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The ethical and social implications of personalization technologies for e-learning

Helen Ashman [a,*], Tim Brailsford [b], Alexandra I. Cristea [c], Quan Z. Sheng [d], Craig Stewart [e], Elaine G. Toms [f], Vincent Wade [g]

[a] University of South Australia, Australia
[b] The University of Nottingham Malaysia Campus, Malaysia
[c] University of Warwick, United Kingdom
[d] University of Adelaide, Australia
[e] Coventry University, United Kingdom
[f] University of Sheffield, United Kingdom
[g] Trinity College Dublin, Ireland

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ABSTRACT

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

1. Introduction

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

As with many other human functions (e.g., banking and sales) that have moved online, e-learning has had mixed success. This form of education was partly motivated by the belief that it would save on human effort, although this belief assumes that a large proportion of the tasks involved in teaching are repetitive and not mentally demanding. E-learning does facilitate the parallel teaching of enormous numbers of students and permits access to the entire Internet of supporting materials. However, the transition to online learning has been accompanied by a reduction in the number of human teachers. This increasing automation and reduction in human staffing can leave students feeling disenfranchised, like "numbers on a computer," ignoring their individual learning needs.

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

* Corresponding author. Tel.: +61 883025335.
E-mail addresses: helen.ashman@unisa.edu.au, helen.ashman@mac.com (H. Ashman), tim.brailsford@nottingham.edu.my (T. Brailsford), A.I.Cristea@warwick.ac.uk (A.I. Cristea), michael.sheng@adelaide.edu.au (Q.Z. Sheng), ab4491@coventry.ac.uk (C. Stewart), e.toms@sheffield.ac.uk (E.G. Toms), vwade@cs.tcd.ie (V. Wade).

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of educational materials that directly contribute to a student's learning.

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

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

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

Despite their potential benefits, there are a number of clear ethical and social issues arising from the use of personalization in e-learning systems. One of the most obvious is that of personal privacy (Section 3.1) because personalization systems can personalize content only by collecting information about users 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 personalization systems perform calculations using these data, creating inferences about users with varying accuracy to extend the user model with the resulting implicit data; this process occurs without allowing users to observe how the personalizing site decides how to serve them, let alone to have control over the process (Section 3.2). The user model is then involved in further calculations that determine what to show the user and what *not* to show the user. These calculations can then influence the user's individual capability, often resulting in reduced exposure to other concepts with the concomitant loss of opportunity and encouraging personal ethical and moral isolation. Personalization also encourages users to be lazy about decision making and to habitually delegate all their thinking to software, rendering them consequently less capable of thinking for themselves, thus either forgetting or even failing to acquire the skills that they need to be able to find information for themselves under other (non-personalized) conditions. It can be especially troublesome when users delegate their thinking and decision making to external agencies that are not education-oriented but commercially oriented or that may even be propagandists and social engineers. This situation is harmful to a society that needs a literate, skilled and, above all, rational population (Section 3.3).

In the e-learning context, personalization should enhance the education of students, with the ideal goal of enabling each student to reach his/her personal best by working to address individual weaknesses. Personalization should have a positive effect on the quality of education, as it should be able to show students what they need to know, when they need to know it. However, some forms of personalization appear to be ineffectual, and with current technology, personalization is not suitable for all forms of education and assessment (Section 3.4).

It could be that not only has personalization not yet been able to achieve its own educational ideal but that it has also inadvertently been the cause of harm to more traditional teaching methods, aiding educational institutions in processing more students more rapidly and inexpensively in their drive for economic self-sufficiency (Section 3.5). Personalization 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]. This concept encourages students to see themselves as *consumers* of education by placing them at the center of their own education, with 'personalized' environments specific to their individual learning needs. The "it's all about you"! theme may be a deliberate policy on the part of institutions, learned perhaps from advertisers, to attract and then retain students. Certainly great emphasis is placed on 'student engagement', which boils down to whether students are adequately interested in their own education or need stratagems to keep them motivated. The personalization of e-learning is one such stratagem that shows real success in engaging students (as discussed above); therefore, despite any other problems arising from personalization, it will nevertheless find a place in e-learning.

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

2. Background: the technology of personalized e-learning

The current e-learning systems used in higher education and company training settings include learning management systems (such as Blackboard) or massive open online courses, i.e. MOOCS. These systems 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 (e.g., SQL, XML), and the presentation part relies on technologies such as HTML, JavaScript, and, more recently, AJAX technology, among others. Traditionally, such systems 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 that provide different services (e.g., scheduling, delivering lectures, hosting forums) either centrally or distributed over a network. Such concepts as 'learning as a service' were also introduced. Furthermore, 'distributed e-learning is gaining more weight in the move toward cloud computing, in which functionality, data, or any type of information can be distributed over a network. This change is also evident 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 must be 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. Although mobile computing introduces some adaptive features, such as context and device specificity, the real benefit to learners comes with personalization to their specific needs, especially their learning needs. This capability has allowed for the development of the areas of intelligent tutoring systems (ITSs) and adaptive educational hypermedia (AEH), supported by actively contributing communities. These areas further add to the above-described e-learning systems by embedding user-related knowledge into the system to address users' specific needs.

