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The Ethical and Social Implications of Personalisation Technologies for e-Learning

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Abstract

Personalisation in information systems can be considered very beneficial but at the same time ethically and socially harmful. Like many other technologies, the uptake of personalisation has been rapid, with inadequate consideration given to its impact. Personalisation in e-learning systems also has potential for both harm and good but less is known about its effects. The ethical and social hazards include privacy compromise, lack of control, reduced individual capability, and the commodification of education. Personalisation is appearing in many systems already, so these hazards may be occurring already. Solutions, more research and community discussion of the issues are needed.

1. Introduction

Formal education aims to select out the most pertinent and reliable information, coaching students to learn and then apply their own judgement and reasoning to that information. For most of human history, formal education has been primarily provided by human teachers. The recent rise of information and communications technology however has seen education moved online, implemented in *e-learning systems*. An e-learning system supports mainly individual learning (but sometimes social learning) over the Internet, allowing access to local or remote organised learning material. The organisation of the learning material is done in view of a learning goal, generally established by a university curriculum or the training demands of a company.

As with many other human functions (e.g., banking and sales) that have moved online, e-learning has had mixed success. It was partly motivated by the belief that it would save on human effort, although this assumes that the tasks involved in teaching are repetitive and mentally-undemanding. It does make feasible the parallel teaching of enormous numbers of students, and permits access to the entire Internet of supporting materials. However, the move online of learning has occurred along with the reduction of human teachers. This can leave students feeling disenfranchised, like "numbers on a computer", ignoring their individual learning needs.

To address this, academics began introducing *personalisation* functions into e-learning systems. Personalisation, in any information system, is intended to make users feel that what is shown has been designed or adapted for their use alone, so they feel as if they matter as individuals in an increasingly impersonal information world [33] [55] [57]. E-learning is one of the earliest areas where personalisation was trialled, such as intelligent tutoring systems [21] and adaptive hypermedia [7], providing the appearance of personal contact and tailored assistance to students in an educational environment of large classes and limited staff/student contact. Personalisation in e-learning is more than simply presenting information to students about their enrolments, deadlines, or similar supplementary materials. In particular it refers to the personalisation of educational materials that directly contribute to a student's learning.

The primary defining characteristic of a personalised e-learning system is that the system becomes *bidirectional*. The Web had a similar transformation from static, read-only pages of the early Web to the subsequent Web 2.0, which is interactive and responsive to the user. Personalisation is a key part of that interaction and responsiveness, and it has the same effect in e-learning systems. Bidirectionality is the key feature of personalisation systems, because the system genuinely is able to interact with users, recognising when they need assistance and guiding them to the right information item or educational activity [14]. This can improve learning outcomes [15] and can increase the speed of learning [9].

Unlike personalisation in a commercial context, which is beneficial based on its return on investment [32], in the e-learning context, there are three types of benefit that may arise from personalisation: *engagement, economy,* and *outcomes.* Education is a very personal experience. Students have different goals, expectations and backgrounds, and learn in diverse ways. In conventional teaching this is largely addressed by *small group teaching*. A teacher with a small group of students will generally tailor the material to the current needs of those students. This is often a dynamic process, in which a teacher will explain a concept and then encourage the learner to reformulate it and explain it back, and the teacher can then personalise subsequent explanations accordingly [50]. Personalised e-learning aims to mimic the individual attention that occurs in small-group teaching, adapting the teaching to students based on knowledge about the individuals, their learning objectives and the context in which they are learning. Personalisation is effective for engagement, with studies showing that students prefer to use a personalised e-learning system [12] and that use of adaptive composition of content motivates users to explore more content than using conventional search systems [74].

The benefits are also in economy. Education providers perceive that they can provide economical, responsive teaching for students while at the same time being able to broaden the student (customer) base. Personalised online presentation of education materials has two economic benefits: i) the provision of teaching with fewer or no actual human teachers, and ii) the ability to provide a satisfactory and responsive learning experience [25] [78] [81] for distance learning students. This makes it feasible for institutions to offer distance learning for perhaps the first time and thus increase student numbers and institution income.

Despite their potential benefits, there are a number of clear ethical and social issues arising from the use of personalisation in e-learning systems. One of the most obvious is that of personal privacy (section **3.1**), since personalisation systems can only personalise content by collecting information about the user so as to calculate what their interests or requirements may be. However it is not only the collection of that personal data that has ethical concerns, but also that personalisation systems perform calculations over it, creating inferences of varying accuracy about the user to extend the user model with the resulting implicit data, although this happens without allowing users to see how the personalising site decides what to serve them, let alone have control over the process (section **3.2**). The user model then is involved in further calculations that decide what to show the user, but also what *not* to show the user. These calculations can them impact the user's individual capability, often resulting in reduced exposure to other concepts with the concomitant loss of opportunity, and encouraging personal ethical and moral siloisation. Personalisation also encourages users to be lazy about decision-making and to habitually delegate all their thinking to software, rendering them consequently less capable of thinking for themselves, either forgetting, or even never acquiring, the skills they need to be able to find information for themselves under other (non-personalised) conditions. It can be especially troublesome when users delegate their thinking and decision-making to external agencies who are not education-oriented but commercially-oriented or who may even be propagandists and social engineers. This can only be harmful to the society that needs a literate, skilled and, above all, rational population (section **3.3**).

In the e-learning context, personalisation should enhance the education of students, its ideal being to enable each student to reach their personal best by working to address their individual weaknesses. Personalisation should have a positive impact on the quality of education as it should be able to show students what they need to know, when they need to know it. However some forms of personalisation appear to be ineffectual and with current technology, personalisation is not suitable for all forms of education and assessment (section **3.4**).

It could be that not only has personalisation not yet been able to achieve its own educational ideal but has inadvertently been the cause of harm to more traditional teaching methods, aiding educational institutions to process more students, faster and cheaper, in their drive for economic self-sufficiency (section **3.5**). Personalisation is complicit in the commodification of education because it is the educational version of the "It's all about YOU!" theme that pervades advertising [29]. It encourages students to see themselves as *consumers* of education by putting them at the centre of their own education, with a 'personalised' environment specific to their individual learning needs. The "it's all about you" theme might be a deliberate policy on the part of institutions, learned perhaps from advertisers, to attract and then retain students. Certainly great emphasis is put on 'student engagement', which boils down to whether students are adequately interested in their own education, or need stratagems to keep them motivated. Personalisation of e-learning is one such stratagem that shows real success in engaging students (as discussed above), so despite any other problems personalisation may manifest, it will nevertheless find a place in e-learning.

In this paper, we present a detailed discussion, and propose solutions to mitigate some of the ethical and social concerns arising from personalisation. The remainder of the paper is organised as follows. Section 2 reviews the technologies on personalisation of e-learning. Section 3 discusses the ethical and social problems and Section 4 proposes some recommendations for addressing these problems accordingly. Finally, Section 5 offers some concluding remarks.

2. Background - the technology of personalised e-learning

Current e-learning systems used in higher education and company training settings are Learning Management Systems (such as Blackboard), or MOOCS. They all focus on the transfer of information. The technologies of such systems rely heavily on information management and presentation. The management part is supported by technologies such as local or distributed databases (SQL, XML, etc.), and the presentation part relies on technologies such as HTML, JavaScript, and more recently, AJAX technology, etc. Traditionally they were based on a client-server architecture, with the client side on each learner's computer, and the server side (including databases and other information structures) on a single central entity. These models were superseded by service-based architectures, which could provide different services (such as scheduling, delivering lectures, hosting forums, etc.) either centrally or distributed over the network. This also introduced such concepts as 'learning as a service'. Furthermore, distributed e-learning is gaining more weight in the move towards cloud computing, where functionality, data, or any type of information can be distributed over the network. This is also the case in the ever-growing area of mobile computing and mobile e-learning, where data can seldom be stored in the limited memory of the mobile device, and instead it is spread across the network.

