~may reduce~~represents~~–~~ people ~~to~~ as ‘objects’ with ‘measured characteristics’ that are used to predict their futures. ~~Rather than supporting their development, this could deprive them of the right to have details about them forgotten.~~ However, a~~A~~ll humans experience different phases of lifelong development~~.~~, so, rather than supporting their development, lifelong data could deprive learners of the right to have details about them forgotten.. ~~However, a problem is that n~~E~~ot all phases are included in records and e~~ducational systems tend to focus on recording specific phases, such as childhood or adolescence.~~–~~ However, for some learners t~~T~~hese may not be phases of ~~the times when some individuals develop~~ rapid development~~ly, therefore the~~ and data from these phases~~–~~ may not accurately~~–~~ illustrate ~~the individual's~~ attainment. There are well-defined moments in time that can become opportunities to forget ~~'points of forgetting'~~, ~~such as when~~for example when data is transferred~~ing data~~ from one ~~educational~~ institution to another~~, which~~. These points in time ~~gives~~ provide learner's opportunity ~~for each individual~~ to ~~have agency in the way~~shape how their progress is documented.

Another ~~further~~ problem is that data collection may undermine the idea of the 'school as a protected space'. Educational institutions are not simply locations where teaching takes place, but also serve as protected spaces where learners are (in theory) free from social, political and economic~~–~~ pressures[11]. The continuous assessment of student performance, as opposed to being tested at milestone intervals, places learners under continuous stress, emulates a business environment, and may give undue influence to contextual factors such as economic pressures. This means that learners who are advantaged by having skilled support networks and resources will find ways of maintaining long-term portfolios that benefit them in their future careers. Thus, lifelong portfolios may reduce equity.

3 Approaches towards better governance of AI and Big Data: the case of the European Union's General Data Protection Regulation

Governments are facing challenges in terms of how they provide quality education or increasing numbers of learners while, at the same time, safeguarding fundamental rights of their citizens. The issues discussed in Section 2 raise ~~a number of~~ questions about how education systems should be governed. The European Union's data protection law GDPR is one approach being used by the EU countries to overcome ~~these~~ human rights~~–~~ issues. The GDPR expressly aims to protect the "fundamental rights and freedoms" of individuals in relation~~–~~ to data protection and privacy (Article 1 (2); see Gutwirth and De Hert, 2006, for the relationship between data protection, privacy and fundamental rights, and ICO, n.d., for an overview of GDPR principles).

In terms of ~~the issue for~~ learners ~~to b~~being able opt out of data collection (see

[11] ~~–~~ http://www.etymonline.com/index.php?term=school

Sections 2.1 and 2.2),~~–~~ GDPR recommends that personal data is processed only if one of several conditions are met (Article 6).~~–~~ One of these conditions is *consent* (Article 7, Article 4 11.). which has to be freely given and in an informed way. ~~Whether~~ There have been intense debates as to whether users give ~~informed~~ consent ~~can function~~in an informed way ~~as intended has been the focus of intense debate and needs to be investigated further~~ (Schiffner et al., 2018).

A second issue is data quality. Section 2.1 illustrated how ~~poor data quality may result from~~ differential accuracy in the ways different people are represented may lead to poor data quality: data from~~–~~ some ~~individuals~~ groups may be missing, while others ~~or groups of individuals~~ may be represented in more advantageous ways ~~than others~~. These differentials in data quality may result from inequality, and, through AI and ~~big data~~ analytics, may reinforce ~~inequities~~disadvantage. The GDPR recognises ~~the need for~~ data quality as ~~one of the~~a foundational principles ~~relating to~~underpinning the processing of personal data ('accuracy', Article 5 (1) d.)~~, i.e.~~ of the individuals represented in a dataset. The accuracy with which populations are represented, is ~~addressed only~~ indirectly addressed, through Recital 71 which requires~~ring~~ procedures that prevent "*discriminatory effects on natural persons*". At the same time, the need ~~to have~~for informed consent outweighs compulsory 'opt-in', even at the expense of~~–~~ data quality.

The law requires and encourages the development and deployment of (often novel) methods to ensure data quality is as good as possible. It is only through the collection of good quality data that equity and fundamental rights can be achieved. These requirements have triggered ~~promising~~ new areas of research in computer science, AI and related fields. These research areas include investigations of anonymous data collection and processing, de-identification, and fairness, particularly in terms of non-discrimination (e.g., Schiffner et al., 2018; https://www.facctconference.org/). ~~In the f~~Future~~, educational~~ uses of AI ~~and Big Data~~in Education~~–~~ should ~~include~~ draw on these developments.