All of the cases above imply the construction of a user model, which is a structured collection of information about a user. A user model has the primary benign goal of adapting the material presented to the user in such a way that it will help them in their learning endeavor. Such systems thus need to have the means of storing such data (again, in databases as described for e-learning systems, but with rather more sensitive user data) in a centralized or distributed manner. Such systems must also be able to retrieve these data from somewhere, building either explicit user models (when a system will ask the user for the information directly) or implicit user models (when the system will deduce or infer the information from the user's behavior). Regardless of how they are obtained, user model data can be made completely accessible to users, partially accessible to users, or not at all accessible to users. The storage of user data can be sessional (stored only for the current session) or permanent (stored for as long as the user is registered with the learning service or beyond), again with different implications for the security of the information, its reliability, and its privacy, among other considerations. Permanent storage of user data allows more precise personalization, comparing past behavior to current behavior and providing better guidance.

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

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

Other types of personalization are related to different areas of personalization. Many personalization application areas are related to e-learning. For instance, a personalized search (or personalized information retrieval) allows for information pertaining to an individual user to be used to alter the retrieved list of items for which the user searches. Personalized recommender systems recommend items (usually from a catalog) based on stated or implied preferences. Recommender systems can be used to recommend to a learner what to learn next, similar to content-based personalization in ITS or AEH. The difference is that in recommender systems, recommendations are often local, whereas in ITS or AEH, the recommendations are based on more global goals and sometimes on pre-designed (or partially designed) lesson plans.[1] Related to recommender systems based on preferences, collaborative filtering systems use opinion mining to recommend popular items or pairs of items, for example; in fact, 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, learners with related interests, or even ratings for a given item. Social media systems store a large amount of user data and are a fertile ground for personalized services, including personalized e-learning services. Such systems can be used to recommend 'friends' or 'learning buddies' or to recommend specific learning material to a social media user.

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

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

[1] Such as those created via Educational Modeling Language; see http://celstec.org.uk/content/educational-modeling-language.

3.1. Privacy, security and ownership of personal data

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

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

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

Personalization relies on the collection of personal data into a user model or profile. This profile is potentially subject to use, often without the knowledge or consent of the subjects. There are many sites dedicated to the collection of data that track a user's activities, sometimes across different sites. One widely used example is Google Analytics, which analyzes data from several universities, including Harvard, Ontario, Queensland, St. Gallen and Sheffield. In the authors' experience, at least one university uses Google Analytics extensively: both students and staff at this institution are tracked as they access apparently every page on the institution's site. Determining precisely what data are collected is difficult, as the data are transmitted back to Google Analytics in a form that is not readable to humans. However, inspection of the http requests did show that the data being sent varied as different users logged into the online learning system; thus, staff or student user IDs were apparently being transmitted. Of course, this issue is not restricted to applications using personalization, but it is exacerbated by the requirement to collect personal data for the purpose of personalizing 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 will influence what will be disclosed later [46]. Users can also be classified according to what type of information they are willing to disclose [47]. However, many sites collect data without users being aware of it. The terms and conditions of a site may explain its data collection, but the use of the site itself often constitutes implicit agreement, thereby necessitating use of the site even simply to access the privacy policy to be able to make an informed decision. However, the user must realize this data collection is occurring and then either explicitly opt out of the data collection process or be unable to view the site at all. The problem is worsened when students use free, commercial tools such as shared documents with no clarity regarding the ownership of the data.

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

However, younger people are sometimes more aware of privacy issues, even if they still permit their data to be collected. A recent survey [67] showed 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 that required a real name and address; thus, up to 64% of the remaining respondents were willing to divulge this information to be able to access the site, despite evident privacy concerns.

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

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

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

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

[2] Even so, the data available to the NSA (a USA government agency) 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/.

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 are not personally identifiable,[3] but because the data sent back to them are not readable to humans, it is unclear what is being sent; however, it appears that data such as individual user identifiers are being collected. Even if data are not 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 (i.e., 'linkability'). Thus, analytics software is being used in universities' online learning systems without any real understanding of what data are being transmitted to the analytics company – university management views the data only after they are processed. In many cases, that data are being sent offshore, which raises issues regarding which nation's legislation applies to the data.

Furthermore, a number of commercial tools that are being incorporated into learning environments do not observe education-specific privacy regulations, as they are not developed specifically for education environments. In the university environment, it is more than simply analytics data being collected. Search engines are now embedded in the education environment, sometimes deliberately by 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 ubiquity may be argued to render search engines more accessible (as well as being more familiar) than any search facility of the e-learning system itself. Even if such a facility is somehow masked, students will still use search engines to seek information outside of seek of 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 breaches of confidentiality. In terms of influence on the online personalized learning process, such parallel channels need to be considered, as students often bypass or avoid the school- or university-provided channels in favor of social networks; various implications arise, including a lack of institution control and particularly a lack of privacy guarantees [8].

