Learning Analytics for Motivating Self-Regulated Learning and Fostering the Improvement of Digital MOOC Resources

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ABSTRACT

Nowadays, the digital learning environment has revolutionized the vision of distance learning course delivery and drastically transformed the online educational system. The emergence of MOOCs (Massive Open Online courses) has exposed web technology used in education in a more advanced revolution ushering a new generation of learning environments. The digital learning environment is expected to augment the real world conventional education setting. The educational pedagogy are tailored with the standard practice which has been noticed to increase student success in MOOCs and provide a revolutionary way of self-regulated learning. However, there are still unresolved questions relating to the understanding of learning analytics data and how this could be implemented in educational contexts to support individual learning. One of the major issue in MOOCs is the consistent high dropout rate which over time has seen courses recorded less than 20% completion rate. This paper explores learning analytics from different perspectives in a MOOC context. Firstly, we review existing literature relating to learning analytics in MOOCs, bringing together findings and analyses from several courses. We explore meta-analysis of the basic factors that correlate to learning analytics and the significant in improving education. Secondly, using themes emerging from the previous study, we propose a preliminary model consisting of four factors of learning analytics. Finally, we provide a framework of learning analytics based on the following dimensions: descriptive, diagnostic, predictive and prescriptive, suggesting how the factors could be applied in a MOOC context. Our exploratory framework indicates the need for

engaging learners and providing the understanding of how to support and help participants at risk of dropping out of the course.

Keywords: Learning analytics, MOOC, self-regulated learning

1 INTRODUCTION

Online education has suffered the lack of learners' engagement which has serious issues generally over time within the educational system. Recent attempts to develop new emerging technologies to determine the future of the digital learning environment in a MOOC context has improved to some extend how contents are revised and tailored to participants. The flexible digital learning environment and design of innovative visualization of learning content has help to improve time management among the learners [17]. However, the most dramatic effect to shaping the future of education comes from big data mining and learning analytics that could be related to educational improvement and learners' engagement. Although, learning analytics and implementation is still in the early stages of experimentation in the digital learning environment, there are several controversial issues lingering around the implementation of learning analytics in educational settings. Undoubtedly, learning analytics has contributed significantly in the future of the digital learning environment. The growing implementation of new technologies and analysis techniques in education has shown the need for continuous research on current methods of engaging learners within digital learning environment.

MOOC has been claimed to solve many educational issues by the provision of free open access courses, that enabling learners to explore independent learning [1]. This paper reviews issues relating to learning analytics in MOOC contexts, considering published data on MOOC learning analytics and discussing factors implicated in previous studies as being related to self-regulated learning [17, 18]. The free nature of MOOCs is said to be behind the reasons for profound risk of dropout [11, 12], and the students ability to self-regulated their learning habits [13]. While other studies point out personal reasons as a factor of learners' high dropout rate [1, 14].

2 RELATED STUDY

In the current literature, learning analytics research focuses on developing predictive models of learners' performance and identify students-at-risk of droping out in a digital learning environment [2, 3]. However, research related to learning analytics in MOOCs carries an intense and intrinsic possibility that might influence learning [4]. Learning analytics over the years faces challenging demands and difficulties when applied in MOOC contexts [5], but as Knox [6] mentioned, learning analytics has a strong potential for discovery when it is applied to MOOC datasets. There were few research studies that combine learning analytics practices in MOOCs [7, 8, 9, 10].

2.1 Significance of Learning Analytics

Learning analytics platform monitors learners' activities in a digital learning environment [15]. The role of learning analytics in both online and traditional education settings could be found in: (1) their role in reform of the learning activities; (2) how this could assist educators to improve educational content, teaching and learning; (3) how lecture videos and audio could be revised for optimum engagement [14, 16]. Learning analytics has been successful as a mechanism that is essential for mitigating against the high dropout rate within online education.

Educational online institutions, academics and students require a standard foundation for which changes could be enacted. For academics, the need for real-time learning and tracking mechanism could facilitate the insight into the performance of learners, including those at risk of dropping-out of the course. This tracking and observations can be of great significant in improving teaching, curriculum planning and learning activities. For the students, this could enable them to acquire better revised educational resources and could help them in effective retention and encourage continuing course engagement. They will also receive independent feedback and information relating to their individual performance and progress in relation to their personal goals and learning objectives. Learning analytics provides unprecedented level of feedback support to students in a digital learning environment. With learning analytics analysis, researchers could narrow their studies on the satisfaction of students in their studies by measuring how specific interactions affect their learning achievements [19, 20].