A third issue is the intentional or incidental re-purposing of data (see Section 2.1). One of the GDPR's key principles is purpose limitation (Article 5 (1) b.): to ensure data is not used for purposes other than those specifically named and (in the case of consent-based processing) agreed at the outset. ~~It is well-known that t~~This principle conflicts with the exploratory nature of AI ~~and Big Data~~ analyses~~. Problems include~~; illustrations include the ~~open~~ complex phrasing of ~~many~~ consent forms, along with the notion of 'compatible purpose' ~~and~~ as well as the general problem of 'mission creep'. These remain major problems in AI research and development which should be ~~stamped out~~controlled.

A fourth issue is associated with 'profiling'. The GDPR highlights a number of risks associated with extensive and fine-grained profiling of people (Article 22 and Recital 71). Profiles (such as e-portfolio profiling described in Section 2.3) are collections of data about individuals that are gathered over an extended period of time. The GDPR mandates that profiling should not lead to discriminatory outcomes.~~[12]~~ These legal provisions have contributed substantially to computer science and interdisciplinary efforts to develop ‘fair, accountable’ and ‘~~-~~non-discriminatory’ algorithms and systems (~~again, see for example~~cf. https://www.facctconference.org). The GDPR has also introduced a “right to be forgotten” (primary name: right to erasure, Article 17). However, this right does not ~~cover~~ include the micro-management of one’s own data~~, and e~~. Exercising this right involves ~~a~~ careful balancing of ~~the~~ the rights of the individual ~~against~~ with the rights of the collective.

A fifth issue is transparency, which is related to data ‘ownership’ (the sixth issue). The GDPR recognises these challenges (highlighted in Section 2.2) and mandates for transparency and fairness~~[13]~~ as key principles that underpin the processing of personal data (Article 5, 1.). It also requires processors to provide various forms of information that form an ‘explanation’ of how and why data are processed, including the AI methods deployed (~~for an overview of this controversial area, see~~cf. Selbst & Powles, 2017 or Schiffner et al., 2018). Arguably the GDPR also makes it impossible to treat personal data as ‘owned’ in the same sense as other ‘objects’ can be owned, since data remain ‘protected’ throughout business or other transactions (Purtova, 2017). These legal provisions have contributed substantially to the efforts of computer scientists to develop ‘Explainable AI ~~(XAI)~~’, aimed at making it easier to interpret AI processing (Guidotti et al., 2019). It remains an ongoing challenge to balance the interests of the public in transparency through, ~~e.g.,~~for example, code being made open-source (and ~~thus~~ scrutable) and data subjects being afforded information and explanation rights, with the interests of companies to protect their trade secrets and competitive advantage (e.g., Schiffner et al., 2018). Certainly, the

~~[12] “ ‘profiling’ […] consists of any form of automated processing of personal data evaluating the personal aspects relating to a natural person, in particular… [to analyse or predict] aspects concerning the data subject's performance at work, economic situation, health, personal preferences or interests, reliability or behaviour, location or movements, where it produces legal effects… concerning him or her or similarly significantly affects him or her.” (Recital 71)~~

~~[13] The GDPR notion of fairness “*means that you should only handle personal data in ways that people would reasonably expect and not use it in ways that have unjustified adverse effects on them. […] Assessing whether you are processing information fairly depends partly on how you obtain it. In particular, if anyone is deceived or misled when the personal data is obtained, then this is unlikely to be fair.*” (https://ico.org.uk/for-organisations/guide-to-data-protection/guide-to-the-general-data-protection-regulation-gdpr/principles/lawfulness-fairness-and-transparency/)~~

legal mandate of the GDPR to consider data protection from the start and throughout product life cycles ("data protection by design", Schiffner et al., 2018, also known as "privacy by design", Tsormpatzoudi et al., 2016), is a step in the right direction.

There remains a fundamental question around the extent to which AI ~~and Big Data~~in education ~~actually~~ maintains the status quo, instead of ~~bringing about~~facilitating innovation (see Section 2.1). ~~There is an~~Basing the future on past data inherently is conservative ~~inherent conservatism in the analysis of Big Data (which, by learning from past data,~~ and is predisposed to reproducing the status quo~~)~~. This issue is at odds with the idea ~~that Big Data and~~of AI leading~~s~~ to 'innovation' (e.g., Barabas et al., 2018; D'Ignazio & Klein, 2018). This issue ~~cannot be regulated easily and~~ makes it ~~all the more~~even important to ~~critically~~ investigate AI systems critically.