From a student perspective, e-learning systems frequently fall into the one-size-fits-all category, which disregards the needs of the individual student. Whilst mobile computing introduces some adaptive features, such as context and device specificity, the real benefit to the learner comes with personalisation to their specific needs, especially their learning needs. This has allowed for the development of the areas of intelligent tutoring systems (ITS) and adaptive educational hypermedia (AEH), supported by actively contributing communities. They are further adding to the above described e-learning systems by embedding user-related knowledge into the system in order to address their specific needs.

This in all cases implies the construction of what is called a user model, which is a structured collection of information about the user. The user model has the primary benign goal of adapting the material presented to the user in such a way that it will help them in their learning endeavour. Such systems thus need to have the means of storing such data (again, in databases as described for e-learning systems, but with rather more sensitive user data) in a centralised or distributed way. They also need to be able to retrieve this data from somewhere, building either explicit user models (when a system will ask the user for the information directly) or implicit user models (when the system will deduce or infer the information from the user's behaviour). This means also different levels of awareness of the user of the data collection, with the former raising a higher level of awareness than the latter. Regardless how it was obtained, user model data can be made completely accessible to users, partially accessible to users, or not at all accessible to users. The storage of user data can be sessional (only stored for the current session) or permanent (stored for as long as the user is registered with the learning service, or beyond), again with different implications for the security of the information, its reliability, its privacy, etc. The latter type allows for more precise personalisation, comparing past behaviour to the current behaviour and giving better guidance.

This brings us to the next component in these systems. There must be a mechanism to process all this data (additionally to what an e-learning system's requirements were), called an *adaptation* (or personalisation) mechanism. Its job is to decide how to change content or presentation for the user depending on this processed user data. Techniques for personalisation include hiding data (e.g., the learner is not advanced enough to see it yet), adding data (the learner is pointed towards more explanations/examples/etc. on a given topic), presenting data in different formats (for instance, highlighting important data), formatting the screen differently to encourage different access to data (for instance, grouping the data into a map format), presenting more appropriate data alternatives (a classical one is to present visual data - images, video, etc. - to users with a visual preference, and text (or audio) data for more textually inclined learners). For AEH systems, Brusilovsky has built a taxonomy of adaptation techniques [14]. ITS and AEH often are based on what is called 'closed systems', i.e., the personalised recommendations they make are based on content which is finite, known, and often contained on a single server. In contrast, open hypermedia systems, and personalised open hypermedia systems were proposed, where the content to be recommended is stored on the open web, and thus inherits both the advantages and disadvantages of the open web: the search space is vast and the information is rich, but links may lead to deleted pages, or even worse, replaced pages (e.g., pornography), etc.

Content-based personalisation is only one type of personalisation. Personalisation comes in two forms. It can be *algorithmic* where rules are applied as described above, or *statistical* where priority is give to what others in a similar situation have done in the same situation, often called recommendation. Recommendation in such systems usually is based on pedagogical relations between pieces of content, and recommend the next piece of content, only after all the relevant predecessors have been read by the student (thus limiting their search space). This is helpful to prevent the 'lost in hyperspace' syndrome, when a student has too many options and doesn't know where to go next, or when a student simply doesn't have enough knowledge to understand the current material, and would need to visit previous material first.

Other types of personalisation are related to different personalisation areas. There are many personalisation application areas related to e-learning. For instance, personalised search (or personalised information retrieval) allows for information about the individual user to alter the retrieved list of items searched for. Personalised recommender systems recommend items (usually from a catalogue) based on stated or implied preferences. Recommender systems can be used to recommend to a learner what to learn next, similar to content-based personalisation in ITS or AEH. The difference is that in recommender systems, recommendations are often local, whereas in ITS or AEH the recommendations are based on more global goals, and sometimes on pre-designed (or partially designed) lesson plans[1]. Related to recommender systems based on preferences, collaborative filtering systems use opinion mining in order to recommend popular items, or pairs of items, etc.; Amazon is a well-known example that relies on collaborative filtering to recommend related products to buy, or highly-valued products. Recommender systems can also recommend non-content items, such as other learners to contact for project work, or learners with related interests, or even ratings for a given item. Social media systems store a large amount of user data and are a very good ground for personalised services, including personalised e-learning services. They can be used to recommend 'friends' or 'learning buddies', or to recommend to a social media user some specific learning material.

[1] Such as created via Educational Modelling Language, see http://celstec.org.uk/content/educational-modelling-language

3. The ethical and social implications of personalisation for e-learning

In this section we discuss in more detail the ethical and social problems arising from the use of personalisation in e-learning systems. The most obvious of these issues is that of privacy, because personalisation can only take place if personal data is collected (3.1). However awareness is increasing of other ethical and social problems arising from personalisation, especially where personalisation apply rules to create inferred data based on the collected personal data, potentially introducing errors into the user model (3.2). There is then the concern that individual capability is being compromised by increased reliance on personalisation to make decisions for the user and student, especially so when those decisions are influenced by commercial personalisation systems (3.3). Personalisation in e-learning systems also should be assessed for how beneficial it is, especially for different types of learning (3.4). Finally personalisation inadvertently contributes to the commodification of education as it is a key technology that enables automation of learning (3.5).

3.1 Privacy, security and ownership of personal data

Privacy problems arise from personalisation because to personalise content, the provider must collect personal data, including activity history, location, other sites visited, and so on. The ownership of this personal data then also becomes a problem. Who keeps and who owns the record of personal preferences? Can individuals see their own records and what right of reply do they have if that information is wrong? What happens if this information is released deliberately [1], or is stolen in a security breach?

This exemplifies the real concern about privacy in the 21st century. In Orwell's 1984's, Big Brother was a tool of the government, but in our society, it is also in the hands of corporations[2] [36]. For students, it is generally their educational institution that holds their student records. However educational IT, including email and group working tools, is increasingly outsourced to private enterprise, and student data will end up in corporate hands, often deemed to be owned by the company providing the resources.

Users are becoming wary of providing data to unknown sites or for unknown purposes - in 1998 Nielsen said "*A lot of privacy concerns have to be addressed before users will be willing to give out as much personal info as is necessary for good personalization*" [60]. In a recent survey of privacy attitudes in Australia, 90% of users sometimes withheld information from websites, and 62% declined to use smartphone apps because of the data collected [61]. Clearly a significant number of people will forego some functionality rather than disclose personal details. On the other hand, there remain many people who do pass on personal information, even when not comfortable doing so, because to not do so would exclude them from the functionality of the site.

Personalisation relies on the collection of personal data into a user model or profile. That profile is potentially subject to use, often without the knowledge or consent of the subjects. There are many sites dedicated to the collection of data that tracks a user's activities, sometimes across different sites. One widely-used example is Google Analytics, which analyses data from several universities, including Harvard, Ontario, Queensland, St. Gallen and Sheffield. In the authors' experience, at least one university uses Google Analytics extensively: both students and staff at this institution are tracked as they access apparently every page on the institution's site. Exactly what data is collected is hard to determine, as it is transmitted back to Google Analytics in a non human-readable form. However, inspection of the `http` requests did show that the data being sent varied as different users logged into the online learning system, so clearly the staff or student userid was being transmitted. This issue is of course not restricted to applications using personalisation, but it is exacerbated by the requirement to collect personal data for the purpose of personalising the information delivery.

