Personalizing Online Educational Tools

Michael J. Lee
Department of Informatics
Ying Wu College of Computing
New Jersey Institute of Technology
Newark, New Jersey 07102, USA
mjlee@njit.edu

Bruce Ferwerda
Department of Computational Perception
Johannes Kepler University
Altenberger Str. 69
4040 Linz, Austria
bruce.ferwerda@jku.at

ABSTRACT
As more people turn to online resources to learn, there will be an increasing need for systems to understand and adapt to the needs of their users. Engagement is an important aspect to keep users committed to learning. Learning approaches for online systems can benefit from personalization to engage their users. However, many approaches for personalization currently rely on methods (e.g., historical behavioral data, questionnaires, quizzes) that are unable to provide a personalized experience from the start-of-use of a system. As users in a learning environment are exposed to new content, the first impression that they receive from the system influences their commitment with the program. In this position paper we propose a quantitative approach for personalization in online learning environments to overcome current problems for personalization in such environments.

CCS Concepts
•**Social and professional topics** → **Informal education;** •**Theory of computation** → *Online learning theory;*

Author Keywords
Learning styles; intelligent tutoring systems; adaptive learning; engagement

INTRODUCTION
People are increasingly using online learning tools for both their compulsory education (e.g., online college courses) and own curiosity. As we move deeper into the 21st century and more people turn to online educational resources to learn new skills, we need to better understand how to support and engage these learners.

Engagement is a necessary condition for learning [21]. Unlike traditional classrooms, learners in discretionary settings have the option to disengage with the content at any time. Traditional educational resources have peers and instructors that can help motivate or engage a struggling learner immediately, but most online resources do not. Therefore, knowing how to keep a learner engaged with the educational material, especially online, is essential for their success. If the learner decides the material is too boring, too easy, or too difficult, they may decide they do not like the subject, which may have long-lasting, negative consequences.

Furthermore, many online educational resources incorrectly assume that users will know how to use and progress through given content content, curricula, or study materials without additional guidance or scaffolding. In their work, Kirschner & Merriënboer challenge these beliefs, arguing that people (especially *digital natives* [34] or *homo zappiens* [41]—those people who have been immersed in computing technologies all their lives) cannot use the knowledge available on the internet to self-educate themselves without instruction [27]. Moreover, they disagree with the widespread and pervasive misconception that learners have specific learning styles and conclude that these ideas are largely unfounded and may actually be hurting learners [27]. They argue that the nature of using self-reported measures to categorize learners [42] is inaccurate and pigeonhole learners into arbitrary categories [27] (which themselves are not well-defined [9]).

If these established categorizations of learners do not exist and learners do not innately know how to effectively teach themselves using online resources, how can we support the millions of people using online resources to learn new skills without teachers? These online educational tools have the potential to reach a wide range of users, especially those in under-served or underrepresented groups, so a static one-size-fits-all approach will not work. We believe that empirical research, grounded in the machine learning literature (especially work in intelligent tutoring systems and recommendation systems) can inform the future direction of teaching by detecting online learners' disengagement and providing interventions and personalization to help them succeed.

RELATED WORK

Engagement in Online Education
Educators have long used engagement to improve learning [7]. According to engagement theory, engaged students learn at high levels, better grasp what they learn, and retain that knowledge [25]. Experts agree that increasing engagement in educational topics is key to success [11]. Though these studies have been largely in the context of compulsory learning settings, engagement is key in online environments as well [29, 31].

Studies have shown that there is a positive relationship between the use the learning technology and student engagement

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and learning outcomes [5, 30]. Herrington et al. found that the use of authentic activities within online learning environments engage learners, and discuss several design considerations to keep users engaged with the experience [22]. Shea & Bidjerano found that *social presence* was an important factor in keeping online learners engaged [38], suggesting that any automated intervention would need to demonstrate mastery or knowledge of the material that exceeds the students'. Moreover, others' work stresses that creating meaningful interactions (and involvement) between the online tool and learners is critical for learner engagement [37, 43]. Charters et al. found that adults who initially had negative preconceptions about computer programming changed their attitudes after playing through an online programming tool [3]. These examples demonstrate that making sure learners are engaged is a key component of their success in learning through online educational resources.

Intelligent Tutoring Systems

Intelligent tutoring systems (ITSs) are designed to model human tutors using artificial intelligence to engage students in sustained reasoning activity and to interact with the student based on a deep understanding of the students' behavior [10]. Educational systems incorporating ITSs have been shown to lead to positive learning outcomes for students in diverse topics such as computer programming, algebra, medicine, law, and reading [32, 33].