The GDPR is influential beyond the EU countries in which it has been implemented. ~~For a number of reasons~~ First, ~~through its construction~~ its implementation across the EU regulates the behaviour of entities outside the EU. This includes ~~Tech~~ technology companies~~, regardless of their own jurisdiction, if they~~ that process the personal data of EU citizens. Second, the implementation – of ~~it is known that~~ GDPR ~~is~~ has influenced ~~ing~~ ~~other~~ some non-EU countries to reconsider their own laws (Kpadonou, 2019). Third, ~~through its~~the implementation GDPR is driving research ~~activity~~on data and human rights. ~~However, d~~Despite these positive outcomes, there are serious limitations of GDPR. First, as a *general data protection* regulation, GDPR is not ~~specific~~ tailored towards any particular domain, such as education. Second, rapid digitalisation is mediated through a number of factors, such as social norms, industry power and industry self-regulation~~, and so on~~. ~~Therefore it is~~This makes it difficult for regulation to keep in-step with ~~these~~ other ~~multiple~~ influences. Approaches to regulation, such as the EU's Ethics Guidelines on Trustworthy AI[14], are one of the many complementary forms of regulation available. However, these tend to be *general* (in this case for AI[15]) and~~, as such, have severe~~ are limitated~~ions in their approaches~~ (in this case being about ethics, which is not legally enforceable~~,~~. ~~although some work with a long-term vision of co-shaping "the next GDPR", a comprehensive regulation of AI).~~

In summary, laws such as GDPR offer important ways to address the issues associated with the use of AI ~~and Big Data~~in education. However, these laws are not

[14] https://ec.europa.eu/digital-single-market/en/news/ethics-guidelines-trustworthy-ai

[15] ~~This is also pointed out in~~See the University of Buckingham's Institute for Ethical AI in Education (IEAIED) position on ~~the~~ EU Guidelines (http://instituteforethicalaiineducation.org/#mission).

sufficient in themselves to solve ~~these~~ major issues. A long-term vision is to co-design “the next GDPR” as a comprehensive regulation of AI.

4 A way forward: promoting learner choice and agency

This article has analysed issues of AI in education, ~~places~~ placing emphasis on human rights and the importance of learners ‘owning’ and ‘controlling’ their ~~own~~ data ~~and profiles~~. ~~Moving beyond questions of~~Enabling ownership and control~~, it is also important to consider the~~ requires support that enables ~~agency of all~~ individual agency sof ~~(~~learners and teachers~~) involved in the learning process~~. Learners should not simplye be considered ~~as~~ ‘data subjects’~~, since there are important considerations around the degree of freedom and~~ and should be enabled to exert autonomy ~~they have~~ over their own data. ~~Key questions include how will students determine the optimal information about them, and how can they later adapt their decisions? Are learner’s choices logged, who can see these logs, and how does this affect their freedom of choice? These questions are~~This is also important for teachers, about whom big personal data are collected and whose expertise and actions may be constrained and undermined by data ~~educational monitoring~~surveillance.

It is important to strike a balance between ~~respecting stakeholders’~~enabling autonomy and burdening ~~them with additional tasks needed~~individuals with the need to manage their ~~identities~~ data as their data footprint expands (see Shamir, 2008). ~~It could be argued that r~~There is a danger that, rather than ~~respecting~~ supporting agency, giving learners options around their data ~~simply~~ provides the illusion of ‘consumer choice’ (Jones et al., 2013, p.153). A pervasive, digital environment may encourage learners to behave as passive consumers, rather than engendering democratic behaviour and choice (Björklund, 2016). These tendencies towards passive compliance are illustrated in the idea of AI systems as enabling ‘personalised learning’, moving away from the philosophy of learning as a collective action and ~~an important~~ civic activity. It is important to consider how governments are introducing AI into ~~their~~ national education systems. Nations that view education as primarily ~~an individual’s investment in their future~~as an investment in future employability, such as the US and UK, ~~may~~ will likely introduce different forms of regulation around AI in education compared with countries that view education primarily as a benefit for society.

In summary, ~~this analysis has~~through ~~considered~~ consideration of the ~~implications~~ effects of AI in education on individual freedoms and fundamental rights~~. T~~, this ~~he~~ article concludes with a call to action to ~~start with consideration of~~foreground fundamental human rights as a ~~platform for the embedding of~~starting point for implementation of AI in educational ~~systems.~~ There is an urgent need to ~~balance the benefits and risks as~~make sure learners and teachers, rather than technology companies and organisations, are the main beneficiaries as AI tools are developed, marketed and ~~deployed~~embedded in education. However, it remains unclear who - which body or organisation - ~~should~~ will take responsibility and how.

