The impact of adaptive personalized learning on student outcome: Do students know when they are at risk?

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ABSTRACT

To be added…

Keywords

1. Introduction and Related Works

Are we investing enough funds and resources to provide college students with intelligent recommender systems that could help them succeed not only by alerting them when they are at risk but also providing them with personalized remedies?

Researchers witnessed a significant evolution in E-commerce pertaining to recommender systems such as Amazon, Netflix, Facebook, etc. Since 1994, Amazon started integrating various concepts, methods, and technical architectures of recommender systems into their E-commerce storefront (Zhuhadar & Nasraoui, 2010). Recently, web users became more familiar with the notion of recommendations through their experience with social media tools, but does education fit this paradigm?

For almost a decade, faculty members from Western Kentucky University (WKU[1]) have been working on designing a variety of intelligent systems, such as *CaseGrader* (Crews & Murphy, 2007) and *HperManyMedia (Zhuhadar & Nasraoui, 2008)*. In *CaseGrader* Crews and various other faculty members from multiple colleges and universities used intelligent methods to provide personalized automated scoring to students based on their performance in solving mathematical or business problems within Microsoft Excel. On the other hand, *HyperManyMedia*[2] platform provided recommendations to students based on their previous browsing activities. These recommendations are based on artificial intelligent algorithms where ontology is defined and semantic web is utilized to provide the most accurate recommendations to students based on their level of understanding within the course. For more details, refer to our previous research (Zhuhadar, Nasraoui, & Wyatt, 2007; Zhuhadar,

[1] http://wku.edu/

[2] http://hmm.wku.edu/

Nasraoui, & Wyatt, 2009a, 2009b; Zhuhadar, Nasraoui, Wyatt, & Romero, 2009; Zhuhadar, Nasraoui, Wyatt, & Yang, 2010; Zhuhadar & Yang, 2012).

Noticeably, we should acknowledge that the *Human-Computer Interaction Institute* at Carnegie Mellon University[3] proved to be the incubator to many studies on intelligent tutoring systems where they analyze educational learning through case analysis of students' interactions with intelligent tutoring system. Many of these studies require tutor specific details such as student choices, timing intervals, student outcomes (predictions), classifiers and type of help given which can be laborious to browse.

Historically, it was considered a challenge to evaluate student models by their impact on the success of help given– which type of help do students really need? For instance, Lallé, Mostow, Luengo, & Guin, (2013), noted the challenge in evaluating student models by their impact on the success of an intelligent tutor's decision about which type of help to offer students. Furthermore, (Beck & Mostow, 2008) considered how much students learn from instruction by assessing learning decomposition which determines the relative adequacy of different types of learning opportunities – a generalization of the learning curve analysis using non-linear regression. Beck and Mostow's model further indicated that when students reread words, effectiveness of learning that word decreases; it is a waste of time for students to see a word repeatedly supporting the argument that students benefit less from massed practice (2008).

Prior research has shown that assessing reading comprehension can be costly and obtrusive. In addressing these issues, (Yuan, Chang, Taylor, & Mostow, 2014) analyze the efficacy of EEG devices in assessing reading comprehension (the correctness of responses) in the classroom taking into consideration that these devices are unobtrusive and low cost. While, the EEG model could not successfully make above chance predictions, it does suggest that some information regarding student comprehension can be teased out through suing the EEG devices (Yuan et al., 2014).

While there is still great debate on what method works the best, there seems to be consensus on the Bayesian Evaluation and Assessment approach (Beck, Chang, Mostow, & Corbett, 2008) which assesses both student and tutorial interventions allowing students to transfer knowledge gained to later problems as a model for predicting learner outcomes and learner factor analysis (Cen, Koedinger, & Junker, 2006).

In general, the common wisdom in the field of intelligent tutoring or scoring systems holds that the system should let students control and organize their own learning process and should intervene *only* when it is necessary. Also, regardless of the variety of methods and technologies used to design intelligent systems, the goal, by and large, is the same—provide the best tool for students to learn and succeed.

In summary, the purpose of this study is not to compare among these systems, but rather to understand the system's capabilities and what impact they have on each student's achievement. As educators in higher education, we noticed, over the last decade, well-known publishing companies in Higher Education, such as *Pearson*[4], *McGraw-Hill*[5], *Wiley*[6], and *CengageBrain*[7] have begun to invest heavily in the design of intelligent systems. Now, not only can the faculty predict if a student is at risk, but also a student can get instant notifications (alert) about his or her performance in each task, quiz or exam; no matter what type of activities he or she was performing. This alert mechanism of student performance could be related to a simple task such as answering a question concerning the reading comprehension section of a chapter to

[3] https://www.hcii.cmu.edu/
[4] http://home.pearsonhighered.com/
[5] http://www.mheducation.com/home.html
[6] http://www.wiley.com/WileyCDA/Section/index.html
[7] http://www.cengagebrain.com/shop/index.html

being involved in solving an equation or even writing a machine learning algorithm.

In this research, we will introduce a pilot project at WKU Information Systems Dept., entitled "The Impact of Adaptive Personalized Learning on Student Outcome."

As a starting point, during this up-coming semester (Spring, 2016), five faculty members are assigned to teach a course titled *Principles of Management Systems* in Information Systems. Two out of five faculty members decided to experiment with Intelligent Systems; more specifically, using the concept of *Adaptive Personalized Learning*. Simultaneously, these five faculty members are teaching the identical curriculum, including the same: textbook, homework assignments, case studies, videos, quizzes, and exams. Each faculty is teaching two to three classes of this course: *Principles of Information Systems.* Some students are taking this course in a blended setting environment (face-2-face and online) and other students are taking this course in a pure online setting environment (no face-2-face meetings). In total, we have 325 students enrolled in 10 classes. Only 5 classes are instructionally designed to utilize the Intelligent Systems technologies. Accordingly, a total of 156 students are introduced to this ***Adaptive Personalized Learning*** environment in both settings (face-2-face and online learning).

In our presentation, we will introduce each technology used in this research including and not limited to the architectural design of these technologies, such as MindTap[8] and CourseMate[9], and SAM Cenagage Study System[10], we will answer questions such as: How we, as faculty, structured the course to provide a monitoring personalized process for each student? How did the engagement tracking system alert students at risk? Did the system improve their grades? What type of instructional design worked the best within these systems? What was the impact of using these systems on student success? Did students enjoy using these systems or the technology used was too complicated? Is there difference between male and female in their way of interacting with the intelligent engaging system? Did blended learning students do better than the online students? Did this technology improve the overall grades in this course compared to students who did not use this technology?

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[9] http://services.cengage.com/dcs/coursemate/
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