MOOC Leaner Motivation and Learning Pattern Discovery – A Research Prospectus Paper

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ABSTRACT

The landscape of online learning has evolved in a synchronous fashion with the development of the every-growing repertoire of technologies, especially with the recent addition of Massive Online Open Courses (MOOCs). Since MOOC platforms allow thousands of students to participate at the same time, MOOC participants can have fairly varied motivation. Meanwhile, a low course completion rate has been observed across different MOOC platforms. The first and initiated stage of the proposed research here is a preliminary attempt to study how different motivational aspects of MOOC learners correlate with course participation and completion, with motivation measured using a survey and participation measured using log analytics. The exploratory stage of the study has been conducted within the context of an educational data mining MOOC, within Coursera. In the long run, research results can be expected to inform future interventions, and the design of MOOCs, as well as increasing understanding of the emergent needs of MOOC learners as data collection extends beyond the current scope by incorporating wider disciplinary areas.

Keywords

Online Learning, learner Motivation, Massive Online Open Courses, Educational Data Mining

1. INTRODUCTION

In this paper, the first section presents a literature review on motivational studies of online learners in both the generic distance learning fields and the ones specific to the MOOC settings. The second section on methodology and progress explains methodologies applied for at the current research stage as well as planned analysis for the in-progress work presented. The third part is the discussion section where potential follow-up studies are proposed. Lastly, aspects on direction of future analysis and where advice is needed are stated.

2. LITERATURE REVIEW

2.1 Motivation of Online Learners

MOOC students have demonstrated varied motivation, beyond just solely utilitarian or learning goals [34]. Kizilcec, Piech, and Schneider [21] presented a classification method grouping MOOC learners by engagement levels. Clow [9] introduced a "funnel of participation" which conceptualized a pattern of highly unequal participation of MOOC learners and further confirmed the challenges of catering to varied needs of MOOC participants with current MOOC models.

High MOOC student dropout rates have been identified and studied by both researchers in academia and journalists [3, 8, 12, 22, 29], though debate is ongoing about the importance of dropout rate within the context of MOOCs. Furthermore, doubts have been cast upon whether completing the course assignments is necessary for MOOC participants [18, 23]. As Anderson [3] pointed out, many MOOC participants enroll in courses only to satisfy their initial curiosities with no intention of completing the course. Although course completion rate is by no means the only meaningful outcome, it has become one of the most discussed metrics in the MOOC environment.

Although MOOCs are a relatively new addition to the field of online learning, the construct of learner motivation has long been seen as essential to learning and learning outcomes. Dweck [13] argued that two key goals characterize most learners: learning goals and performance goals. Learning goals or mastery goals [2] indicates learners who strive to increase their competence and master the given skill; whereas performance goals suggest that learners seek to obtain favorable assessments from others. Since then, researchers have argued for two types of performance goals [17].

2.2 Goal Orientation of Online Learners

More recently, it has been argued that different goal orientations are actually symptoms of underlying student mind-sets. Students with growth mind-sets hold beliefs that intelligence is malleable; whereas students with fixed mind-set considers intelligence an unchangeable entity [14, 15]. A study conducted by Blackwell, Trzesniewski, and Dweck [7] measured and monitored seventh grade students of these two aforementioned mind-sets and found out that students with a growth mind-set outperform their counterparts who accept a fixed mind-set, over the long-term term.

Many motivation theorists have also argued that learning/mastery goals sustain intrinsic motivation [11, 16, 20]. According to Ryan and Deci [30], intrinsic motivation refers to executing a learning activity out of one's inherent interests, whereas extrinsic motivation implies one intends to gain a separate outcome. MOOC students presumably consist of learners possessing each (or both) types of motivation. For example, out of intrinsic motivation, one might register for an educational data mining course purely out of curiosity. In contrast, out of extrinsic motivation, one might register for the same course because the skill sets covered in this course are useful for the student to advance in his or her career.

Intrinsic motivation has long been praised to predict effective learning; however such kind of motivation is also vulnerable to various non-supportive [31]. Keller and Suzuki [19] reasoned that students of E-learning platforms confront more motivational challenges due to that they have to work independently at a distance in most cases. It is also noticed that a relatively high dropout rates have been consistently observed across E-learning platforms [27], but these environments are generally more effective for students with self-regulated learning skill.