AI in education extends beyond data privacy and impacts fundamental human rights. ~~This means e~~Educational institutions are too ~~small and~~ narrowly focussed to take on this role, because of their inability to influence broader impact beyond educational policy into labour law, consumer protection law and so on. At a national, governmental level, the consideration of human rights will ~~take into consideration~~include different perspectives, depending on each country and its associated culture. While l~~L~~aws, such as the European Union's data protection law GDPR, begin to address ~~several of the~~some key challenges ~~identified. However~~, these ~~laws~~ are not sufficient to solve the problems associated with AI in education~~al systems~~. Issues raised by the use of AI in education are of global proportion and ~~r~~~~There is a significant opportunity, therefore, to introduce regulations~~ are needed at a trans-national level, overseen by (f~~(f~~or example) the UN,~~)~~ to monitor and regulate AI systems development ~~for use in~~across different ~~parts~~ sections of society, including education. ~~AI, big data, and education analytic business is multi-national, and like the global ecommerce and social networking platforms, regulation at the national level is generally not workable.~~ The sooner regulation is implemented, the faster learners, teachers and all citizens can avoid the risks of AI in education undermining their fundamental human rights.

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We thank the reviewers for their thoughtful and valuable comments. In the following paragraphs, we explain how we addressed each one. We hope to have addressed all issues in a satisfactory way.

Reviewer(s)' Comments to Author:

Reviewer: 1

Comments to the Author
I commend the author on a well-written and cogently argued piece on an important and very relevant topic. The case studies in particular make a valuable contribution to this emerging field and the analysis of the GDPR makes an important link between theoretical discussion and legal framework.

We thank the reviewer for this positive feedback.

I have noted a few possible areas for revision:

The author(s) refer to the paper as a 'study' in the abstract, but the methodology is unclear. From where is the argument drawn? It would be helpful to make this clear.

We have added a note in the last paragraph of the Introduction.

There is very little up-front discussion of what is understood as human rights, individual freedoms or fundamental rights. It would be helpful to add a paragraph about this early on, and an acknowledgment that these values are defined and protected by law. This would connect the two strands of the article more clearly.

We have added a detailed footnote in the Introduction. Given the quite technical nature of these distinctions, the passage would have broken the flow of reading, and we have therefore opted for a footnote rather than a paragraph in the running text of the Introduction.

The author(s) tend to refer to education as a single entity, without specific reference to differences in educational context, age group, types of provision etc. WhilstI understand this is largely beyond the scope of this discussion, it would be helpful to make reference to the heterogeneity of education as a field, and how this relates to the particular human rights of, for example, children vs adults. The work of Sonia Livingstone might be useful here. Also - Lupton, D and Williamson, B (2017), 'The datafied child: The dataveillance of children and implications for their rights', New Media & Society 19(5), 780-794.

Thank you for these pointers. We have added a footnote at the beginning of Section 2 to explain our scoping.

Throughout the text, particular in the discussion of case studies, there could be more careful referencing. eg. in section 2.2 "The headbands are being used to
force students to focus on their lessons and it is reported they achieve higher scores." eg. 2.3 "achievement is better demonstrated through analysis
of day-to-day activity and outcomes, rather than through assessment per se."Please add references to support this claim.This type of statement needs to be consistently referenced (even if the source is mentioned further down in the article), as it is important for the reader to be able to check each claim.

We have added references where it appeared appropriate to us, but also used common strategies of scientific writing so as not to unduly block the flow of reading: scoping of a reference over a group of sentences that report on one semantic unit, and no references in cases of statements that can be regarded as common knowledge in the field, or that represent our own judgement. We are aware that it is an ongoing meta-theoretic debate as to what exactly constitutes "common knowledge in a field" and that therefore these rules of scientific writing are not mathematically precise. Still, we are also aware that this is not a problem that can be solved with mathematical rigour, and we have applied our best judgement of what the community would consider clear attributions of claims in a readable text.

Reviewer: 2

Comments to the Author
This paper discusses a significant and highly relevant topic, i.e. issues of learner choice and fundamental rights in the context of AI applications in education. In this way, the article presents a somewhat unusual and highly interesting perspective on AI in education - while oftnetimes the aim is to justify the significance of AI technologies by

demonstrating their positive effects and benefits, the presented work takes a more critical position on AI in education, in general, and reflects on potential risks in terms of data ownership, transparency, and legal aspects.
The revised structure of this resubmitted version of the paper and way of argumentation is much better readable and understandable, the argumentation line much clearer.

We thank the reviewer for this positive feedback.

Nevertheless, I would like to share some suggestions for further refinement/enrichment of the paper:
* I am not sure whether the definition of AI used in the intro is the best or most appropriate for this paper - since it refers to computer-controlled robots. Maybe you can find a more suitable definition that is more targeted to educational applications.