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[2] Even so, the data available to the USA government agency the NSA still outweighs that of Google, see http://arstechnica.com/information-technology/2013/08/the-1-6-percent-of-the-internet-that-nsa-touches-is-bigger-than-it-seems/

Some studies show that, when explicitly asked, users are less willing to disclose information about themselves. In fact, disclosure follows certain patterns, such as what information is disclosed early influences what will be disclosed later [46]. Users can also be classified according to what type of information they are willing to disclose [47]. However many sites collect data without the user being aware of it. The terms and conditions of the site may explain the data collection, but often the use of the site itself constitutes implicit agreement, thereby necessitating use of the site even just to access the privacy policy to be able to make an informed decision. Even so, the user must realise this data collection is occurring, then either they must explicitly opt out of the data collection process, or be unable to view the site at all. The problem is made worse when students make use of free, commercial tools such as shared documents, with no clarity about ownership of the data.

Social pressures are shaping the views of younger people in quite subtle ways. We live in a society where collection of private data is increasingly commonplace, sometimes to the point of surveillance, and people are becoming more relaxed about this. They are accustomed to putting personal details on social networking sites (although up to 33% report later regretting doing so on at least one occasion [61]), and routinely signing up to all sorts of web sites that, at the very least collect e-mail addresses, and sometimes much more - for example, personally-identifying behavioural biometric data is now being collected to identify individual users [77].

On the other hand, younger people are at times more privacy-aware, even if they still permit their data to be collected. A recent survey [67] shows that 86% of internet users have taken steps to reduce their online visibility. However, only 36% of this same set of respondents claimed to have not used a website which required a real name and address, so up to 64% of the remaining respondents were willing to divulge this information so as to be able to access the site, in spite of evident privacy concerns.

So how relevant are general privacy concerns within an e-learning context? In some countries there are regulations (such as the Family Educational Rights and Privacy Act in the USA) governing the collection, use and disclosure of personal information from students. In other countries, stringent laws exist with regard to any online-content user, for example, in Germany user logs must be discarded at the end of a session to comply with Code 5 in Section 2.2 of the German Teleservices Data Protection Act [30]. However there are many reasons why such regulations are not yet adequate to defend the privacy of students, and of staff.

The first is that legislation is generally retrospective, so privacy disruptions must first occur before legislation is enacted. But even when the legislation exists, it varies greatly across country boundaries. FERPA, for instance, is active in the USA only, and there are other countries providing e-learning facilities that have different rules about student data, and in some places there is no regulation at all. Furthermore, some corporations apparently disregard legislation where it exists, especially when data collection is trans-border (for example, the collection of home network data by Google Streetview cameras, a practice reported widely in the press and now discontinued after public anger in numerous countries).

An additional complication is that there is a lack of clarity and some conflict about what comprises personal data as opposed to 'non-personal data', with some sites claiming that data they collect is 'non-personal' and hence not subject to privacy laws. This however ignores the 'linkability' of data, namely that various items of data collected may be in themselves harmless, but taken as a whole can give a highly detailed picture of a user.

Negligent observation of data security requirements puts personal data at risk. There have been high-profile cases of large corporations who failed to properly secure customers' data, e.g. Sony who had a lot of data stolen by a 'hacktivist' group and this was attributed to lack of due care with security procedures for such data [58]. In this case, the data was publicly posted by the hacktivists to demonstrate a point, but the more insidious concern is that if hacktivists were able to steal it, so too could any criminal organisation.

Universities themselves are complicit in the collection of personal data, with widespread use of analytics software. Google claims that the analytics data sent to them is not personally identifiable[3] but because the data sent back to them is not human-readable, it is unclear what is being sent, although it appears that data such as individual user identifiers are being collected. Even if data is non-personally identifiable in the context of the e-learning system, the conjunction of that data with data collected from other sites using the same analytics software may make it possible to identify individuals (this is 'linkability' once again). Thus analytics software is being used in universities' online learning systems without any real understanding of what data is being passed to the analytics company - the university management only see the data after it is processed. In many cases, that data is being sent offshore, which raises issues about what nation's legislation applies to the data.

There are also a number of commercial tools being incorporated into learning environments, and these tools do not observe education-specific privacy regulations, as they are not developed specifically for education environments. In the university environment, it is more than analytics data being collected. Search engines are now embedded in the education environment, sometimes deliberately by the e-learning system designers. Furthermore, the inbuilt search text entry box in mainstream browsers makes it easy to search directly, seemingly from within the e-learning system and its very ubiquity may be argued to render search engines more accessible (as well as being more familiar) than any search facility of the e-learning system itself. Even if such a facility is somehow masked, students will still 'google' for information outside the learning system.

Social networking tools are increasingly common in the workplace [69] and in study, and study-related discussion and materials will inevitably appear in these fora [8], with associated issues of plagiarism and breach of confidentiality. In terms of influence on the online personalised learning process, such parallel channels need to be taken into account, as students often bypass or avoid the school- or university-provided channels in favour of the social networks, with various implications, including lack of institution control, and in particular the lack of privacy guarantees [8].

However, leaving aside the well-known problems of the public social tools, learning providers need to consider how privacy could be compromised by specific personalisation tools in e-learning systems. A personalisation system of necessity collects personal data about the user, so that subsequent actions can be tailored to that user. This is done in different ways with the users able to identify themselves fully, partly or not at all. The partial disclosure of identity occurs when a user creates a unique user identifier whose profile only they can access and alter, but without necessarily imparting any personal information such as name or address – this is a pseudonymous user model, and is often persistent between sessions. An anonymous user model may not even have persistence between sessions, the system being not aware of whether they have visited the site before (although cookies, flash cookies and other evidence make it difficult to be genuinely anonymous).

Full disclosure is most likely in academic information systems, which have access to the student’s entire academic, attendance and financial record. A personalised e-learning system adds to this by collecting detailed data about the student’s access of materials and progress through courses and individual lessons, as well as partial results. While this data is collected for genuine educational reasons, ensuring the confidentiality and integrity of these personal profiles is essential, especially when online assessment is used.

It could also be a problem for student users if their learning profile were used for other purposes. This could happen as part of national security activities, as exemplified by a large number of recent data requests by government national security agencies to search engine companies. On a personal level, an employer could demand from graduate applicants a copy of their student profile, so as to assess whether a candidate was a quick or slow learner, whether their assignment submission was generally timely, whether they had any academic misconduct recorded, or whether they received special academic procedures for dealing with

[3] See https://www.google.com/analytics/learn/privacy.html

disabilities, health issues or family situations. The existence of such student information means that students may come under pressure to authorise its release. While legislation can be enacted to make such demands illegal, there could still be pressure on graduates to 'voluntarily' make such data available to prospective employers and for a refusal to be interpreted as the person 'having something to hide'.