Some of the intelligent tutoring system literature explores detection of undesired behaviors such as off-task activities and disengagement. Baker et al. found that some students succeeded on tasks by exploiting parts of their intelligent tutoring environment ("gaming the system"; for example, clicking rapidly to collect all the tutor's hints), leading to poor learning outcomes [12]. They created a model using three data sources (user action log data; human-coded observations; user learning outcomes), and made a classifier to detect this gaming behavior [2] (Walonoski & Heffernan used similar data to create a classifier to detect gaming for another intelligent tutoring system [44]). To counteract this gaming behavior, they added an animated agent (i.e., a dog character) to the interface that would visually change its emotional state from happy to progressively more angry as continued gaming was detected, and provide additional positive messages (e.g., "You know how to use the tutor right!") to encourage non-gamers to continue their system-preferred behavior [12]. Moreover, the system gave gaming students up to three additional supplementary multiple-choice question exercises covering concepts they may have missed (number determined by whether they answer a question correctly). They found that including their tool led to a decrease in the total number of people gaming the system, and that the gamers' completion of additional multiple-choice questions exercises led to learning gains that were comparable to those who did not game [12].

Many other studies examine motivation and (dis)engagement detection within the intelligent tutoring and e-Learning literature. Some are based on the ARCS Model [26], using inference rules on data from a short quiz [13], or from learners' attention and action log data including data such as: time to perform the task, time to read text related to the task, time when learner starts/finishes the task [35]. Some studies use log data such as problem-solving time, help requests, and mistakes, in combination with Bayesian networks [1] or data-mining techniques [8], to infer attitudes towards the tutor [1]. Others, such as engagement tracing, is based on Item Response Theory [14], and models disengagement by using the estimation of the probability of a specific action occurring given a specific response time [24]. These types of detection mechanisms can be applied to a wider context to help online learners succeed with their learning tasks.

PROPOSAL

Personalization in online learning environments is needed as discussed in the previous sections. We discussed several works that focused on detecting and counteracting on undesired learning behaviors. Many of these detection mechanisms rely their inferences on historical behavioral data of users, which creates a bootstrapping problem where the system can only provide the user a personalized after a period of use (i.e., once the system has gathered enough behavioral data). Although other quantitative or qualitative methods (e.g., questionnaires, quizzes) would solve this problem, they have the drawback of interrupting the interaction flow between the user and the system. Not being able to provide a personalized experience from the start may be problematic for (new) users. The first impression that users experience from the system may be crucial for further commitment, especially in a learning environment where users are often exposed to new, unfamiliar, and perhaps difficult content. What we propose in this position paper is a way to facilitate a personalized experience from when a user begins using the system, which will also benefit current detection mechanisms of undesired learning behaviors.

Systems are increasingly incorporating connections with external sources (e.g., Facebook, Twitter, Instagram) through mechanisms such as single sign-on (SSO) buttons [1] to provide convenience to the user. Through SSO mechanisms, the system asks permission to access a user's social media account. While only the basic profile information of a user is needed, systems often ask for additional permissions for accessing other parts of a user's account as well [6]. This creates an additional source of information that systems can utilize for personalization. As not all the information that becomes available may be directly applicable, a connection with a general user model (e.g., personality traits) is needed. Personality traits have shown to be a suitable general user model as it characterizes a person's thoughts, feelings, social adjustments, and behaviors, which subsequently influences their expectations, self-perceptions, values, attitudes, and their reactions to others, problems, and stress [28, 45].

There is an increasing body of work that independently looks at personality-based personalization (e.g., [15, 16, 20, 23, 40]) and personality acquisition from user-generated content (e.g., social media traces; e.g., [17, 18, 19, 36, 39]). For example, in the field of recommendation systems, Hu & Pu found that personality-based recommendation systems are more effective

[1] Buttons that allow users to easily register and log in to a system with their social media account.

in increasing users' loyalty towards a system and decreasing cognitive effort compared to systems without personality information [23]. Works on several social networking services have shown that the user-generated content from these services can be effectively used to predict users' personality (e.g., Facebook [18], Twitter [36, 39], and Instagram [17, 19]). Ferwerda, Schedl, & Tkalcic have shown that personality traits can also be reliably inferred from restricted Facebook accounts by examining whether/which profile sections are disclosed by the user [18]. This provides opportunities to infer users' personality even when information is limited (e.g., when a social media profile is not completely accessible through single sign-on mechanisms).

Currently, there is a limited amount of work done on personality-based relationships in online learning environments. By analyzing usage data, Chen et al. [4] found relationships between users' personality traits and different strategies users adopt for learning. Based on prior works in other domains (e.g., recommendation systems) we believe that online learning environments would also benefit from personality-based personalization. By further exploring the relationships between personality traits and variables influencing learning efficiency, and with the methods to implicitly acquire personality traits from external information sources, we can take the next steps on improving and personalizing online learning environments for users.

As more people turn to online resources to learn, there will be an increasing need for systems to understand and adapt to the needs of their users. We believe that the knowledge provided by the intelligent tutoring systems and recommendation systems literature, especially in areas such as off-task and disengagement detection and user modeling, can inform the next generation of online educational tools.

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