The definition of AI that we use indeed refers to computer-controlled robots, but only as one of two possibilities ("the ability of a digital computer or computer-controlled robot to …"). We use this definition for two reasons. The first reason is that we would consider it confusing to readers if we re-defined a term with a meaning and definitions that are widely accepted throughout the technical communities as well as in the more general and also popular-science usage. Second, while indeed we do concentrate on digital computers *as agents in the sense of the definition, we also discuss one example of the use of* computer-controlled robots *(see Section 2.2), and we believe that in general, the use of robots in educational settings will increase in the near future, and that it is important to subsume these agents under more general analyses of AI.*

* Foot note number 3 on page 4 is missing.

Thank you for pointing this out. The footnote sign was a typo, and it has now been removed.

* Page 5, line 23: delete 'learner' after 'Similarly'

Fixed.

* In section 2, I think it might be a good idea to introduce one (or even two) more subsections - section 2.1 ('opt out'), page 6, from line 28 on would be more suitable to represent a separate section (maybe on 'data handling', in general). Similarly, in section 2.2 ('limited opt out'), page 9, from line 28 on more general aspects are discussed that may be suitable to shift in a separate section.

We agree that more subsections can be helpful in principle. However, we have carefully balanced the pros and cons of doing so in the current article, only to arrive at the conclusion to leave the section structuring as it was.
Our reasoning was as follows: Indeed, there are different issues discussed within the current Sections 2.1 and also within 2.2. However, they all emanate from a discussion of the effects of two different (and key) design choices in educational systems: whether opt-out is possible and whether long-term records are created. To reflect the importance of the choice to allow for opt-out in principle or whether to limit opt-out by design, we have distributed a discussion of the former into two sections (i.e. 2.1 and 2.2). The remainder of the paper is also structured into sections at a rather coarse level of granularity (e.g. there is only one section for the complex legal discussion). In fact, only Section 2 even contains any *subsections. We therefore decided, after extensive deliberation of your suggestion, to not "de-balance" the text further by adding a further level (sub-subsections) into Section 2.*

* In section 2.2, page 9, line 26 a reference to criminal justice systems using AI is made - I think this is irrelevant and should be skipped.

We have removed this sentence.

* As indicated in my earlier review, based on the topic elaborated and examples discussed I would expect the paper to mention/introduce the term 'learning analytics' - since many of the mentioned AI examples clarly refer to learning analytics. I think by an explicit reference to this topic, the paper could stimulate increased interest and gain additional readers from the field of LA.

We have highlighted the connection to learning analytics in the Introduction.

* I would find it highly interesting if the paper could elaborate in more detail on the issue of transparency and how to deal with it - in terms of scrutability, the algorithms used behind AI technologies, the relevance of opening up and informing stakeholders about the foundations/algorithms and the conflicting interests of tech companies in case of proprietory software.

We have added a sentence and a reference to highlight this problem in Section 3. Unfortunately, within the length limits of this paper, we cannot elaborate more.

* In section 2.3 (p.11), blockchain is mentioned. Since blockchain is a hot topic I think it would be good to elaborate a bit more on it and to include one or two more relevant references, especially also in order to substantiate the claim that it is maybe just a 'less insecure' approach than other data security methodologies.

We have added further remarks and references. Unfortunately, within the length limits of this paper, we cannot elaborate more.

* I find the thought that some sorts of risks may be not inherent to the technology itself, but arising from unintended or unanticipated consequences of the use of AI system, highly relevant.

We agree. Unfortunately, the length restrictions of the journal do not permit us to delve further into this important topic. We have added a reference to an overview article (Pringle, Michael, and Michael, 2016). that points the reader to further relevant literature.

Another aspect that I think is relevant and which I would therefore suggest to introduce and discuss in the paper is the idea and approaches on ethics-by-design - where ethical considerations are already and explicitly taken up in the design and development stage of a new software or technology.

We agree that by-design mindsets and engineering practices are central to making progress in this area, and have added a remark and references at the end of Section 3. On the other hand, we do not believe that ethics-by-design (at least in its meaning as defined by Dignum et al.(AIES '18: Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society. December 2018 Pages 60–66, https://doi.org/10.1145/3278721.3278745), i.e. "methods, algorithms and tools needed to endow autonomous agents with the capability to reason about the ethical aspects of their decisions", is helpful for the purposes described in our article. Whether this is due to intrinsic limitations of autonomous agents or to the limitations of the current state of AI technology, remains a point of debate, but would go far beyond the scope of the current paper.