3.2 The accuracy of inferencing

We now consider how personalisation systems make assumptions and inferences about the user, what Brusilovsky called "implicit" user model data [13], derived by recording the user's behaviour and inferring characteristics about them. These assumptions can be a problem if the user does not know the data is being collected, how accurate they are or what inferences are being made on that basis (for example, buying a child's toy doesn't mean the user has children). Too often, there is no transparency about the inferencing rules, nor any guarantee of their accuracy. The privacy of the inferred information is a grey area, as it is not provided by the user, but is calculated by a third party, casting doubt on to whom it belongs.

There are implications of such inferencing rules, in particular, political and social implications, whether correct or not. This could be especially damaging in a changing political climate. Even commercial corporations such as credit card providers and supermarkets collect details about an individual's race, religious beliefs, sexual preferences, union membership, marital status, and number of children, among other things, which can only have been inferred from the user's spending patterns [36]. Personalisation creates associations, even where not explicit, generally by focusing objects explicitly around an entity, such as text alerts to a mobile phone, or purchase interests in “my ebay”. All these things may have little importance individually, but analysed together can be used to build up a comprehensive picture of a person and their activity. In a time of political unrest and fear, even student records can contribute towards a case against an individual.

Personalisation systems necessarily make inferences about the user and their personal preferences, skills and knowledge, using this to decide what further information to offer them. However, the decisions made are often error-prone where rules applied to personal data give false or misleading results [59]. Examples include the CEO of amazon.com being publicly recommended an embarrassing movie and the TiVo system misclassifying users as gay [87].

Inferencing that goes wrong is bad enough, but even when it goes right it could prove equally embarrassing or harmful to individuals. Jernigan and Mistree [41] report on their success in identifying homosexuals through their network of Facebook 'friends', This occurred even where the participant did not have a public profile, but since their Facebook friends did have public profiles, their friendship was visible and could be used to accurately infer their sexuality.

The personalisation of search results relies on inferencing that can have even more insidious effects. Sweeney [76] reports on a racial bias being detected in paid results (advertisements) that appeared on search results. It appears that first names are frequently attributable to race, and that otherwise-identical searches were giving results that suggested a higher level of criminality among one race. A similar problem occurs for individuals whose name may be associated with criminal activity in a search bar with the autocomplete function. This is where the searcher starts typing in their search term, and a number of options pop up, starting from the text that the searcher is typing. The options are based previous searches by other people, and it tends to list the most popular searches with those opening digits, and sometimes those previous searches have falsely associated a person with criminal activity. While these unfortunate associations might easily be generated algorithmically [4] [5], in at least one case, it seems that someone has deliberately created an entry in the autocomplete function by sending in a scurrilous query so many times that it appears in the autocomplete function [6]. But deliberate or algorithmic, the reputational damage is equally significant, such as the erroneous photograph in numerous news articles reporting a child-abuse case and propagated widely on search engines [51].

Such associations can be quite harmful not only to the groups or individuals subjected to such implications, but to the community at large, as it propagates harmful beliefs to one of the widest of all audiences, namely search engine users. One can imagine a student using a general search engine for finding materials by a given author and being sent advertisements implying that the named author was involved in criminal activity, or perhaps having the autocomplete function fill in risible suggestions about the author.

In e-learning, the issue of inferencing errors has not appeared in the literature, perhaps because personalised e-leraning systems are not as widely-used as general search engines. However, we cannot afford for inferencing errors to happen, as disadvantaging any student via a miscalculation could lead to reputational damage for the institution, or even litigation, as well as compromising the student's education.

In a way, personalisation is all about inferencing - inferring the user's needs or interests from their history and context. Sometimes the inferencing is easy; for example a student who fails a test clearly needs some additional assistance on the materials being examined. But at other times, the inferencing may be error-prone, prioritising materials that are less helpful for the student's task in hand. A wrongly labelled data chunk, or a strategy with essential missing parts may hamper students instead of supporting them in their learning process, or inadvertently filter out essential information.

The quality of inferencing also depends how good the user model is. If the stereotypes are poor or too general, then there is a potential problem. The impact of it as a problem depends upon the user interface. With some systems (such as link ordering or link colouring) the worst-case scenario then is that links are ordered sub-optimally, or there is an eccentric colour scheme. However, with other interface designs (such as hiding links or adapting content), students could end up not being given important information.

Also students may come to dislike the personalisation process if the interface does not give them the feeling of control. It is a basic tenet of human-computer interaction that users should ideally feel in control of their experience. This is what is known as *scrutability* - the user is aware of and able to manage the personalisation facilities [43]. However with personalisation systems students may feel a sense of disempowerment. Again this depends upon the user interface. If the personalisation is presented as recommendations (such as in link ordering), or if it is an opt-in system, then this is less likely to be a problem. If it is an adaptable system that is under some form of user control, then the user can feel very much empowered [44] [84].

However there seem to be few personalisation systems other than experimental ones that offer the student the ability to control the personalisation applied to their interactions with the system. A very basic level of control is afforded by going outside the system in some cases, for example the Startpage search proxy[4] allows users to access Google search results but without passing on any personal or context information. However this merely turns the personalisation on or off, not making it possible to contextualise search in controlled ways, for example by releasing one's location or device type. Fine-grained personalisation control does not seem to be possible in mainstream personalisation systems. Nor is there any transparency about the inferencing process, so the user frequently is left guessing why the results have been personalised in the way they see. Some sites such as amazon.com allow feedback on recommendations but most do not clarify why the recommendations were made in the first place, nor provide any way to turn them off.

3.3 The effect of personalisation on individual capability

The aim of personalisation is generally to alter the content shown to the user so as to meet the perception of what the user is most interested in. However, a by-product of this process is that it filters out what is not designated as being of interest to that user, and presents to them only what fits the system's belief of what their interests are [17].

[4] See https://startpage.com/ or a similar tool Ixquick which interfaces to numerous search engines https://ixquick.com/

This filtering comes with a number of potentially harmful side-effects on the user's individual capability and personal experience. The first such problem is the loss of serendipitous exposure to the unexpected. When reading a general-interest newspaper or magazine, we are exposed to beliefs and lifestyles that may be very different from our own personal experience and which may trigger new ideas. Such encounters with the unexpected when seeking something else are called serendipity, and can sometimes bring benefit or at least interest to the discoverer. However personalisation reduces the potential for serendipitous connections with alternative beliefs, lifestyles and culture, and even novel solutions to new or old problems. If a personalisation system helps users to filter out information that does not meet their immediate needs or interests, they are exposed to fewer alternative belief patterns. Not only is it restricting their information diet, promoting an insular way of thinking, it reduces understanding between different ways of thought and might even be argued to be divisive. It encourages an ignorance of the lives and world view of others.

We called it *serendipity* in [3] but it goes by other names. Pariser later called the lack of it *the filter bubble* [62], and it is also colloquially known as *google goggles*[5] [18]. It occurs at the hands of service providers, but users can also personalise their social media environment in a similar way, filtering out users they do not wish to hear from, further self-censoring their information world and narrowing their viewpoint[6]. This isolation of the student shows how personalisation goals to some extent conflict with society (or group) goals, because they are there to serve the individual and not the collective. For students in particular it can be a barrier between the individual and the cohort, because the material one student would see would be different to that of others.

There is however some element of apparent serendipity in personalised systems, because users often receive results they do not specifically ask for in a search. In recommender systems, the users are exposed to items that they may not have requested themselves but are what other similar users have already accessed. So it may be that a form of collaborative filtering-based serendipity will broaden students' perspectives. For example, when students seek information on a topic for an assignment, they might be recommended other works to read ("other students searching this topic have also been reading these") that may induce new connections.