However, apart from the well-known problems of public social tools, learning providers should consider how privacy could be compromised by specific personalization tools in e-learning systems. A personalization system of necessity collects personal data about the user, such that subsequent actions can be tailored to that user. This collection occurs in different ways, with 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, as the system may not be aware of whether users have visited the site before (although cookies, flash cookies and other evidence make it difficult to be genuinely anonymous).

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

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

It can also be a problem for student users if their learning profiles is used for other purposes. Such a situation could arise as part of national security activities, as exemplified by a large number of recent data requests by government national security agencies to search engine companies. On a personal level, an employer could demand from graduate applicants a copy of their student profile to assess whether a candidate was a quick or slow learner; whether their assignment submission was generally timely; whether they had any academic misconduct recorded; or whether they received special academic procedures for handling disabilities, health issues or family situations. The existence of such student information means that students may come under pressure to authorize its release. Although 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 the potential for a refusal to be interpreted as the person 'having something to hide'.

3.2. The accuracy of inferencing

We now consider how personalization systems make assumptions and inferences about users, what Brusilovsky called "implicit" user model data [13], derived by recording a user's behavior and inferring characteristics about them. These assumptions can be a problem if a user does not know the data are being collected, how accurate the data are or what inferences are being made on that basis (for example, buying a children's toy does not mean that the user has children). There is often no transparency with respect to such inferencing rules and no guarantee of their accuracy. The privacy of the inferred information is a gray area, as it is not provided by users but is calculated by a third party, casting doubt on its ownership.

There are implications of such inferencing rules, particularly political and social implications, whether they are correct or not. Such implications can be especially damaging in a changing political climate. Even commercial corporations such as credit card providers and supermarkets collect details about an individual's race, religious beliefs, sexual preferences, union membership, marital status, and number of children, among other things, which can only be inferred from the user's spending patterns [36]. Personalization creates associations, including some that are not explicit, generally by focusing objects explicitly around an entity, such as text alerts to a mobile phone or purchase interests in "my eBay". All these things may have little importance individually but can, when analyzed together, be used to paint a comprehensive picture of individuals and their activity. In a time of political unrest and fear, even student records can contribute to building a case against an individual.

Personalization systems necessarily make inferences about users and their personal preferences, skills and knowledge [23,38], using this information to decide what further information to offer users. However, the decisions made are often error-prone when the rules applied to personal data yield 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].

Failed inferencing is a poor outcome, but even successful inferencing can prove equally embarrassing or harmful to individuals. Jernigan and Mistree [41] reported their success in identifying homosexuals through their network of Facebook 'friends'. This identification appeared to occur even when a participant did not have a public profile, but because their Facebook friends did have public profiles, their friendship was visible and could be used to accurately infer their sexuality.

The personalization of search results that relies on inferencing can have even more insidious effects. Sweeney [76] reported a racial bias being detected in paid results (advertisements) appearing in search results. First names appear to be frequently attributable to race, and otherwise identical searches appeared to be 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. In this case, the searcher begins typing in his/her search term, and a number of options arise, beginning with the text that the searcher is typing. The options that arise are based on previous searches by other people, and the list tends to include the most popular searches with those opening characters; sometimes those previous searches have falsely associated a person with criminal activity. Although these unfortunate associations could be easily generated algorithmically [4,5], in at least one case, it appears 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]. However, deliberate or algorithmic, the reputational damage is equally significant; for example, an erroneous photograph in numerous news articles reported a child-abuse case and was propagated widely on search engines [51].

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

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

In a way, personalization is all about inferencing – inferring users' needs or interests from their history and context. Sometimes inferencing is easy; for example, a student who fails a test clearly needs additional assistance on the materials being examined. However, at other times, the inferencing may be error-prone, prioritizing materials that are less helpful for the student's task at hand. A wrongly labeled data chunk or a strategy with essential parts missing may hinder rather than support students in their learning process or inadvertently filter out essential information.

The quality of inferencing also depends how good the user model is. If the stereotypes are poor or too general, then there is a potential problem. The effect of this problem depends on the user interface. With some systems (such as link ordering or link coloring), the worst-case scenario is that links are ordered suboptimally or that there is an eccentric color scheme. However, with other interface designs (such as hiding links or adapting content), students could fail to receive important information.

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

However, there appear to be few personalization systems other than experimental systems that offer students the ability to control the personalization applied to their interactions with the system. A basic level of control is afforded by going outside of the system in some cases; for example, the Startpage search proxy[4] allows users to access Google search results without passing on any personal or context information. However, this option merely turns the personalization on or off, disabling the ability to contextualize search in controlled ways, for example, by releasing one's location or device type. Fine-grained personalization control does not appear to be possible in mainstream personalization systems. Furthermore, there is no transparency in the inferencing process; thus, the user is frequently left guessing as to why the results have been personalized in the way that it appears. Some sites, such as amazon.com, allow feedback on recommendations, but most do not clarify why the recommendations were made in the first place or provide any way to turn them off.

3.3. The effect of personalization on individual capability

The aim of personalization is generally to alter the content shown to users to match the perception of users' greatest interests. However, a byproduct of this process is that such systems filter out what is not designated as being of interest to users and rather presents to them only what fits the system's belief of what their interests are [17].

