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, loss of serendipity, de-skilling, widening commercial influence, and the commodification of education. Personalisation is appearing in many systems already, so ethical and social harm is occurring already. Technical solutions and more research are needed to stem and prevent further damage.

1.1 What are e-learning and personalisation?

One of the major problems facing education in the online world is the sheer volume of information that users are faced with, some of it of variable quality. *Finding* information has never been easier, but finding *appropriate* information for the task at hand is often quite hard. Formal education aims to select out the most pertinent and reliable information, coaching the student to learn and then apply their own judgement and reasoning to information.

For most of human history, formal education has been primarily provided by human teachers. The rise of computer technology however has seen many human functions moved across to computer software, at times with great success, such as with banking and online sales. Education is one function that has moved online, implemented in e-learning systems. An e-learning system is a system that 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.

The great shift online has had many real benefits. It generates *savings* in human effort, with the greatest savings for repetitive and undemanding tasks. Also some tasks such as arithmetic, filing and retrieval, are performed *better* by software, being less error-prone and much faster. Indeed, its speed an enormous capacity makes *possible* some complex human functions that could not feasibly be performed in anything but software, for example encryption, chemical modelling and real-time calculation of spacecraft trajectories.

As with many functions 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. Whether it is better than the human equivalent is uncertain, and we discuss this in detail below. It does make possible or feasible some forms of learning such as teaching of enormous numbers of students, and access to the entire Internet of supporting materials.

However the move online of learning has occurred in parallel 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 the user 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]. Even if a system does little more than greet the user with their name, many people consider it is performing personalisation. More personalisation is found at online sales sites which recommend purchases based on users' prior purchases. Even search engines now offer personalisation, and the search results vary according to the search engine's perceptions of what the searchers want.

E-learning was one of the earliest areas where personalisation was trialled, providing the appearance of personal contact and tailored assistance to students in an educational environment of large classes and limited human 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.

So what is personalisation, especially in the e-learning context? 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 (some authors call this web with both social interaction and personalisation 'Web 3.0' [56]). Bidirectionality is the key feature of personalisation systems, because the system genuinely be able to interact with the user, 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].

Personalised e-learning was first implemented by intelligent tutoring systems [21], then adaptive hypermedia [7] and shortly after, personalisation started to be used by online bookshops[1]. It traditionally comprises the adaptation of content and presentation to take into account the student's context and history. Now that many students rely on general search engines as research tools, with up to 82% using Google and Google Scholar as their first choice for seeking information [27], it also encompasses personalisation of search, although this folding of general-purpose tools into e-learning environments can cause of friction. Most e-learning systems are purpose-built for assisting students with learning but search engines are mostly motivated by commercial imperatives, and are not designed for educational purposes.

1.2 What motivates personalised e-learning?

Personalisation in a commercial context is beneficial based on its return on investment [32]. The e-learning context is, however, quite different because the intention of personalisation is primarily to enhance the student's learning experience, rather than to promote further sales (although economy considerations can also play a role). In the e-learning context, there are three types of benefit that may arise from personalisation:

- *engagement*: are students more motivated to learn with personalised e-learning?
- *economy*: can personalised e-learning yield more cost-effective education?
- *outcomes*: is student achievement improved by personalised e-learning?

In this context, the importance of Massive Open Online Courses (MOOCs) is growing. In the USA, MOOC providers such as Coursera [22] have millions of students. Europe is now joining this trend as well and many universities have already joined FutureLearn [63] [79], a consortium of UK universities providing online access to education in a similar way to USA MOOC providers.

[1] www.amazon.com was amongst the earliest.

However, MOOCs often fail to provide students with assistance tailored to their individual learning needs. MOOCs have a high student-to-teacher ratio, sometimes with thousands of students and a single teacher [52]. The enormous enrolments but almost equally enormous attrition rates suggest that MOOCs are not meeting the needs of students [48]. Essentially, education is becoming increasingly “mass-produced”, and students increasingly disengaged, therefore anything that can combat the dehumanisation of this is likely to be valuable. There is therefore a good case for personalising courses using techniques such as adaptive hypermedia [14].

Education is a very personal experience. Students have different goals, expectations and backgrounds, and learn in diverse ways. In conventional teaching this was 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 these individuals, their learning objectives and the context in which they are learning.

There is evidence that personalisation is effective for engagement. Studies show that students prefer to use a personalised e-learning system [12]. In particular, use of adaptive composition of content motivates users to explore more content than using conventional search systems [74]. Through questionnaires, the students typically rate their experience with personalised systems higher than with non-personalised ones. For instance, students give very positive feedback on adaptive e-learning, both in terms of usefulness and ease of use, when allowed to ‘feel in control’ [40] or in environments which mimic others with which they are already familiar with in a different context (e.g., the Facebook look and feel in a personalised e-learning context, as in [70]).

As both distance and traditional education become more student-driven, the student's engagement and commitment are vital [26]. A number of educational innovations tested in research labs fell short of expectation in a real classroom due to students' lack of motivation to use it. It seems this motivation can be significantly increased by providing personalisation. Long-term user studies of ELM-ART, one of the first adaptive e-learning systems, demonstrated that students working with the adaptive version of the system are willing to spend twice as much time learning with a personalised e-learning system than a non-personalised one, with no additional incentives [85]. Longitudinal studies confirm this effect exists and show its magnitude [12]. Students working with an adaptive version of an e-learning portal put in two to three times more work than those using a non-adaptive system. Similar results of students provided with adaptation spending longer time in the system have been obtained [24].

Student engagement is not the only benefit of personalisation. 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.