Recommendations based on activities of other students may be more useful than algorithmic recommendations by software. Personalisation works because users trust the judgements offered to them by software [72]. However it is a well-established problem in Web search that this *trust bias* subtly influences the choice of searchers who assume that the top few search results are the 'best' because they are at the top [42]. There is of course a sensible rationale behind this trust of search engine result rankings. However, search result rankings may be influenced by priorities of the provider, those priorities arising from misunderstanding of the user’s need, or perhaps other more commercially-motivated reasons. In a personalised e-learning system, this ought not be a problem, since students often rely upon the judgement and recommendations of others, especially instructors, when seeking information. Where the personalised e-learning system becomes a proxy for the teacher, students will accord it the same level of trust. It shows however that the developer (or author) of personalisation facilities in an e-learning system is the one in the position of authority, and if this person is not the actual teacher but instead is a professional content developer, this could lead to student trust being placed in a person whose educational credentials are not established.

There is however a significant difference between trust of human teachers and trust of search engines, namely that human teachers are primarily motivated by a desire to help students learn, whereas search engines are motivated by commercial imperatives. So, however accurate or mistaken their beliefs, the intentions of human teachers are to help students understand, learn and think. Search engines are not developed for educational purposes, even though students put them to such.

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[5] Not to be confused with the software of the same name http://www.google.com.au/mobile/goggles/ or the Google Glass device

[6] See item 27 in http://www.edrants.com/thirty-five-arguments-against-google-glass/

Interestingly, result (re-)ordering is one of the common techniques for implementing personalisation, and this is effectively leveraging trust bias in order to point users at what is believed to be the most appropriate content for them. However it is possible that exploiting trust bias is itself harmful to the student. Choosing the top-ranked link or search result every time will encourage a reliance by students on the judgement of the personalisation algorithm, and leaves them less practised at making their own decisions.

Personalisation systems aim to make relevant information more easily accessible for the user, but this presupposes that making information more easily accessible is always a good thing. While in some areas such as e-commerce, this may be true, in education the ultimate goal is always to help users learn, and learning is about far more than the access, reproduction and retention of information. It is about the internalization and reflection that leads to genuine understanding, and in order for effective deep learning to take place, learners should be actively involved in the design of their own learning experiences [53]. Learners need to work at learning if they are to develop deep understanding. If personalisation makes exactly the right information too easily accessible, this could undermine the learning process. Indeed, the entire intent of personalisation is to render information into constructs that are already understood by the recipient. However students need to acquire the ability to synthesise knowledge from disparate sources. Because personalisation assists the user to do this, there is a real risk that the learning process might become 'de-skilled', with the system synthesising knowledge rather than the learner having to do it themselves. It also creates an unrealistic expectation of how information will be available to them once outside the educational environment. If the educational environment does not encourage students to learn to think for themselves, it will be too late by the time they leave education and join the work environment.

The more users come to rely on others for decision-making, the less practised and hence less capable they will be themselves when the need arises to make their own decisions, without the aid of digital props. This degradation in user skills may arise from the trust bias if users become habituated to delegating their decision-making. It can also be detrimental to students' ability to distinguish not just the best results from good results, but even to distinguish when all results are poor.

If students are going to make effective use of any online resources, they need to learn to be discriminating because the web is well-known to include material of dubious quality, and it can take practice to distinguish this from high-quality content. A student's own discrimination does not always function effectively enough to recognise and reject poor results and may be a result of the trust bias, that belief that the search engine must be 'right'. On the other hand, poor selection may appear to exist when the users are using the results to inform themselves, as part of their learning process [73]. In this situation, do not have the knowledge to assess the quality of the results, and necessarily must trust the search engine to be providing relevant results.

If students need to learn to think for themselves without being told how to think by personalisation providers, it is an even more critical skill when reviewing materials provided by commercial personalisation providers. One potential threat to the community is the influence that personalising systems wield on the population at large. It has been suggested[7] that:

> Algorithms or systems which provide advice, contextual information or social feedback exert a powerful influence over decision making and society at large. We need legal restrictions and auditing requirements both to prevent abuse and to prevent concentration of power.

They go on to speculate about the level of trust that users place in these algorithms:

- You no longer think about anything for longer than 0.5 seconds. Instead you refer to your device and believe what it tells you.

[7] http://stopthecyborgs.org/about/

- You check how your actions are perceived by your peer group, the public, your employer, some ranking algorithm. You self censor and internalize the preferences of the system.

Something of this sort already happens in education. A high proportion of students use search engines to locate information for research and assignment purposes [27]. Yet the personalisation functions of search combined with a tendency to look no further than the first page of results [19] [71] suggest that students' research is limited to the ten or so results top-ranked by the search engine. While the ranking is intended to suit what the search engine believes the user is looking for, the educational value of the search results to the task in hand may not match what the teacher would agree is most relevant. Search engines are not e-learning systems.

We need to ask how much control of the education of students should be under the influence of search engines, data mining corporations and social networking sites, partly because of the uncertain usefulness of their results to the global student community, but also because of the potential for social engineering. Should a handful of unqualified social networking and search engine providers be permitted to determine what learning content students are exposed to? Does society want students' education to be shaped by professional educators or by search engines and social networks?

3.4 Personalisation and the different forms of learning and assessment

Learning comes in different forms, which reflect the different outcomes that are expected, and which involve different types of tasks in order to achieve those outcomes. These can be broadly classed as follows:

- *Vocational learning*: this is where vocation-specific skills and comprehensive information about the area of the vocation are taught. Students are motivated by the desire for accreditation and for the specific (e.g., technical) skills that will enable them to work in a given role. To be successful, students need to learn these specific skills in ways that make them competent to practise their chosen vocation.
- *Knowledge learning* this is where more general reasoning and analytical thinking are taught. The student is motivated by a desire to learn how to think deeply and come up with innovative solutions. To be successful, the student needs to learn how to think critically and to extend their existing knowledge.

The two are not mutually exclusive, as to gain a deep understanding of a subject and be able to think innovatively, students must have comprehensive information about the subject to be able to analyse it deeply and extend their understanding. However one clear distinction between the two types of learning is the level of human input required to successfully teach the student the necessary skills. True knowledge learning in research degrees such as doctorates, is almost always very demanding in terms of teacher (supervisor) input. While it may be acceptable for a single teacher to take charge of very large classes in undergraduate lectures, it is not seen as acceptable to mass-produce research students, and few research supervisors would have more than one or two dozen research students in their care, without doubt being cast on their genuine, personal involvement in the student's research. It is just too time-consuming.

This is important when considering personalised systems. Until personalisation systems incorporate genuine artificial intelligence or other methods to capture human judgement of research skills, it is going to be difficult to apply any sort of online learning technology to the teaching of critical thinking and innovation. This suggests that it may never be feasible to distil expertise about knowledge learning in a way that can be used in a personalisation system. This is exacerbated by the need for a research student to show originality, and in a personalised e-learning system, novel situations are the opposite of what it has been designed to deal with. Personalised e-learning systems normally coach a student towards predetermined outcomes, as represented by retained information and methods to arrive at those outcomes. With knowledge learning, there may be accepted methods, but the outcomes are by definition not predetermined, but must be original.

There is also the challenge of automatically assessing a student's outputs for critical and analytical skills. But without the ability to firstly judge a student and then to give feedback on how to improve, the personalisation system will bring no benefit. There have been trials of automated marking of essays in MOOCs, but it is not an accepted technology and has been challenged by academics [34] [39] [64].