This filtering is associated with a number of potentially harmful side effects on users' individual capabilities and personal experiences. The first problem is the loss of serendipitous exposure to the unexpected. When reading a general-interest newspaper or magazine, we are exposed to beliefs and lifestyles that may differ from our own personal experience and that may trigger new ideas. Such encounters with the unexpected when seeking something else can be called serendipitous and can sometimes yield benefits or at least interest to the discoverer. However, personalization reduces the potential for serendipitous connections with alternative beliefs, lifestyles and culture, and even novel solutions to new or old problems. If a personalization system helps users to filter out information that does not meet their immediate needs or interests, then they are exposed to fewer alternative belief patterns. Not only is it restricting their information diet, promoting an insular way of thinking, but it also reduces understanding between different ways of thought and may even be argued to be divisive. Such systems thus encourage ignorance of the lives and worldviews of others.

We referred to *serendipity* in [3], but the concept can be expressed by other names as well. Pariser subsequently called the lack of it *the filter bubble* [62], and it is also colloquially known as *google goggles*[5] [18]. This phenomenon occurs at the hands of service providers, but users can also personalize their social media environment in a similar manner, filtering out users from whom they do not wish to hear, further self-censoring their information world and narrowing their viewpoint.[6] This isolation of students shows how personalization goals conflict with society (or group) goals to some extent because such goals exist to serve the individual and not the collective. For students in particular, it can be a barrier between the individual and the cohort because the material that one student views differs from that viewed by others.

There is, however, some element of apparent serendipity in personalized systems, as users often receive results that they do

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

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

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

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

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

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

Interestingly, result (re-)ordering is one of the common techniques for implementing personalization, which involves effectively leveraging trust bias to point users toward what is believed to be the most appropriate content for them. However, it is possible that exploiting trust bias is itself harmful to students. Choosing the top-ranked link or search result every time will encourage students to rely on the judgment of the personalization algorithm and will leave them less practiced at making their own decisions.

Personalization systems aim to make relevant information more easily accessible to users, but this aim presupposes that making information more easily accessible is always beneficial. This assumption may be true in some areas, such as e-commerce; however, in education, the ultimate goal is always to help users learn, and learning is about far more than the access, reproduction and retention of information. Learning also involves the internalization and reflection that leads to genuine understanding, and in order for effective deep learning to occur, learners should be actively involved in the design of their own learning experiences [53]. Learners need to work at learning if they are to develop deep understanding. If personalization makes exactly the right information too easily accessible, then such a system could undermine the learning process. Indeed, the entire intent of personalization is to render information into constructs that are already understood by the recipient. However, students must acquire the ability to synthesize knowledge from disparate sources. Because personalization assists users in this synthesis, there is a real risk that the learning process might become 'de-skilled', with the system synthesizing knowledge rather than learners synthesizing information themselves. This situation also creates an unrealistic expectation of how information will be available to students when they are outside of the educational environment. If the educational environment does not encourage students to learn to think for themselves, then it will be too late by the time they leave education and enter the work environment.

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

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

If students need to learn to think for themselves without being told how to think by personalization providers, then this skill is even more critical when reviewing materials provided by commercial personalization providers. One potential threat to the community is the influence that personalizing systems wield on the population at large. The following suggestion[7] has been made:

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.

The authors proceed to speculate about users' level of trust in these algorithms:

You no longer think about anything for longer than 0.5 s. 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.

This situation can already be observed in the education context. A high proportion of students use search engines to locate information for research and assignment purposes [27]. However, the personalization functions of search combined with a tendency to look no further than the first page of results [19,71] suggest that students' research is limited to approximately ten results that are the most highly ranked by the search engine. Although the ranking is intended to suit what the search engine believes the user is looking for, the educational value of the search results to the task in hand may not match what the teacher would agree is the most relevant. Search engines are not e-learning systems.

We need to ask how much control of students' education 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

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

providers be permitted to determine the learning content to which students are exposed? Does society want students' education to be shaped by professional educators or by search engines and social networks?

3.4. Personalization and the different forms of learning and assessment

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

Vocational learning: in this type, vocation-specific skills and comprehensive information about the area of 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 practice their chosen vocation.

Knowledge learning: in this type, more general reasoning and analytical thinking are taught. Students are motivated by a desire to learn how to think deeply and produce innovative solutions. To be successful, students must learn how to think critically and extend their existing knowledge.

The two types are not mutually exclusive; to gain a deep understanding of a subject and to be able to think innovatively, students must have comprehensive information about the subject to be able to analyze it deeply and extend their understanding. However, one clear distinction between the two types of learning is the level of human input required to successfully teach students the necessary skills. True knowledge learning in research degrees such as doctorate programs is almost always demanding in terms of teacher (supervisor) input. Although it may be acceptable for a single teacher to take charge of large classes in undergraduate lectures, it is not regarded as acceptable to mass-produce research program students. Moreover, 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 students' research, as such involvement would simply be too time-consuming.