2.3 LAK and EDM on MOOCs

Among students who do not effectively regulate themselves during online learning, disengaged behaviors may emerge, such as "carelessness" -- not demonstrating a skill despite knowing it [32] and "gaming the system" – where learners use help and feedback provided by the online learning system to avoid learning [4]. It is not yet clear what the full range of disengaged behaviors are in MOOCs, but understanding this, and the role these behaviors play in the reduction of participation in MOOCs, is a key research question. Research applying learning analytics and data mining on MOOCs has helped identify distinct behavioral patterns. As an emerging filed, existing MOOC research has focused on classifying learner behavioral patterns by levels of engagement [9, 21]; adapting existing modeling techniques to MOOC data [28]; as well as developing new models for the MOOC environment [1, 35].

3. METHODOLOGY AND PROGRESS

3.1 Research Context

The exploratory stage of the proposed project has been carried out in the context of one MOOC, titled "Big Data in Education", offered through Coursera by Teachers College, Columbia University. (https://www.coursera.org/course/bigdata-edu). This course spanned 8 continuous weeks with 8 weekly assignments. The weekly course composed of lecture videos. Students and teaching staff participated in forum discussion accompanying weekly course releases. The motivational survey was distributed through Coursera to students who have enrolled in this course prior to the course start date. This course has an enrollment of about 48,000 students.

3.2 Survey Data

Given the heterogeneity of the motivations of MOOC learners and the current interest in course completion and other measures of participation, this proposed research intends to expand our understanding of MOOC learners by analyzing how MOOC learners' motivation correlates with students' degrees of course completion and participation. Two categories of motivational aspects including both general items and MOOC-specific ones has been taken into account in this initial research attempt. Specifically, both MOOC-specific motivational items including those tested by existing MOOC studies [5, 26] and two subscales of the PALS survey [24] measuring goal orientation and academic efficacy are included in a pre-course survey. The MOOC-specific items include questions such as the familiarity of the MOOC environment and course content; whereas the PALS subscales focus on learner orientations towards learning or performance goals, across learning contexts. The survey was distributed through broadcast E-mail to all registered students. As of the end of the course, the pre-course survey has gathered 2,792 responses.

3.3 Log Analytics

Learning analytics and educational data mining techniques will also be applied to study student participation. Specifically, drawing from past research in monitoring participation within online learning [10, 25], this project will analyze indicators of participation such as use of discussion forums, quiz completion rate, and video usage. All the above-mentioned data collected will then be linked to the MOOC survey, and correlation mining will be used to determine which motivational indicators can predict participation metrics, employing FDR post-hoc correction [6] to control for running too many tests. Patterns of changes in participation across the course will also be analyzed by means of sequential pattern mining. Motivational response and participation will be used as predictors of MOOC completion.

4. PROPOSED CONTRIBUTION

Although MOOC participants represent a diverse population of learners with a diverse range of motivations, they do form a new learning community with common features. The low retention rate observed across different MOOC platforms is an important engagement issue to investigate further. A low retention rate may not be inherently negative in the context of MOOCs [21, 28, 35], given that MOOC participants registering for the same course can have very different motivations and goals in mind. At the same time, some failure to complete may not be simply due to lack of student interest in completing. Therefore, understanding MOOC learners' motivation is imperative in helping us understand course participation and completion in this new context; which failure to complete is simply an artifact of student goals? Which is due to other factors, and therefore a problem to address? Research results of the present study is expected to inform intervention of MOOC learning environments as well as providing MOOC faculty members resources in planning and modifying their courses.

5. ADVICE NEEDED FOR FUTURE ANALYSIS

The first stage of analysis serves as initial research attempt to study how different motivational aspects of MOOC participants correlate with course participation and completion. Moving forward, research and advice is needed toward further understanding of learning patterns of MOOC learners and to inform future design of interventions.

Specifically, advice on how to extract MOOC data based on existing knowledge of other online learning platforms especially intelligent tutoring systems is needed for the progressing of the current research stage. For example, what are some of the knowledge components identified in ITS can be adapted in the MOOC models? How to synchronize forum textual data with clickstream data? How can unrecognized similarities or features between MOOCs and other well-studied online learning platforms be detected? Additionally, general and specific advice on designing experimental intervention is needed in ensuring internal validity, external validity, as well as research feasibility.

6. ACKNOWLEDGMENTS

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