So can personalisation be useful for vocational learning? Much of the online learning that institutions are providing now is vocational, with courses to teach students to program and use IT packages being popular examples. However there are many sorts of vocation that require hands-on practice, and while it is possible for a student to observe an expert performing, for example, surgery or fine woodworking, through a video, there is no way that feedback about the student's own activities of such type can be captured and processed by the personalised learning system. This means that the bidirectionality of the personalisation system, that key characteristic as discussed in the introduction, is missing. Without this bidirectionality, the e-learning system is not personalised because it knows too little about the student's capabilities to form judgements.

So where there is a physical, hands-on component of learning, a personalisation system is not feasible. However, there are many areas of learning where data capture is possible, and such areas include IT, mathematics, and engineering, as well as the theoretical aspects of many of the more hands-on areas. For example, a student would not be permitted to operate on a patient or to dovetail a joint until they had shown that they already had a theoretical grasp of what they needed to do, and this theoretical knowledge can easily be part of a personalised e-learning system. Also there is in the not-too-distant-future the possibility of using virtual, augmented and mixed reality technologies to allow a student to practise a hands-on procedure without causing harm or damage; flight simulators are a well-established example of this, and there is also research on personalised virtual reality environments [28]. This would be one mechanism through which data about the student's performance could be captured and personalised feedback and assistance given.

This brings us to the assessment of student work. In personalised e-learning systems, ongoing assessment of the student's requirements, abilities and outputs needs to occur so as to judge how to further personalise content. There are different types of assessment, some of which are easy to mark online, such as multiple-choice questions, short-answer questions, and mathematical proofs. Other forms of assessment are harder to mark automatically, including the writing of essays and reports.

One key task associated with learning which has not changed significantly with the digital age is the way in which learning is assessed: the assignment of a designated *task*, e.g., write a report, essay or proposal on a topic whose outcome is associated with how much learning transpired. Personalisation could potentially assist with the performance of the task.

While personalisation is generally considered from the perspective of the student, and concerns tailoring content to student characteristics and behaviour, we can also consider how personalisation may be applied at the level of task, where a task has “a defined objective or goal with an intended and potentially unknown outcome or result” and is accomplished by performing one of more activities [80]. Given a group, for example, a class, all students may perform the same task regardless of the knowledge, experience, insights, etc. that each brings to that task, and each task is a multi-faceted unit for which learning is required at each stage.

We often treat such a task as a single unit, but a task such as “write a paper…” has a designated set of actions or sub-tasks that personalisation could service without compromising security and privacy, or negating serendipity. Kuhlthau [49] and Vakkari [82] [83] looked at how information is used within this process and identified a distinct set of phases through which all students go in the process of writing a paper or proposal: 1) task initiation, 2) topic selection, 3) pre-focus exploration, 4) focus formulation, 5) information collection and 6) search closure. A student’s need for and ability to consume information depends on the particular phase a student is in. For example, in the initial stage, students need to identify a topic during which they are attempting to understand the scope and nuances of a particular area. Once a topic is selected and understood at some level, students need to explore it more broadly and deeply. By the time they are finished, they need to simply ‘fill in the gaps’ with missing information. Yet search engines treat all requests with the same level of specificity, regardless of which phase a student is it; a preferable solution would be providing a reduced, encyclopaedic-like level of knowledge at the beginning, so the student understands the nature of the issue or domain, and then unfolding more specific levels of granularity, as a student learns about the topic [31]. Thus, in this case, the search engine has the potential to personalise the outcome to both the student, and the task.

Some students may move through these phases faster than others, and also may start at differing levels of specificity. The challenge from a technical perspective is in monitoring the flow to the process, rather than the outcome to deliver information that is pertinent. This process calls for more effective learning environments – novel interfaces – that are tailored to the learner, personalised to learning task, and not just to the programme or module administration procedures that we see in existing systems, e.g., Blackboard.

So in summary, there is at present a limited scope for the use of personalisation technologies in e-learning and its assessment, applicable mainly to areas related to vocational learning, and dealing with known learning outcomes, but not currently usable for research-based, in-depth learning or where automated assessment is needed. However, as other complementary technologies, such as augmented reality and even artificial intelligence, develop to a viable stage, personalisation may one day be applicable to all areas of learning.

There remains one consideration, namely that as supporting technologies develop to a point where personalisation can be widely-used for different types of learning and assessment, we need to justify its use.

Personalisation has been shown to be well-received by students (see section 1). However, it is less clear how much it contributes to improving learning outcomes. It might even be argued that personalisation is detrimental to learning, since it enables the learner to remain within or very near their 'comfort zone', as opposed to learning practice that best outcomes are achieved when a student is pushed outside their comfort zone.

It is plausible to expect improvement of learning outcomes through personalisation in e-learning, based upon drawing parallels with conventional teaching. In small group teaching, if a student doesn’t understand a particular concept, the teacher adapts the session to help the student achieve understanding. This corresponds to the Laurilard model of learning [50] where the teacher explains something to the student; the student formulates their own mental model of the concept, and explains it back to the teacher; the teacher then uses this to modify their explanation to the student, and so on, until the two mental models match. This is a good argument for personalisation when e-learning systems are attempting to model small group or one-on-one teaching styles. However even if we accept that personalisation will help to facilitate learning by embodying something akin to the Laurilard model, it remains still only a theoretical reason why it should be beneficial.

These theoretical benefits do not always occur in practice. A good example here is on matching learning content to student learning styles. A number of adaptive hypermedia system assume that students with specific learning styles may benefit most from a specific kind of content, e.g., visual learners will need more content presented as pictures. Yet few reports based on post-production user studies have been published. Other research indicates that students may learn better when they start with the least beneficial form of content [45], i.e. pushing students outside of their comfort zone. In fact, there may be no effect at all in terms of improved student achievement with personalisation based on learning styles, with one study evaluating two particular learning style systems [11] and finding that not only did personalising content to a student's preferred learning styles give no significant difference in learning outcomes, it also found that matching the personalisation to the opposite of their preferred learning style likewise had no impact. This was true for both undergraduates [11] and in 8-10 year old children [10], supporting the work of learning style critics [20].

However, personalisation takes many forms, and personalising according to learning styles is only one form. Evidence is hard to gather because large user trials can be difficult to design without creating ethical problems by experimenting with control groups whose education may be compromised by lack of equivalent learning opportunity. In search and e-commerce, research on the efficacy of personalisation has quite likely been done by corporate providers such as Google and Amazon, but this research is rarely published, even though their continued use of personalisation indicates that there must be some benefit in it.

However, there is less evidence of outcomes-based benefit in personalised e-learning systems. One experiment found that personalisation in the e-learning system improved the outcomes of a less-able student group within a cohort [74] but this was accompanied by improved engagement, so it is uncertain whether the improvement was in part due to the increased engagement of students using the personalised e-learning system, as observed in the same experiment. This, and other confounding factors, such as the reduction in contact time with teachers and the increasing reliance on IT skills for learning, make it challenging to isolate the true effect of personalisation in e-learning systems on student outcomes.

While there is little evidence either for or against use of personalisation in e-learning, it remains unknown whether it works in educational terms. Is it ethical to trust people's education to what is essentially unproven technology? While researchers might be willing to risk trialling something of an unknown quality, it is not surprising that mainstream teachers are less enthusiastic.