One of the primary drawbacks of the “one size fits all” e-learning approach is that it is not responsive to the different student requirements. Students join a class with differing levels of ability, background and interest, but non-personalised systems lead all students through identical materials at the same pace, unaware when students are facing difficulties with the materials, or when they are bored by materials they find too simple. Essentially, a non-personalised system is the equivalent of the formal lecture where the teacher presents ready-made materials to a class, often with no interaction between class and teacher. By contrast, a personalised e-learning system mimics small-group teaching, interacting with the student, perhaps via quizzes or observation, and determining how well the student is absorbing the materials, perhaps giving remedial materials when appropriate. In some respects, the personalised e-learning system is able to replace human instructors, theoretically at least, as it is responsive to student needs (although most solutions opt for a complementary, hybrid approach – see [88]).

So the case could be made that personalised online presentation of materials has two economic benefits:

- the provision of *"small-group" type teaching* with fewer or no actual human teachers, and;
- the ability to provide a satisfactory and *responsive learning experience* [78] for distance students or other students who cannot attend usual hours. This makes it feasible for institutions to offer distance learning for perhaps the first time and thus increasing student numbers and hence institution income.

Purely from an economic point of view, the argument that online, personalised systems can reduce or even replace human-led teaching is not yet demonstrated. The effort required to set up and maintain such systems is non-trivial, and the effort required to author adaptive materials is significant [23] [38], and well as challenging, since most humans have learned to write linearly, yet adaptive materials require the ability to section (or "chunk") materials into re-orderable small parts, while still retaining narrative flow. Thus from the point of view of authoring cost, reuse and repurposing of sectioned materials seems to be the only plausible way to reduce costs. Ten years ago this was just not feasible, given that most learning materials were written linearly and very difficult to "chunk" for reuse, since the context presumed in each chunk was often missing. However, such reuse is progressively becoming easier now, since online writing is now tending toward self-contained chunks by default, and included into other contexts via and links or transclusion. The reuse and repurposing of sectioned materials and adaptation strategies may reduce costs at times, but the high initial human input requires significant reuse to make it pay for itself, which may not be possible with educational topics that need regular updating. On the other hand, when class sizes are of the scale seen in MOOCs, the effort invested in authoring personalisable materials is much less on a per-student basis and may make it cost-effective.

Nevertheless the reduction in human input required to teach students is itself potentially damaging. For an institution offering fully online courses with pre-recorded lectures and personalised e-learning "tutorials", students may question the value of enrolling with the institution at all, unless it is particularly prestigious. The institution must offer something to induce the student to enrol, generally some form of supportive human contact, both staff contact and the student's social experience. The high drop-out rates of MOOCs potentially suggest that many students find fully online courses to be too challenging.

This form of human support is found in the methods used by one of the longest-operating distance education institutions, the Open University in the UK. While most course material is presented online, human tutors are available at specified times for consultation by telephone or email. Other Open Universities (e.g. in the Netherlands and Australia) function in a similar way.

Therefore, even if online personalised systems can reduce or replace human instructors, the initial costs of authoring materials are unlikely to be lower, especially if materials require regular updating, so class sizes have to be large in order to make personalisation a cost-effective technology in e-learning. There is also the concern that dehumanising the learning process may repel students and have a negative impact on the institution's income, so personalisation in e-learning systems needs to be effective enough to engage the students.

This makes an interesting contrast to the personalisation of services offered by recommender systems belonging to commercial sites. While details are generally not made available, it is evident that there is a financial motivation behind the personalisation functions in these systems, presumably the increased sales that come from exposing the user to other items they may find attractive. However, there is a significant difference to e-learning systems, because the authoring of materials can be very simple to automate, and often is in fact based on various forms of collaborative filtering [68], for example, the aggregation of purchasing and viewing histories of numerous previous users where the users do the 'authoring'. This is a highly economical way to offer users personalised recommendations, as it requires primarily data collection and mining, and little paid staff effort, the bulk of the personalisation "rules" being defined implicitly by the past users.

The cost versus benefit of implementing personalisation is less clear-cut in e-learning systems than it is for recommender systems. The simple commercial model of online retail recommender systems does not map onto e-learning personalisation systems, as it may not be feasible to automatically map across prior students' activity for use in an e-learning system, since students are, by definition, not experienced in the study area and not the best judges of the most useful information. It would also be subject to error propagation where many students made the same error or accessed the same unreliable material from a search – just because many students have a certain belief does not make it true, as was discovered in [2] where it was noted that "three axolotl pictures were labelled [by humans] "fish" … The crowd does not always manifest wisdom". This is however a matter of numbers, and while the likes of Wikipedia can provide gradual filtering of erroneous information through sheer number of its users, smaller-scale learning systems have significantly fewer users at any one time, and thus misconceptions can last longer. In this context, moving from the more traditional small scale learning systems to MOOCs can provide the more appropriate scale for collaborative filtering; this approach is taken, for example, in KnowledgeSea [16], which highlights items clicked frequently by previous students.

As a second possible economic benefit, it seems that personalised e-learning systems would make it feasible for institutions to offer a satisfactory learning experience delivered primarily online to remote or working students [25] [81]. While large-scale data are not available, the experience of the authors (including from previous research projects looking at personalised workplace learning, like the FP7 EU Prolearn network of excellence) is that these distance students can find the wholly-online experience to be frustrating when their specific needs are not addressed. While the online e-learning systems are not fully personalised, they do have some personalised aspects with the system recognising the student and some of their preferences. However, the more sophisticated forms of personalisation are generally not present, and the students require significant personal interaction with instructors in order to feel that their individual needs are being met.