This is important when considering personalized systems. Until personalization systems incorporate genuine artificial intelligence or other methods to capture human judgment of research skills, it will be difficult to apply any type of online learning technology to the teaching of critical thinking and innovation. Thus, it may never be feasible to disseminate expertise about knowledge learning in a way that can be used in a personalization system. This issue is exacerbated by the need for student researchers to show originality, and novel situations are the opposite of what personalized e-learning systems have been designed to address. Personalized e-learning systems normally coach students toward predetermined outcomes, as represented by the information retained and methods used to arrive at those outcomes. With knowledge learning, there may be accepted methods, but the outcomes are by definition original, not predetermined.

There is also the challenge of automating the assessment of a student's outputs for critical and analytical skills. However, without the ability to first evaluate a student and to then provide feedback on how to improve, the personalization system will bring no benefit. There have been trials of automated essay marking in MOOCs, but it is not an accepted technology and has been challenged by academics [34,39,64].

Hence, can personalization be useful for vocational learning? Much of the online learning that institutions are currently providing is vocational, such as popular courses to teach students to program and use IT packages. However, many types of vocations require hands-on practice, and although it is possible for a student to observe an expert performing, for example, surgery or fine woodworking through a video, there is no way for feedback about a student's own activities of this type to be captured and processed by the personalized learning system. Thus, the bidirectionality of the personalization system, which is the key characteristic discussed in Section 1, is missing. Without this bidirectionality, the e-learning system is not personalized because it knows too little about students' capabilities to form judgments.

Thus, when there is a physical, hands-on component of learning, a personalization system is not feasible. However, there are many areas of learning in which 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 personalized e-learning system. There is also the not-too-distant future possibility of using virtual, augmented and mixed reality technologies to allow a student to practice a hands-on procedure without causing harm or damage. Flight simulators are a well-established example, and there is also research on personalized virtual reality environments [28]. This capability would indicate one mechanism through which data on student performance could be captured and personalized feedback and assistance given.

The discussion above brings us to the assessment of student work. In personalized e-learning systems, ongoing assessment of students' requirements, abilities and outputs must occur to determine how to further personalize content. There are different types of assessment, some of which are easy to mark online, such as multiple-choice questions, short-answer questions, and mathematical proofs. Other forms of assessment are more difficult to mark automatically, including essays and written reports.

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

Although personalization is generally considered from the student perspective and concerns tailoring content to student characteristics and behavior, we can also consider how personalization may be applied at the task level, with a task having "a defined objective or goal with an intended and potentially unknown outcome or result" and being accomplished by performing one of more activities [80]. Given a group, such as a class, all students may perform the same task regardless of the knowledge, experience, insights, and other factors that each student brings to that task, and each task is a multifaceted unit for which learning is required at each stage.

We often treat such a task as a single unit, but a task such as "write a paper..." has a designated set of actions or subtasks that personalization could service without compromising security and privacy or negating serendipity. Kuhlthau [49] and Vakkari [82,83] examined how information is used within this process and identified a distinct set of phases through which all students go in the process of writing a paper or proposal: (1) task initiation, (2) topic selection, (3) pre-focus exploration, (4) focus formulation, (5) information collection and (6) search closure. A student's need for and ability to consume information depends on the particular phase in which a student is engaged. For example, in the initial stage, students need to identify a topic while 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. When finished, students simply need to ‘fill in the gaps’ with missing information. However, search engines treat all requests with the same level of specificity, regardless of which phase a student is in; a preferable solution would be providing a reduced, encyclopedic level of knowledge at the beginning to ensure that 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, search engines have the potential to personalize outcomes for both the student and the task.

Some students may move through these phases faster than others and may begin at differing levels of specificity. The challenge from a technical perspective is in monitoring the flow of the process rather than the outcome of delivering pertinent information. This process calls for more effective learning environments – novel interfaces – that are tailored to learners and personalized according to learning tasks and not merely personalized according to the program or module administration procedures that we observe in existing systems (e.g., Blackboard).

In summary, there is currently a limited scope for the use of personalization technologies in e-learning and its assessment; such use is applicable primarily to areas related to vocational learning and contexts with known learning outcomes but not currently to research-based, in-depth learning or contexts in which automated assessment is needed. However, as other complementary technologies, such as augmented reality and even artificial intelligence, develop to a viable stage, personalization may one day be applicable to all areas of learning.

There remains one consideration: as supporting technologies develop to a point at which personalization can be widely used for different types of learning and assessment, we must justify its use.

Personalization has been shown to be well received by students (see Section 1). However, it is less clear how much personalization contributes to improving learning outcomes. It might even be argued that personalization is detrimental to learning because it enables learners to remain within or near their ‘comfort zone’, as opposed to learning practices in which optimal outcomes are achieved when students are pushed outside of their comfort zone.

It is plausible to expect improvements in learning outcomes through personalization in e-learning based on drawing parallels with conventional teaching. In small-group teaching, if a student does not understand a particular concept, then the teacher adapts the session to help the student achieve understanding. This situation corresponds to the Laurilard model of learning [50], in which the teacher explains something to the student, the student formulates his/her own mental model of the concept and explains it back to the teacher, and the teacher then uses this reformulation to modify his/her explanation to the student and so on, until the two mental models match. This model is a good argument for personalization when e-learning systems are used to model small-group or one-on-one teaching styles. However, even if we accept that personalization will help to facilitate learning by embodying something akin to the Laurilard model, only theoretical reasons can be used to explain why it should be beneficial.