3.5 The commodification of education

Online learning and hence personalisation are seen by some as the future of education [35] and many universities are scrambling to get their MOOC offerings ready (mostly, without personalisation) so as to not be left behind. Online learning is what both providers and students think they want: providers because they can process many more students, and with a lower per-student cost to service, and; students because it gives them access to education without needing to attend in person, with the significant relocation costs that can incur, and at a potentially better institution than the ones available locally.

This means that education is increasingly a high-volume process, but what does this do to the quality of the teaching and learning? The first and most obvious change is the radical reduction in the number of staff servicing students. This will necessarily impact the quality of the education, which, while overseen by a human teacher, is poorly-monitored by humans in contrast with traditional teaching. Even established distance learning institutions like the Open University UK have large numbers of human tutors available at specified hours for students to consult, but MOOCs and personalised e-learning systems do not do this, and indeed cannot do this, due to the different order of magnitude they deal with, in some cases, many thousands of students per course, instead of hundreds or fewer.

There are many other issues arising from high-volume teaching, including the appropriateness of the content for online-only teaching (as discussed in 3.4 above), as well as working conditions for staff who are generally the first point of contact for students. Larger numbers of students will generate many more enquiries when the online materials are not understood by the student, and when students pay for the courses they take, they expect and demand a higher level of contact with staff. However the personalised e-learning system is frequently tasked to supplement or even in extreme cases to replace the human teacher [26] [86].

Also the online-only learning environment, whether personalised or not, can reduce networking opportunities for students. Attending a university in person gives students access to new friends and social activities, as well as potential employment contacts, plus informal and sometimes off-topic conversations with staff, giving them better insight into academic life, motivational drives and additional contextual and non-contextual information. When students are not attending in person, the university experience is very different. When personalisation is introduced into the learning materials, the student may have even less contact with peers and staff, as their learning requirements may be met through clever presentation of content, rather than by discussing the content with others. This concern can perhaps be met through the use of further online tools such as social networks, as there are many students who are happy to 'meet' with 'friends' through such media.

Personalisation cannot address all the problems arising from the shift online of education, but it has the potential arrest and to some extent reverse the damage being done by the online shift, if only as far as the student's learning experience goes. Personalisation would make online learning feasible by repairing the main damage that would make MOOCs otherwise much less acceptable, namely the apparent lack of human monitoring of students' progress.

Interestingly, however, personalisation technologies could actually contribute to the online shift and dehumanisation of learning by their very success. This much is evident from the success of online book sales - fewer people would go to Amazon online if it were nothing more than a list of books for sale, but people are happy to shop there because of the recommendations based on what other humans have bought or viewed, and the comprehensive human reviewing system. Thus personalisation could have potential to damage traditional educational methods, including face-to-face teaching, if it compensates for their removal too well.

So how do all of these problems fit with the educational institution's requirements for online learning? It could be argued that there is a fundamental and insoluble conflict between the commercial imperatives of learning institutions and the human needs of students and staff. Also the needs of the society in terms of well-rounded and well-educated graduates are not always being met, because some institutions no longer prioritise turning out better-educated students who have learned how to think, but require students only to meet the necessary conditions to gain a credential.

This commodification of tertiary education in many countries arises because tertiary education is no longer a government-funded priority, especially after the global economical recess. At the undergraduate and taught postgraduate level, some universities are seen as being businesses that supply credentials rather than being hothouses of knowledge. This is doubly unfortunate for students who in many countries end up paying part or all of the education cost but still end up with intensive, high-volume practices being introduced into their education, because the universities are increasingly needing to operate as self-funded businesses. They need more students, processed quicker and cheaper, to fund their business model.

The servicing of ever-growing cohorts is what lies behind personalisation in e-learning. Originally it was with the best of intentions. Concerned academics witnessed the degradation in teaching quality as they were expected to service more students but with much less time to spend on a per-student basis. In response, they tried to address the reduction in time with better technical support, trying to 'work smarter, not harder'. This is how personalised e-learning systems came about - the intentions were honourable and aimed to repair some of the damage arising from the commodification of taught tertiary education.

However the success to date seems to have only aggravated the situation, by giving education providers additional tools that might justify further expansion of class sizes and staff reduction, even where those technologies may have ethical and social problems. For institutions, the 'return on investment' is measured by how much money can be made or saved by using a given technology, rather than how well-educated and well-rounded their graduates are. Employers do have some influence here, as they are seeking 'work-ready' graduates who can start work without too much additional training and this has a knock-on effect with parents who also prioritise their children's post-graduate employability.

4. Recommendations

Above we have discussed a number of ethical and social issues that arise from the use of personalisation in e-learning systems. For some of these it is feasible to mitigate the problems by modifying the technology of personalisation, and for others, we may be able to address the problems by changing the way we use personalisation. In some cases, more research and education of users may be required. In this section we consider possible solutions, technical and otherwise, that could mitigate the ethical and social effects of personalisation while retaining its benefits.

4.1 Reclaiming some privacy

The privacy issue includes privacy of data collected within the institution for educational purposes and privacy of data collected when students access systems external to educational institutions. There are a number of privacy-enhancing technologies that can be used as scaffolds in light of the limitations of mainstream technologies. Students can deploy simple, readily-available tools such as anonymising search engines like Ixquick and DuckDuckGo that do not collect personal data. In addition, scriptblocking tools such as NoScript can prevent data collection by analytics software. These tools are controlled by the individual so students can prevent analytics scripts from operating on their devices, regardless of institutional policy. These applications prevent or modify the data used by personalisation systems, and will change the way that personalisation is carried out. In such a situation, the system will default to a non-personalised generic presentation, like a textbook that is not personalised to the student. There are some sites[8] that refuse any access to their content if scripts are blocked, but such a response should never be seen as acceptable by any teaching institution.

It would however be better if institutions did not feel the need to outsource analytics software from third parties. Analytics providers receive raw data to process back into information for institutions, however it would be equally possible to operate such software within the institution so that raw data never leaves the institution.

Within the institution's own systems, data collected for personalisation systems needs to have been shown to be important for the personalisation, and that personalisation needs to be shown to be beneficial to students. This requires both research to determine what personalisation is beneficial, and strict adherence to programming practices to ensure unnecessary data is not collected.

Better control over what data is collected should be feasible. Scriptblockers and anonymising proxies are fairly blunt instruments that do not give detailed control over what personal data is released. Software should be developed to release user-selected information such as location or browser version while suppressing other data.

4.2 Controlling inferencing

The inferencing performed by personalisation systems is in most cases completely opaque to the student. Students do not know what calculations are being performed or why, nor what data is being used in those calculations. They may not even be aware that the personalisation is taking place.

Information and control are the solutions to these problems as it is for the previous one. All personalisation systems should give the student the ability to turn off the personalisation as well as identifying what information is being collected and how it affects the results. After all, leaving the user in control is a cornerstone of systems development. More transparency is desirable if the user is to trust such systems and accept the personal data collection involved. On the other hand, perfectly scrutable user models may not always be desirable; it is not always possible to show a learner all the data a system has been gathered about them, for example private comments by academic staff. However, an adaptive system should provide at least some explanation and summary of what is being gathered and why. For instance, the personalisation system should have an "About Me" link on every page that clearly shows the student what inferences are being made about them on that page, ideally explained in non-technical terms.