In summary, even if personalised e-learning systems cannot in the foreseeable future entirely do without human interaction with students, it can reduce the interaction required with humans (and reduce overall costs) by anticipating some of the individual requirements, generally those occurring most frequently, leaving the human instructors to deal with the more individual requirements of each student.

1.3 Ethics and Social Responsibility

There are a number of clear ethical and social issues arising from the use of personalisation in e-learning systems and elsewhere. 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 (section **3.2**). The user model then is involved in further calculations that decide what to show the user, and by the same token, what *not* to show the user, these calculations often resulting in loss of exposure to other concepts with the concomitant loss of opportunity, and encouraging personal ethical and moral siloisation (section **3.4**).

Not only does a personalisation system constrain what the user sees, but the personalisation system generally does not allow users to control it by turning off or changing the personalisation. Most systems do not even allow users to see what is happening or what factors motivate what content the user sees (section **3.3**).

Personalisation makes it easy for users to be lazy about decision-making and habitually delegate all their thinking to others, 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 (section **3.5**; section **3.6**). 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 (section **3.7**).

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 personal 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. But will this happen? Is the ideal achievable or has it been derailed by ineffective application (section **3.8**) and commercial imperatives? Certainly some forms of personalisation appear to be ineffectual at best (section **3.9**), but at worst they make it easy for students to delegate decision-making, discouraging the development of independent reasoning skills, and promoting intellectual laziness. This can only be harmful to the society that needs a literate, skilled and, above all, rational population.

It could be that not only has personalisation not yet been able to achieve its own educational ideal but has at the same time caused harm to more traditional teaching methods, aiding educational institutions to process more students, faster and cheaper, in their drive for economic self-sufficiency (section **3.10**). 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 in section 1.2), so despite any educational problems personalisation may manifest, it will nevertheless find a place in e-learning.

We considered some of these issues previously [3] but in this paper we significantly extend and give a more detailed discussion, and additionally propose solutions to mitigate some of the ethical and social concerns arising from personalisation. Personalisation, like all technologies, comes with both costs and benefits/opportunities, and, after a review of personalisation and e-learning in section 2, section 3 discusses the ethical problems and social costs, while section 4 is given to recommendations for addressing the problems.

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, 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 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 - i.e., a (often structured) collection of information about the user - which 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 both 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 thus 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 volatile (e.g., only stored for the current session) or permanent (stored for as long as the user is registered with that particular 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), also called an *adaptation* (or personalisation) mechanism, 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 textual (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 contained on, e.g., a single server. In opposition to this, 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 advantages and disadvantages of the open web: the search space is vast and 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 (Google, for instance, is allowing users to log in to provide such services). Personalised recommender systems recommend items (usually from a catalogue) based on stated or implied preferences. Recommender systems can be used to recommend 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[2]. 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, even ratings one would use for a given item, etc. 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', to recommend to a social media user specific learning material.

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

3.1 Privacy, security and ownership of personal data

Privacy is one of the most obvious of the problems arising 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 either deliberately, such as with the AOL500k query logs [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[3] [36]. For students, it is generally their educational institution that holds their student records, but with educational IT increasingly being outsourced to private enterprise, student user models will end up in corporate hands[4], perhaps even deemed to be owned by the company providing (or just managing) the personalised 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], a comment that is borne out by the recent survey of privacy attitudes in Australia where it was found that "*a growing number of people are taking pre−emptive measures to protect their information, from nine in ten (90%) refusing to provide personal information in some circumstances ... to six in ten (62%) opting not to use smartphone apps because of concerns about the way personal information would be used*" [61]. The latter point in particular highlights the fact that a significant number of people are willing to forego some functionality in order to avoid disclosing personal details. On the other hand, there still remain many people who do pass on personal information, even when not comfortable with 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 profile, whether it is session-only or more persistent. That user data is recorded and henceforth is potentially subject to use and abuse without the knowledge or consent of the subjects. In some cases, academic staff and students are not being notified that data is being collected about their use of institutional information systems and being sent to a third party for analysis. There are a large number of sites dedicated to the collection of data that tracks a user's activities, sometimes across different sites, and one increasingly widespread example is Google Analytics, which is currently analysing data from several universities (e.g., Harvard, Ontario, Queensland, St. Gallen, Sheffield, to name but a few). In the authors' experience, at least one university uses Google Analytics extensively: both

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

[3] Even so, the data available to 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/

[4] At least on of the authors' institutions has fully outsourced student email facilities to Microsoft.

students and staff at this institution are tracked as they access apparently every page on the institution's site, although 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.

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]. Furthermore, users can be classified according to what type of information they are willing to disclose [47].

However, the awareness of what is being collected is often lacking, and an increasing number of 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[5], 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 first realise this data collection is occurring, then either they must explicitly opt out of the data collection process, or in some commercial cases, be unable to view the site at all. The problem is worse where students make use of free, commercial tools such as shared documents, with no clarity about ownership of the data.

These social pressures are shaping the views of younger people in quite subtle ways. In recent years, the potential for abuse has to some extent ceased to discourage many people. Because we are living in a society where collection of private data is increasingly commonplace, sometimes to the point of constituting surveillance[6], many people are becoming more relaxed about this, in particular those who place great value on social networking sites. They are becoming 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, the younger generation are at times more privacy-aware, even if they still permit their data to be collected, so they can participate in the site. 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, according to German law, 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 a number of reasons why such regulations are not yet adequate to defend the privacy of students, and of staff:

- firstly, legislation is generally retrospective, so harm must first occur before legislation is enacted;
- secondly, legislation 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 sometimes there is no regulation at all;

[5] See for example the caveat appearing on most ebay pages stating "Use of this Web site constitutes acceptance of the eBay User Agreement and Privacy Policy".