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

However, personalization takes many forms, and personalizing content according to learning styles is only one form. Evidence is difficult to gather because large user trials can be difficult to design without creating ethical problems by experimenting with control groups whose education may be compromised by a lack of equivalent learning opportunity. In search and e-commerce, research on the efficacy of personalization has likely been conducted by corporate providers such as Google and Amazon, but this research is rarely published, despite their continued use of personalization apparently indicating some benefit.

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

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

3.5. The commodification of education

Online learning and hence personalization are regarded by some as the future of education [35], and many universities are scrambling to prepare their MOOC offerings (largely without personalization) to avoid being left behind. Online learning is what both providers and students think that they want: providers want it because they can process a larger number of students with a lower per-student cost to service, and students want it because it gives them access to education without needing to attend in person, with the significant relocation costs that can be incurred, and at institutions that may be superior to those available locally.

Thus, education is increasingly a high-volume process, but how is this transformation affecting the quality of teaching and learning? The first and most obvious change is the radical reduction in the number of staff servicing students. This change will necessarily influence the quality of education, which, although overseen by a human teacher, is poorly monitored by humans in contrast with traditional teaching. Even established distance learning institutions such as the Open University UK have large numbers of human tutors available at specified hours for students to consult, but MOOCs and personalized e-learning systems do not and cannot employ such tutors because of the different order of magnitude that they address – in some cases, many thousands of students per course rather than hundreds or fewer in traditional courses.

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

Furthermore, the online-only learning environment, whether personalized 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, in addition to informal and sometimes off-topic conversations with staff that can provide better insight into academic life, motivational drives and additional contextual and non-contextual information. When students do not attend classes in person, the university experience differs greatly. When personalization is introduced into the learning materials, students may have even less contact with peers and staff, as their learning requirements may be met through the clever presentation of content rather than through discussions of content with others. This concern can perhaps be addressed through the use of further online tools such as social networks, as many students are happy to 'meet' with 'friends' through such media [70].

Personalization cannot address all the problems arising from the online shift of education, but it has the potential arrest and to some extent reverse the damage being done by the online shift, even if only as far as the students' learning experience. Personalization 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, personalization technologies could actually contribute to the online shift and dehumanization of learning by their very success. This potential effect is evident from the success of online book sales – fewer people would visit Amazon online if it were simply 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, personalization could have the potential to damage traditional educational methods, including face-to-face teaching, if it overcompensates for the removal of such methods.

How do all of these problems fit with an 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. Moreover, society's need for well-rounded and well-educated graduates is not always met because some institutions no longer prioritize producing better-educated students who have learned how to think but rather require students only to meet the necessary conditions to gain credentials.

This commodification of tertiary education in many countries arises because tertiary education is no longer a government-funded priority, especially after the global economic recession. At the undergraduate and postgraduate levels, some universities are viewed as businesses that supply credentials rather than being hothouses of knowledge. This situation is doubly unfortunate for students in many countries who end up paying part or all of their education costs but still have intensive, high-volume practices introduced into their education because universities must increasingly operate as self-funded businesses. Such institutions need more students processed more rapidly and inexpensively to fund their business model.

The servicing of ever-growing cohorts is what lies behind personalization in e-learning. Originally, however, such systems were implemented 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, academics attempted to address the reduction in time with better technical support, aiming to 'work smarter, not harder'. Thus, personalized e-learning systems emerged – the intentions were honorable and were aimed at repairing some of the damage arising from the commodification of tertiary education.

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

4. Recommendations

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

4.1. Reclaiming some privacy

The privacy issue includes the privacy of data collected within an institution for educational purposes and the privacy of data collected when students access systems external to educational institutions. A number of privacy-enhancing technologies can be used as scaffolds in light of the limitations of mainstream technologies. Students can deploy simple, readily available tools such as anonymizing search engines (e.g., Ixquick and DuckDuckGo) that do not collect personal data. In addition, script-blocking tools such as NoScript can prevent data collection by analytics software. These tools are controlled by the individual; thus, a student can prevent analytics scripts from operating on his/her devices, regardless of institutional policy. These applications prevent or modify the data used by personalization systems and will change the way that personalization occurs. In such a situation, the system will default to a non-personalized generic presentation, such as a textbook that is not personalized to the student. Some sites[8] refuse any access to their content if scripts are blocked, but such a response should never be considered acceptable by any teaching institution.

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

Within an institution's own systems, data collected for personalization systems should be of demonstrated importance to personalization, and personalization should be proven beneficial to students. Such efforts require both research to determine what

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

personalization is beneficial and strict adherence to programming practices to ensure that unnecessary data are not collected.

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

4.2. Controlling inferencing

In most cases, the inferencing performed by personalization systems is completely opaque to students. Students do not know what calculations are being performed or why and are unaware of what data are being used in those calculations. Students may not even be aware that the personalization is occurring.