4.3 Reintroducing serendipity

One thing that is not always helpful in education is the filter bubble, as the whole point of learning is expanding understanding. Serendipity enables one to find novel solutions to problems that are not being examined, or to identify novel, unexpected findings.

Randomly-selected items (similar to Google's "I'm Feeling Lucky") or peripherally-relevant items (such as Wikipedia's "On this day") can briefly expose the student to things they may never have thought to look for. However they do not fully account for the serendipity that occurs when students make valuable connections that they did not plan on the outset.

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[8] An example is www.qantas.com.au which merely gives the script-blocking user instructions on how to enable scripts in their browser.

Serendipitous exposure will not only expand the student's personal horizons, it will also reduce the effect of the trust bias which will be gradually weakened as students grow aware of the fact that something on every page is not chosen for its apparent relevance. This should encourage them to assess for themselves the impact of what they see and help halt the skill degradation that occurs when too much unquestioning trust is placed in personalisation systems.

4.4 Dealing with external providers

Without regulations or legislations we cannot control how external agencies use personal data (apart from the privacy-enhancing technologies discussed in 4.1). Knowing what calculations have occurred is almost impossible, although taking control of the personalisation of results, however, may be feasible using the non-mainstream search services.

The methods for ensuring more serendipity and reducing trust bias (in 4.3) clearly apply to external providers at least as much as with local services. One can ensure that at every call to external providers (primarily search) incorporates serendipitous results, even if the search engine does not return them itself, since technology can insert them at the point of receipt.

For search, it is equally feasible to do some in-house personalisation of results, and in fact this has already been trialled [75]. One first needs to turn off the normal personalisation at the search engine's end, perhaps by routing all search engine requests from within the e-learning system to an anonymising proxy. Then the personalisation system at the institution's end can perform the personalisation on the non-personalised results that the search engine returns. This means that teachers are able to use personalisation rules that are more suited to the specific purpose of the educational institution, and the assigned learning task.

4.5 Non-technical solutions

To complement the technically-oriented solutions to some of the ethical and social problems arising from the use of personalisation, there are also some non-technical solutions. These are *information* and *education*.

The free provision of information is essential to ensure students know what is being done in such systems and what the possible effects are, both generally but more importantly on themselves. It has to be easy to read and understand, at least for the average undergraduate. To withhold this information denies the student the opportunity to exercise their own judgement. It further suggests that there is some illicit management of the student's behaviour occurring in the background, and while this is sometimes merely a social 'nudge'[9] in what is deemed by someone to be the 'right direction', at worst this sort of social engineering becomes little more than propaganda. This can be especially concerning when the nudging is performed by a third party with no affiliation to the student's educational institution.

The education of people about the ethically and socially responsible ways of using personalisation technology is the other main solution. Ethics and social responsibility do not often feature in taught degrees[10], yet it is important to educate people to behave in ethically and socially acceptable ways, not just students, but staff and university policy makers. Students need to be aware of how personalisation has both ethical and social problems, and consider whether they should put their personal benefit above that of society's.

In addition to educating people in ethics and social responsibility, students need to be educated about their rights and not blindly accept everything the educational institution throws at them. They also to be aware of when they are outside of the somewhat protected boundary of the institution, such as when they decide to discuss their coursework on a social networking site, and what might be the outcomes of doing this.

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[9] See https://en.wikipedia.org/wiki/Nudge_theory

[10] Griffith University in Australia runs such a course, see http://www.griffith.edu.au/__data/assets/pdf_file/0009/290691/Ethical-behaviour.pdf

E-learning providers need to be educated about where ethics and social responsibility do not overlap and consider closely whether they really need to do the right thing for the institution at the cost of doing the right thing ethically (for the students and staff). Students and staff need to consider how their individual rights incur responsibilities to their social group, including the institution. There is a contest between ethics and social responsibility in many respects, for example privacy concerns about widespread communications surveillance has significant ethical implications but at the same time, makes it easier to detect or prevent crime or terrorism.

4.6 The insoluble problems

It may be that addressing some ethical and social problems requires more than simply changing the technology or educating users. Probably the most pressing problem is the commodification of education, because this underlies the commercial imperatives of education providers, driving the provision of learning primarily according to delivery cost. However no institution can be held accountable for this problem, nor any corporation or a single government; rather it is a global mindset that prioritises money, power and influence above all else, plus a belief that individuals should pay directly for what they use, even of critical infrastructure. While the user-pays principle does ease the burden on taxpayers, at the same time it allows denial of responsibility, even for core functions, and promotes a commercial focus for the provision of essential services such as education. Until this mindset changes, technologies such as personalisation will continue to be used and extended in reach, too often *supplanting* human contact and teaching support instead of *supplementing* it.

5. Conclusions

Above we have raised a number of social and ethical issues that occur in the use of personalisation in an e-learning context. While there is much promise of benefit to students, both in terms of their engagement with learning and potential for improved learning outcomes, there are problems arising, either seen already in personalised educational systems or predictable problems, as judged from observations of non-educational personalising systems. The problems are likely to have an impact on the individual student and more generally on the community as a whole. We are already experiencing some of the problems arising from personalisation as it occurs in search, in particular the privacy, serendipity and deskilling problems. The widespread use of search makes it hard to correct these problems, whereas personalised e-learning, because it is not yet so commonly used, still has the opportunity to be designed in such a way as to mitigate these problems.

We propose that everyone should have the information about what information is being collected about them and how it is used in conjectures about them, how personalisation technology works and how it is being used in education but also in commercial systems. More importantly, everyone should have the ability to control personalisation technologies so that no personalising system could deny them access to the same information seen by others. However the most important solution we propose is a clearer and more complete understanding of what personalisation can achieve for e-learning, and for this a robust programme of experimentation is required to attest to the value of personalisation for all types of teaching where it is applied.

There is great promise of benefit from using of personalisation technologies in e-learning, but there are also pitfalls to be dealt with before it becomes mainstream. One of the main problems regarding the ethical and social impact of projects is that of evaluating technologies sufficiently early, so as to enable useful influence on fundamental concepts and design. Personalisation has its pitfalls and needs to be thought about more before leaping into its use. This paper has conjectured about the potential harm of personalisation technologies, so that future e-learning and other systems can be designed in a way that minimises that potential harm - some things are hard to 'bolt on' afterwards and need to be designed in. We hope that the introduction of personalisation into e-learning would be in contrast to the way other Internet-based technologies have been introduced, in the past with inadequate thought given to potential problems, and thus needing significant corrective action which often fails due to inertia. Online security and online privacy are obvious cases in point here.

One of the most positive points in favour of personalisation is the ability to create increasingly detailed student profiles. Guthrie [35] writes that MOOCs alone will not transform tertiary education, but rather that the Next Big Thing for online learning will be the personalisation of learning that is enabled by the collection of masses of personal data from many sources. This use of what is now known as Big Data will, with the appropriate safeguards, be able to facilitate personalisation on a scale not possible in the experimental systems to date.

In summary, there is evidence to suggest that personalisation can have benefits in the e-learning context, as it has for e-commerce. We have growing evidence that students like personalised e-learning. With further research and a better understanding, we can more wisely apply personalisation to avoid the possible harm that might come to students through its use, while enhancing student learning. Although there has been experimentation with personalisation since the 1990s, we are still waiting for more data about what type of personalisation is useful and in what areas we can use it (and that will change as complementary technologies develop). So now is the right time to consider all the possible pitfalls and work out how to address them, before personalisation in e-learning becomes mainstream.

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