[6] And likely to become ubiquitous if wearable devices such as Google Glass have a high take-up.

- thirdly, 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 widespread anger in numerous countries);
- fourthly, there is a lack of clarity and some conflict about what comprises personal data as opposed to 'non-personal data', with some sites[7] claiming that much collected data is 'non-personal' and implicitly is not subject to privacy laws. This however ignores the 'linkability' of data, namely that various bits of data collected may be in themselves harmless, but taken as a whole can give a highly detailed picture of a user;
- fifthly, 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[8] 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[9]. And even if it 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 with knowing what nation's legislation applies to the data;
- sixthly, negligent observation of data security requirements put student data at risk. There have been high-profile cases of large corporations who failed to properly secure their customers' data. One example was 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], but there are many other examples. 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;
- seventhly, there are a number of commercial tools being incorporated into learning environments, and these tools do not observe education-specific privacy regulations. This is not just the analytics software as discussed above, but also more general tools such as social networks and general search engines which are increasingly a part of e-learning environments. We discuss this further next.

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 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].

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[7] For example, Rovio, a provider of games to children and adults, see http://www.rovio.com/Privacy

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

[9] We used Wireshark, a packet capture tool, and an `https` proxy to inspect packets being transmitted to google-analytics.com from the login page (used by both students and staff) of a university's online learning system. The packets being sent were not in human-readable form, but by changing various inputs from the login page, we established that the password was not being transmitted, but that the unique user id was being transmitted.

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[10]).

Full disclosure is more likely to occur in academic information systems, which may even 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 user if their learning profile were used for other purposes. For example, an employer could demand that a student applying for a position give a copy of their learning profile, so as to assess whether a candidate was a quick learner or needed longer to pick up new skills, or whether their assignment submission was generally timely, whether they had any academic misconduct recorded, or whether they received special academic procedures for dealing with 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

Other than the obvious concerns about privacy, there are more insidious issues at stake. Think about 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 whom it belongs to.

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. As noted in [36] "*A particularly worrying example is that of the Morgan Stanley Dean Witter bank who "collect", among other things, details about an individual's race, religious beliefs, sexual preferences, union membership, etc. As this information is never required as part of the credit application procedures, it is most likely inferred by analysing the individual's subsequent spending pattern. This is similar to the way supermarket chains infer such things as marital status, number and age of dependents etc. using their "loyalty cards" to analyse purchasing patterns. Morgan Stanley Dean Witter also claim the right to disseminate this information*".

A related side-effect of personalisation is that it creates associations, even where not explicit, generally by focusing objects implicitly around an entity, such as text alerts to a mobile phone, or purchase interests in "my

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[10] See http://www.seomoz.org/blog/the-evil-side-of-google-exploring-googles-user-data-collection

ebay". All these things may have little importance individually, but taken together can be used to build up a comprehensive picture of people 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. It is generally known that corporations collect data for "marketing purposes" which often entails making inferences about user preferences based on stereotypes. 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 infer their sexuality.

The personalisation of search results relies on inferencing that can have even more insidious effect. 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 possibilities pop up, starting from the text that the searcher is typing. The possibilities are based on what other people have typed in previous searches, and it tends to list the most popular searches with those opening characters, 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 that are subject to such implications, but to the community at large, as it propagates harmful beliefs to one of the widest of 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 person 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 such 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, in addition to 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. This can be due to faulty or incomplete authoring, as mentioned previously. A wrongly labelled data chunk, or a strategy with essential missing parts may encumber students instead of supporting them in their learning process, or, in attempting to reduce students' search space, filter out essential information which could impact on the overall learning outcomes.

The quality of inferencing also partly depends how good the user model is. If the stereotypes are poor or, more likely, too general, then there is a potential problem. The impact of it as a problem is dependent upon the user interface. With some systems (such as link ordering or link colouring) the effect of a poor user model is going to be relatively subtle. The worst-case scenario then is that the links are ordered sub-optimally, or there is an eccentric colour scheme. However, with other interface designs (such as hiding links or adapting content), the consequences could be more severe, and students could end up not being given important information. They may also be aware that their peers do have access to alternative or more advanced materials, and this may be seen as being unfair. This brings us to the issue of scrutability and user control.

3.3 Scrutability and user control of personalisation

It is a basic tenet of human-computer interaction that users should ideally be in control of their experience, or at the very least *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]. There is a real danger with personalisation systems that the user knows are adapting their content, that they feel a sense of disempowerment. This does, however, depend 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, presenting the user with too many options to choose from may also lead to unwanted cognitive overhead. Thus, the amount and type of scrutability advisable remains an open research question.

However there seem to be few personalisation systems other than experimental ones that offer the user and 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[11] 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.

3.4 Retaining serendipity

There are other aspects of personalising that need rethinking - what becomes of serendipitous exposure to alternative beliefs, lifestyles and culture? If users filter out information that does not meet their immediate needs or interests, they are exposed to fewer alternative belief patterns. Not only is restricting one's information diet in this way promoting an insular way of thinking, it reduces understanding between different ways of thought and might even be argued to be divisive.

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. Such encounters with the unexpected when seeking something else are labelled serendipity, and can sometimes bring benefit or at least interest to the discoverer.