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

4.3. Reintroducing serendipity

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

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

Serendipitous exposure will not only expand students' personal horizons but also reduce the effect of the trust bias, which will be gradually weakened as students become more aware of the fact that something on every page is not chosen for its apparent relevance. This change should encourage students to personally assess the effects of what they see and help halt the skill degradation that occurs when too much unquestioning trust is placed in personalization systems.

4.4. Dealing with external providers

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

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

For searches, it is equally feasible to perform some in-house personalization of results, and in fact, this work has already been trialed [75]. One must first turn off the normal personalization on the search engine end, perhaps by routing all search engine requests from within the e-learning system to an anonymizing proxy. Then, the personalization system on the institution's end can perform the personalization on the non-personalized results that the search engine returns. Hence, teachers are able to use personalization rules that are more suited to the specific purpose of the educational institution and the assigned learning task.

4.5. Non-technical solutions

To complement the technically oriented solutions to the ethical and social problems arising from the use of personalization, non-technical solutions also exist: *information* and *education*.

The free provision of information is essential to ensure that students know what is being done in such systems and what the possible effects are, both in general and, more importantly, specific to themselves. Such information must be easy to read and understand for the average undergraduate. Withholding this information denies students the opportunity to exercise their own judgment. Such a lack of information further suggests that there is some illicit management of the student's behavior occurring in the background, and although this is sometimes merely a social 'nudge'[9] in what is deemed by someone to be the 'right direction', this type of social engineering becomes – at worst – little more than propaganda. The situation can be especially concerning when the nudging is performed by a third party with no affiliation to a student's educational institution.

Educating people on the ethically and socially responsible ways of using personalization technology is the other main solution. Ethics and social responsibility do not often feature in instructional degrees,[10] yet it is important to educate people to behave in ethically and socially acceptable ways, not only students but also staff and university policy makers. Students need to be aware of how personalization has both ethical and social problems and must consider whether they should emphasize their personal benefit above that of society.

In addition to educating people on ethics and social responsibility, students should be educated about their rights rather than blindly accept everything that an educational institution offers to them. Students should also know when they are outside of the somewhat protected boundary of their institution (e.g., when they decide to discuss their coursework on a social networking site) and what outcomes could arise from such activity.

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

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

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

4.6. The insoluble problems

Addressing some ethical and social problems may require more than simply changing the technology or educating users. The most pressing problem is likely the commodification of education, which underlies the commercial imperatives of education providers, thus driving the provision of learning primarily according to delivery costs. However, no institution, corporation or individual government can be held accountable for this problem; rather, it is a global mindset that prioritizes money, power and influence above all else, as well as a belief that individuals should pay directly for what they use, even critical infrastructure. Although the user-pays principle does ease the burden on taxpayers, it also allows for denial of responsibility even for core functions and promotes a commercial focus on the provision of essential services such as education. Until this mindset changes, technologies such as personalization will continue to be used and extended in reach, often *supplanting* rather than *supplementing* human contact and teaching support.

5. Conclusions

In this article, we have raised a number of social and ethical issues that arise in the use of personalization in an e-learning context. Although there is much promise of benefit to students, both in terms of their engagement with learning and in the potential for improved learning outcomes, problems are arising already in personalized educational systems, and other problems are predicted to arise based on observations of non-educational personalizing systems. Such problems are likely to have an effect on individual students and more generally on the community as a whole. We are already experiencing some of the problems arising from personalization as found in search functions, especially privacy, serendipity and deskilling problems. The widespread use of search makes it difficult to correct these problems; by contrast, because personalized e-learning is not yet as commonly used, it still has the opportunity to be designed in such a way as to mitigate these problems.

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

There is great promise of benefit from the use of personalization technologies in e-learning, but there are also pitfalls to be addressed before such technologies become mainstream. One of the main problems regarding the ethical and social effects of such projects is the issue of evaluating technologies sufficiently early to enable a useful influence on fundamental concepts and design. Personalization has its pitfalls and needs to be considered more extensively before an institution hurriedly adopts such a system. This paper has conjectured about the potential harm of personalization technologies, indicating that future e-learning and other systems can be designed in a way that minimizes that potential harm – some things are difficult to 'bolt on' afterwards and need to be incorporated into the design. We hope that the introduction of personalization into e-learning would differ from other Internet-based technologies have been introduced in the past, with inadequate thought given to potential problems and thus needing significant corrective action (which often fails because of inertia). Online security and online privacy are obvious cases in point here.

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

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

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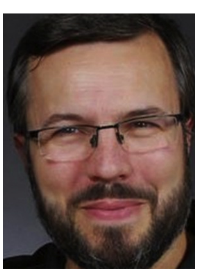
Helen Ashman leads the Web Technologies and Security Lab at the University of South Australia. Prior to that, she led the Web Technologies Lab at the University of Nottingham. She has around 20 years of experience in user profiling projects, applied to topic areas such as security, privacy and e-learning.