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*[12] [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[13]. This isolation of the student shows how personalisation goals to some extent conflict with society (or group) goals, because

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

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

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

they are there to serve the individual and not the collective (and basically represent a local maxima and not a global one). For students in particular it also can serve as a barrier between the individual and the collective, as the material, for instance, one student would see, would be different to that of the collective.

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 belief of what their interests are [17]. The danger is that this creates an ignorance of the lives and world view of others. Thus personalisation might be seen to be promoting a narrow-minded viewpoint as it suppresses alternatives, or, even worse, hinders the user's exposure to serendipitous discoveries. Exactly the same suppression of 'irrelevant' results occurs in search engines, leading to the deliberate design of "random" search engines that return results not selected for relevance[14].

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").

Serendipitous learning may well be more suited to informal learning than to formal learning, however it has been seen to encourage knowledge retention, due to the increased motivation of the chance discovery[15]. Thus the personalisation of content should be tempered with the recognition that a little serendipity, in the form of exposure to unexpected content, may be beneficial. The likelihood of serendipity is one of the great benefits of a rich information universe, and this encourages learners to 'think outside of the box'.

3.5 Managing trust bias

A closely-related problem to the lack of serendipity is the tendency of users to trust the judgements offered to them by software, particularly in search, but also in recommender and other personalisation systems [72]. It is a well-established problem in Web search that the "trust bias " subtly influences the choice of searchers, generally without them being aware of the influence. The trust bias is essentially that a particular search result must be good if it is at or near the top of the list of search results [42].

There is of course a sensible rationale behind the trust of search engine result rankings, and in general the results are pertinent to at least one sense of the search term. However, in search engines generally, users trust the system to provide an honest return, but we get returns whose ranking may be influenced by priorities of the provider which override the user’s need, those priorities arising from misunderstanding of the user’s need, or perhaps other more commercially-motivated reasons.

In a personalised e-learning system, this need 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.

A similar problem occurs with search engines. In search, trust bias is likely to be a problem in circumstances where the underlying ranking algorithms may not match the user's needs, and could even be a result of

[14] http://www.education.ed.ac.uk/e-learning/gallery/gritton_serendipitous_learning/serendipitouslearning/serendipitouslearning.html

[15] http://www.futurelab.org.uk/resources/publications-reports-articles/web-articles/Web-Article795

exploitation by search engine optimisation agents. 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.

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. As with all personalisation, this is only as good as the user model and the prioritisation logic, but if that is reliable, then exploiting trust bias in this way can be a highly effective technique of adaptation, and one which allows users to opt out of the adaptation at any time, by making a conscious decision to click on a link further down the list.

One care still remains, and that is that trust bias is sometimes due to the user not wishing to take the trouble to compare content - choosing the top-ranked link or search result every time will create a reliance by users on the judgement of the personalisation algorithm, and leaves them less skilled in making their own decisions, as we discuss next.

3.6 Skill degradation

One of the aspirations of many personalisation systems is to make appropriate information more easily accessible for the user, given their current context and goals. However, although this seems superficially very reasonable and worthwhile, it presupposes that making information more easily accessible is always a good thing. While in some areas of application, such as e-commerce, this may be true, there are some important applications, such as education, where this is not necessarily the case. In an educational system, 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]. If a user is to develop real understanding of the subject matter, then sound pedagogy is critical and the user needs far more than easiest possible access to the subject matter. In a very real sense, learners need to work at learning if they are to retain information and develop deep understanding. Personalisation, without careful thought about the pedagogy underpinning the instructional design, can make exactly the right information too easily accessible and this could undermine the learning process. Indeed, the entire intent of personalisation is to render information into constructs that are already understood, perhaps even preferred, by the recipient. This removes many of the challenges involved in understanding the material and can reduce opportunities for cognitive development.

We live in a complex world, and the acquiring the ability to synthesise knowledge from disparate sources is a vital skill. Because personalisation effectively attempts to do this for the user, there is a real risk that the learning process might, to some extent, 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.

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.

More importantly, if the educational environment does not encourage them to learn to think for themselves, it will be too late by the time they leave education and join the work environment. If overenthusiastic personalisation of learning materials prevents the student from acquiring and refining information discovery and interpretation skills, that student will finish up as an unemployable graduate.

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 be full of 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, i.e. as part of their learning process [73]. In this situation, their selections are necessarily less discriminating, because students do not have the knowledge to assess the quality of the results, and necessarily must trust the search engine to be providing relevant results.

So if a personalisation system works really well, there is a danger that people come to rely upon the recommendation of the system, rather than learning to apply their own judgement and make their own decisions. This is already happening with search engines, as seen with the trust bias, but worse, users are not even viewing or assessing a comprehensive set of results. A more recent sample of over 8 million clicks shows that less than 6% of users visit the second page of the Google result list [19].

In summary, people believe trusted sources of information. Teachers and e-learning systems are trusted sources of information. The same problem occurs with Wikipedia; people trust it because usually it is right - however, sometimes it is wrong[16]. There are several well-documented cases of plausible fallacies that have made it in to mainstream thinking and become widely accepted as the 'truth'. The deskilling that could occur in personalising e-learning systems is very similar, as students will assume the learning system is always right.

The net result of this is that users who habitually rely on software to make decisions or prioritise activities for them may become increasingly inept at doing so without the support of the software. While this may not be soluble within the personalisation system itself, educators should ensure that students still learn how to discriminate between resources provided by a personalisation system, and judge the quality of them without relying on software, either commercially-provided or purpose-built for e-learning, and above all, to learn to think for themselves without being told how to think by commercial personalisation providers. We turn to this issue in the next section.

3.7 Focusing influence in the hands of external providers

One potential threat to the community is the influence that personalising systems wield on the population at large. It has already been suggested[17] 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.
- 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 is already happening in education. A very high proportion of students use search engines to locate information for research and assignment purposes [27]. So the personalisation functions of search, combined with a strong tendency to look only the first page of results [71], suggest that the student's research is increasingly limited to the ten or so results top-ranked by the search engine. While the ranking is nominally intended to suit what the search engine believes the user is looking for, the educational value of the

[16] See for example http://www.newswise.com/articles/survey-finds-most-wikipedia-entries-contain-factual-errors

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

search results to the task in hand, as determined by the search engine, may not match what the teacher would agree is most relevant. Given that search engines are not e-learning systems, such a mismatch is highly plausible; however, there is as yet no experimental data to indicate the effect of personalised search on students' outcomes, or even how significant the problem may be.

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 trained, professional educators or by search engines and social networks?

Universities and similar institutions have developed over the last millenium to become specialist providers of education to students with a range of learning needs and expectations. They have been the centres of learning and deep thinking, and in more recent times, they have become providers of training for vocational pursuits as well. In the next section we consider why personalisation suits some forms of learning better than others.

3.8 Different requirements of different types of teaching

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 vocational learning and knowledge learning:

- *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.

This is not to say that the two are 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. Also, knowledge learning can be seen as a special case of vocational learning, if the student has a desire to go into research as a vocation.

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, as manifested in research degrees such as doctorates, is almost always very demanding in terms of teacher (supervisor) input. It is seen as acceptable for a single teacher to take charge of sometimes very large classes, often in the hundreds, even for face-to-face undergraduates lectures. However, it is not seen as acceptable to mass-produce research students in the same way, 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 education. It is just too time-consuming. This is important when considering personalised systems.

So until personalisation systems incorporate genuine artificial intelligences or otherwise a method to capture some representation of 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. In fact, even humans have difficulty agreeing on the quality of students' (and others') research skills when judged by their outputs, as is evident by the peer review process, which in many cases can return contradictory results.

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] [64]. An academic-led petition criticises the use of automated scoring given the high stakes, but also asks that teachers additionally refrain from using "*data generated by machine scoring of student essays to shape or inform instruction in the classroom*" [39], which clearly indicates doubt that automated scoring of essays can underlie personalisation.

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. Additionally, personalisation on the open web (see for example [54] [75]) can be a tool that can help discover new resources and information (potentially leading to knowledge acquisition) in ways which may not have been considered by the initial designers, leading to serendipitous outcomes. 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 an obvious, well-established example 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.

So in summary, there is at present a limited scope for the use of personalisation technologies in e-learning, applicable especially to areas related to vocational learning, and dealing with (mostly) known learning outcomes, and not currently usable for research-based, innovative, in-depth learning. 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. Until that time, however, the value of using personalisation in e-learning systems must be confirmed, something which requires further investigation, as discussed in the next section.

3.9 The effects of personalisation in e-learning systems

3.9.1 Personalisation in e-learning systems

Above, we noted that personalisation has been shown to be well-received by students. However, it is less clear how much personalisation contributes to improving learning outcomes. It might even be argued that personalisation is detrimental to the learning process, 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 (especially if the learner is to learn not only the material that is immediately presented, but is also to acquire learning skills that are applicable elsewhere).

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, students are often not given the same materials, regardless of their backgrounds or goals. 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], i.e., 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, this doesn't take into account the fact that that isn't always the case. There are probably more "virtual lectures" on the web than there are "virtual tutorials". If the model isn't a "computer as learning partner" model (i.e., the e-learning equivalent of small group teaching) then that argument carries little weight (i.e., if the model is more didactic, as it often is on the web). 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.

A good example here is the research on matching learning content to student learning styles. A number of style-adaptive hypermedia system were created with an assumption that students with specific learning styles may benefit most from specific kind of content, for example, visual learners will need more content presented as pictures. Yet, few success reports based on post-production user studies have been published. In contrast, other research indicates that students may learn better when they start with the least beneficial form of content [45], i.e., pushing students out of their comfort zone. In fact, it may be that there is no effect whatsoever 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 user's preferred learning styles give no significant difference in learning outcomes, even mismatching the personalisation to the opposite of their preferred learning style had no impact. This was true for both undergraduates [11] and in 8-10 year old children [10]. This agrees with the work of learning style critics [20], but it appears to contradict the orthodoxy of the adaptive hypermedia community that personalisation should be beneficial in all its forms.

This suggests that even by the age of 8-10, people are already well-practised at extracting information from a range of sources, including ones that are sub-optimal for the individual. Students might prefer information presented to them in one particular manner, but it does not appear to make a difference to how effectively they learn. However, if personalisation is genuinely effective, then it is possible that the learning process could actually be damaged if presenting people with information in their preferred styles prevented them from getting practice at dealing with information in other forms. When we acquire information from any source – online or otherwise – we get by. The information may not be in the perfect form for us, but we develop coping strategies to allow us to make effective use of it. Indeed, to do so is one of the most important skills that people need to learn to be able to function effectively in an information-rich society. Especially in terms of combining information coming from a variety of sources, in a variety of formats, and from a variety of devices via a variety of platforms, using a multi-tasking mind-set, the young generations (second generation "digital natives") mostly outperform the old in being able to use a variety of mobile devices, social media platforms, communication and search services, etc., in their daily lives (see [37] [65] [66]).

However, it should be noted that personalisation takes many forms, and personalising according to learning styles is not the same as personalisation in general. Evidence is hard to gather because large, and especially longitudinal 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.