Tim Brailsford After a PhD in Zoology at the University of Bristol, Tim Brailsford joined the University of Nottingham in 1988. While researching and teaching in Life Science there he became interested in the potential of new technologies to facilitate communications and education. This lead to his involvement in a wide range of electronic publishing and educational projects, and an interest in multimedia, hypermedia, adaptive hypertext and hyperstructure, that continues to this day. In 2000 he joined the School of Computer Science, and since 2010 he has been an Associate Professor, based at the University of Nottingham's Malaysia Campus where he is the head of Computer Science.

Alexandra I. Cristea is Associate Professor (Reader), Chair of the Graduate Studies Committee of the Faculty of Science, Director of Graduate Research, and Head of the Intelligent and Adaptive Systems group (of 14 academics and 19 research students). Her research includes user modelling and personalisation, semantic web, social web, authoring, with over 200 papers on these subjects ($\sim$ 2200 citations on Google Scholar). Especially, her work on frameworks for adaptive systems has influenced many researchers and is highly cited (with the top paper with 182 citations and growing). Similarly influential is her pioneering work on adaptation languages, Dr. Cristea being one of the first to propose them (with the top paper with 129 citations and growing). Since then, work in these new research areas has spread. She is within the top 50 researchers in the world in the area of educational computer-based research according to Microsoft Research. Dr. Cristea has been highly active and has an influential role in international research projects. She is experienced in running research projects and has led various projects - EU Minerva projects ALS (06-09) and ADAPT ('02-'05); Warwick-funded project APLIC (11-12) as well as participated as university PI in several EU FP7 projects - BLOGFOREVER ('11-'13), GRAPPLE ('08-'11), PROLEARN ('07) and as co-PI in the Warwick-funded Engaging Young People with Assistance Technologies ('13-'15) also featured by the BBC. She has been organizer of workshops, co-organizer, panelist and program committee member of various conferences in her research field (including, for example, UMAP, ED-MEDIA, Hypertext, Adaptive Hypermedia, ICCE, ICAI). She is executive peer reviewer of the IEEE LTTF Education Technology and Society Journal and she is co-editor of the Advanced Technologies and Learning Journal. She has given invited talks in various countries, e.g., UK, Netherlands, Spain, Japan, Finland, Romania, etc. She acted as UNESCO expert for adaptive web-based education at a high-level (Ministry of Education and Educational institutes) meeting of East European countries, as well as EU expert for FP6, FP7 and eContentPlus. She is a BCS fellow, and an IEEE and IEEE CS member.

Quan Z. Sheng is an associate professor and Head of Advanced Web Technologies Research Group at School of Computer Science, the University of Adelaide. He received the PhD degree in computer science from the University of New South Wales in 2006. His research interests include service-oriented architectures, distributed computing, Internet computing, and Web of Things. He is the recipient of Chris Wallace Award in 2012 and Microsoft Research Fellowship in 2003. He is the author of more than 160 publications.



Craig Stewart has worked in the area of HCI, IT & multimedia research and education for over 20 years. He has a great deal of experience in many fields from working in various departments, disciplines and positions. His academic background reflects this diversity with a PhD in Computer Science from the University of Nottingham and an MSc in Molecular Genetics and a BSc in Genetics (from the universities of Leicester and Nottingham respectively). He is the Lecturer for the MSc in Information Technology and the MSc in Computing at Coventry University. Dr Stewart's research interests cover the following areas: eLearning, TEL, User Modelling, Adaptive Hypermedia, Intelligent Tutoring Systems, Cultural Studies and HCI & HF. His doctoral research (entitled A Cultural Education Model: Design and Implementation of Adaptive Multimedia Interfaces in eLearning) consists of examining the effect that TEL is having on cultural education and how HCI impacts on this. This research direction addresses the rapid spread of technologies (the Internet, the Web, various eLearning applications) whose development has often been rooted in Western (US English) culture, how the globalisation of education through eLearning can be best be applied, so that learners receive appropriately personalised interface in their lessons. By bringing a more unbiased and personal approach to HCI and eLearning through the application of cultural variables to a user model and personalised interface, the learner receives a lesson that minimises (ideally even eliminates) cultural bias.

Elaine G Toms is a Professor of Information Science at the University of Sheffield in 2011, after holding a post at Dalhousie University, Canada as Canada Research Chair in Management Informatics, and prior to that as an Associate Professor, Faculty of Information Studies, University of Toronto, Canada. She heads the Information Retrieval Research Group in Sheffield's prestigious Information School.

Vincent Wade Vincent is Professor of Intelligent Systems in Trinity College Dublin. He holds a BSc (Hons) in Computer Science, an MSc (by research) and PhD from Trinity College Dublin (2006). In 2002, Vincent was awarded a Fellowship of Trinity College for his contribution to research in web-based personalisation and adaptive technologies.He is the Director (and co-founder) of CNGL, a world leading multi-institutional research centre focusing on multilingual, multimodal globalisation of digital content, leading a research team of 140 staff and 18 industry. In 2011, Vincent founded the Learnovate Centre (Centre for Applied research in Learning Technology) where he is the Academic Director. Vincent has over 260 scientific publications, and an H-index of 24 (Google Scholar) with over 2450 citations.