Whether or not personalisation works in educational terms is challenging to establish. The problem is that very little research has been published about this. In education, it is largely because the research is difficult to do properly, since there are so few mainstream users of personalisation in e-learning. 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 is rarely published, even though their continued use of personalisation demonstrates that there must be some benefit in it.

However, no such clear outcomes-based benefit has been demonstrated in personalised e-learning systems, to show if and when the use of personalisation can improve learners' outcomes. One experiment found that personalisation in the e-learning system seemed to improve the outcomes of a less-able student group within a cohort [74] but this was accompanied by improved engagement, and it may be that the improvement was in part due to the increased engagement of students using the personalised e-learning system as opposed to a non-personalised one, 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.

Thus we can conjecture that there are types of learning for which personalised e-learning seems unsuitable (as discussed in the previous section) but there is not yet the comprehensive body of research to help decide what types of learning and content are suitable and show improvement in student outcomes.

While there is almost no evidence either for or against use of personalisation in e-learning, it remains unknown whether it actually works in educational terms. This raises ethical issues for any real-world applications. Is it ethical to trust people's education to what is essentially unproven technology? While researchers might well be willing to take the risk of trialling something that is an unknown quality, it is not surprising that mainstream teachers are less enthusiastic. It also creates a vicious circle - mainstream teachers don't use personalisation because it isn't supported by mainstream software (e.g., Moodle). It will not be supported by that software until there is the demand. Without strong evidence that it actually works, or some other motivation, the demand will not arise. However, until that cycle is broken such evidence is going to be hard to come by.

3.9.2 Personalisation according to 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 task may be defined as a “piece of work to be done” (Oxford English Dictionary 8th ed.). 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.

One of the key tasks 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 designated or self-selected topic whose outcome is associated with how much learning transpired. 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 on security and privacy.

Kuhlthau [49] and subsequently 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. From their research, it is clear that 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 personalises the outcome to both the student, and the task.

Notably, 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 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.

3.10 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. Whatever we may think of it, 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 potentially a better institution than the ones available locally.

Concomitantly, this means that education is increasingly becoming 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 agent, is poorly-monitored by humans by contrast with traditional teaching. Even traditional distance learning institutions like the Open University UK or Open Universities Australia 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 additionally many other issues arising from high-volume teaching, including the appropriateness of the content for online-only teaching (as discussed in in 3.9 above), as well as working conditions for staff who are generally the first point of contact for students to approach for their study. 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 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, additional contextual and non-contextual information, etc. When students are not attending in person, the entire 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. And where they do generate innovative research, the funding often comes from industry sources, and this in turn necessarily introduces partisanship in research directions. This is doubly unfortunate for students who in many countries end up paying part or all of the education cost (even 100% of it if they are international students), and then 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 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 ten ethical and social issues that arise from the use of personalisation in e-learning systems. For some of these it is feasible to correct or 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 able to assist. In this section we consider possible solutions, technical and otherwise, that could mitigate the harmful ethical and social effects of personalisation while retaining its benefits. All three types of solution are important and complement each other: the technology because it can enforce correct use of its functions; use of the technology because not all solutions can be technically implemented but must be a result of policy, and; information and education because these bring discovery and awareness of the issues.

4.1 Reclaiming some privacy

There are two aspects of privacy to consider here. The first is the privacy of data collected within the institution for educational purposes, the second is the privacy of data collected by external agents, accessed by the student either within the institutional environment or elsewhere.

There are a number of privacy-enhancing technologies that can easily be implemented. For the use of external agents, simple, readily-available tools exist such as anonymising search engine proxies such as Ixquick which can prevent the transfer of personal data to search engines. These proxies are under the control of the student, although institutions can assist by making them the default search engine selection when working within any institutional information system.

Scriptblocking tools such as NoScript can prevent data collection by analytics software. Scriptblocking is another tool that is under the control of the individual so students can prevent analytics scripts from operating on their devices, regardless of institutional policy. The caveat here is that the operation of scripts also underlies the functionality of many personalisation systems, including the collection of the personal and context data needed in calculations, so turning off scripts may change the way personalisation is carried out. In such a situation, the system should then default to a non-personalised presentation, like a textbook, so that the lack of personal data would not impose any penalty on the student. There are some sites[18] that refuse any access to their content if scripts are blocked, but such a response should never be seen as acceptable by any 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. It should be possible to release select information such as location or browser version while suppressing other data.

Privacy-enhancing technologies need to be backed up by legislation and good practice. For example, how could one address the problem of the employers demanding educational records from students, even 'voluntarily'? One response is to make such requests illegal, and punished significantly. This may not fully solve the problem, but it can help and will send a strong message that the practice is unacceptable. There are some proposals to ensure data shared is used for its primary concern, by policing outcomes of misuse. These however are only possible if the entities to be 'punished' (reduced access, denied access, etc.) are traceable in some way. For instance, if a university is aware of what type of data from the students is provided to what type of (personalised elearning) service, it can react to complaints about the data use (here, e.g., outsourcing the data in a manner outside the original contract) by moving to a different provider, blacklisting that provider, etc.

This can only happen if the outsourced systems are known to the university, of there exists some contract between them, and if the university, as said, is aware of the type of data shared.

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

So, for instance, a university could prevent any use of systems which don't fall into the categories above - but then it would need to ensure the same type of services to the students based either on own resources, or on known external provides with which it has contracts.

4.2 Introducing scrutability and controlling inferencing

The inferencing performed by personalisation systems is in most cases completely opaque to the student. Students will 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. And if they are aware of the personalisation, they may resent it or question its value.

Information and control are the solutions to these problems. All personalisation systems should give the student the ability to turn off the personalisation (i.e. "show me what most people get"). They should also clearly tell the student what information about them and their context is being collected, and how it affects the results shown. Students should even be given the opportunity to try out different presentations such as may be seen by other students, rather than merely turning the personalisation 'on' or 'off'.

More transparency is desirable if the user is to trust such systems and accept the personal data collection involved. However, perfectly scrutable user models are not always desirable. Indeed, It is not always possible (nor recommendable) to show a learner all the data a system has gathered about them. In most cases, it would only be confusing. So instead, 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. The student should have the capability to turn off calculations they felt were harmful or prejudicial, and to report incorrect outcomes.

4.3 More serendipity and less trust bias

One thing not always helpful in education is the filter bubble. The whole point of learning is expanding understanding. At times it is necessary to focus, perhaps when the information has been gathered, but there is also a need to be able to gather information from numerous sources without prejudicing what is available for review. Students also need to comprehend the inherent prejudice that exists in almost every presentation of 'relevant' materials, and to learn how to distinguish arguments from counter-arguments.

One clear solution is to put at least one serendipitous item in every online session or page, or perhaps even counterarguments to what the student is researching. Counterarguments are obviously useful for broadening the student's understanding of their topic and making them aware of alternative viewpoints.

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. While the student may not agree with or find pleasant the unexpected items they encounter, it will aid them in keeping an open mind, and being less prone to prejudice and total self-focus.

Inserting a random item into every session 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.

Another way of dealing with this is to have time-dependent personalisation. For instance, when first introducing a topic, presenting only the essential elements making it necessary to grasp that topic, and later gradually allowing the student access to a wider variety of information with regard to that topic, and perhaps, depending on their progress, at some point allowing completely free access, without any recommendations (or with much more discreet recommendations, such as when the information is not removed, but instead, the relevant information is highlighted in some way). In this way, students would be gradually exposed to the complexity of information available, and would still benefit from the advantages of personalisation, without paying the price for an overly customised world-view.

4.4 Dealing with external providers

With external providers of personalised services, such as search engines, it is not easy to control the release of personal data (apart from the privacy-enhancing technologies discussed in 4.1). Knowing what calculations have occurred is almost impossible. Taking control of the personalisation of results, however, is feasible.

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 canonical 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.

4.5 Raising the quality of teaching

The quality of teaching can be augmented by careful use of personalisation technologies. At present there is not enough experimentation to know which of the different types of education can be assisted with personalised e-learning, or how much they could be improved. However a well-structured programme of experimentation will be able to show where personalisation technologies are most helpful and where they have little effect or even unhelpful side-effects.

When constructing this programme of experimentation, firstly the measures of success have to be determined. Above we suggested that the motivations for personalised e-learning were engagement, economy and outcomes. To this should be added considerations such as whether the student learned faster, retained information longer, or was able to innovate more. Academic staff should be interviewed for their opinions on whether personalisation has been beneficial in any way.

Once such a programme of research is complete, it will then be clear which of the different types of learning will benefit from personalisation technologies and which are not well-serviced by it. It will become evident in what scenarios personalisation is a reasonable substitute for human tuition, and when it can only be used as an aide to human tuition. Personalised e-learning should only be used where it is demonstrably at least as good as human tuition and until this is known, it should not be used as a substitute for human tuition.

4.6 Non-technical solutions

The earlier sections suggest a number of technically-oriented solutions to some of the ethical and social problems arising from the use of personalisation. There are also some non-technical solutions that apply equally to all of the issues. 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'[19] 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[20], 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 can cause them harm both ethically and socially, 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 such.

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 socially (or for the institution) at the cost of doing the right thing ethically (for the student or staff). Students and staff need to consider whether their individual rights do not also 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, it makes it easier to detect or prevent crime and terrorism.

For other problems, however, it may be that fixing the problem 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, motivating the provision 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 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 ten social and some 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 (section 2) and potential for improved learning outcomes (section 4), there are problems arising, either seen already in personalised educational systems or plausible problems, judged from the point of view of non-educational personalising systems. The problems are very likely to have an impact on the individual student or 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 avoid these problems.

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

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

Having pointed out these ten problems, we then propose solutions, some technical, others not so, to address or at least mitigate the 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 certain types of teaching.

There is great promise of benefit from personalisation technologies, but there are also pitfalls need to be found and dealt with before it becomes mainstream. One of the main problems regarding the social impact of projects is evaluating technologies sufficiently early, 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 aims to point out the potential harm of personalisation technologies, so that they can be designed appropriately into future e-learning and other systems in a way that minimises that potential harm - some things are hard to 'bolt on' afterwards and need to be designed in. We would wish the introduction of personalisation to be in contrast to the way other Internet-based technologies have been introduced, 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 greatest positive points in favour of personalisation is the ability to create increasingly detailed student profiles. Guthrie [35] writes that "*MOOCs are not a transformative innovation that will remake academia. That honor belongs to a more disruptive and far-reaching innovation—Big Data and its application, and the adaptive education that results. The vast numbers of data sets that are collected daily, or Big Data, will likely revolutionize online learning by allowing educators to customize learning to individual students through adaptive learning*". 'Adaptive learning', or 'adaptive hypermedia' is the term long used by the adaptive hypermedia community for what is now more commonly known as personalised e-learning. Big Data, with the appropriate safeguards, will 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, although not yet whether it systematically improves student outcomes. So there is enough promise that it can justifiably continue to receive investigation. 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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