3 eLDa MOOC PLATFORM

This study has introduced a novel platform to explore the four factors of the learning analytics described in this paper. eLDa is an online platform that supports a novel approach to MOOC development, which aims to actively involve participants in directing and regulating their own learning. It provides the necessary framework and support for participants to set their own learning goals and to access resources suitable for their needs. In order to support users' self-directed learning through informed choice, the system offered advice on (but not enforce) recommended prerequisites for each topic and provided a map for learners to visualize the elements they have studied so far in the learning environment. The course platform was designed for A-level teachers of Computer Science who participated in an online version of the platform. The platform was also applied in a blended-learning classroom to deliver undergraduate modules to student of Computer Science discipline from a top UK university. The online version of the course was also available for external participants worldwide. The platform has over 150 registered participants and about over 80 active participants engaging fully with the course elements.

3.1 Aims and Objective

The platform should support good data collection and analyses features to evaluate participants' self-regulated learning levels, the path followed and needed to integrate a variety of acknowledged MOOC 'good practice' features to support learners and mitigate participants' dropout.

3.2 Platform Design

The front end and back end of the design of eLDa platform was developed using Wordpress content management system, PHPMyAdmin, MySQL, PHP and Sensei plugins. The online module curriculum has 4 courses, 4 modules, 10 sessions and 50 lessons. The instructional course includes lecture content, PowerPoint narration and slides, audio and video lectures and transcripts of all audio and video lecture content. The transcript was provided to support non-speaker of English language to understand the lectures effectively by reading the transcribed scripts. Figure 1 illustrate the course interface.

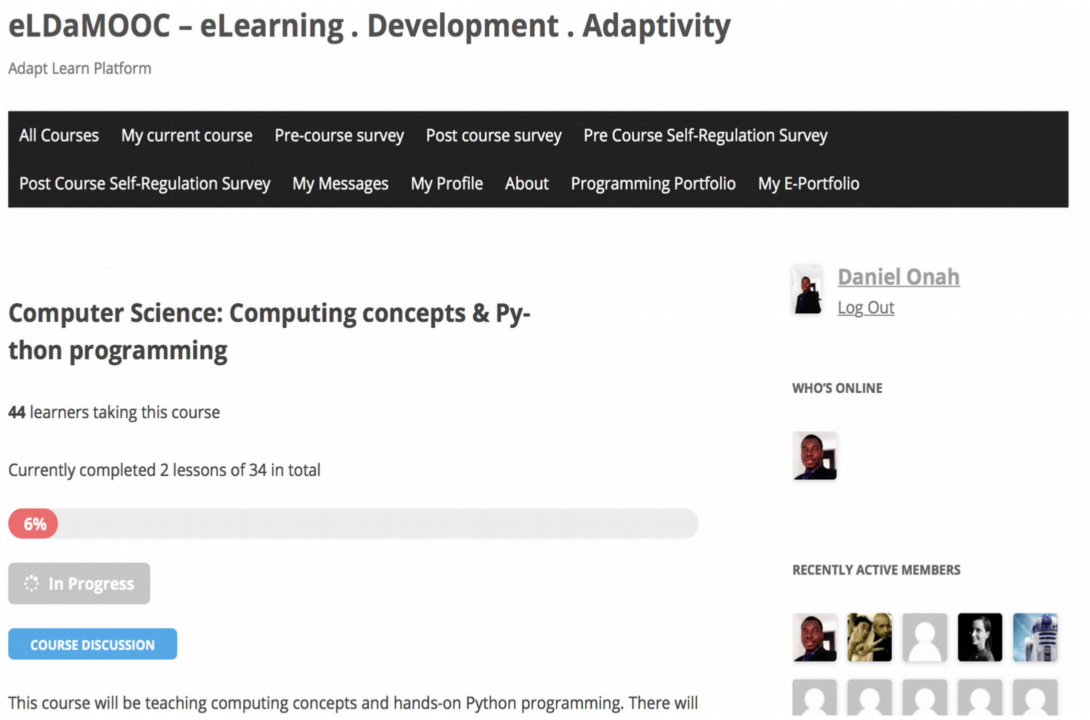

Figure 1. Visualization of eLDa course interface and online participants

Figure 2 shows visualization of lesson completed and lessons yet to be studied. This visualization of the whole course enabled learners to manage their study time effective and self-regulate their learning habits.

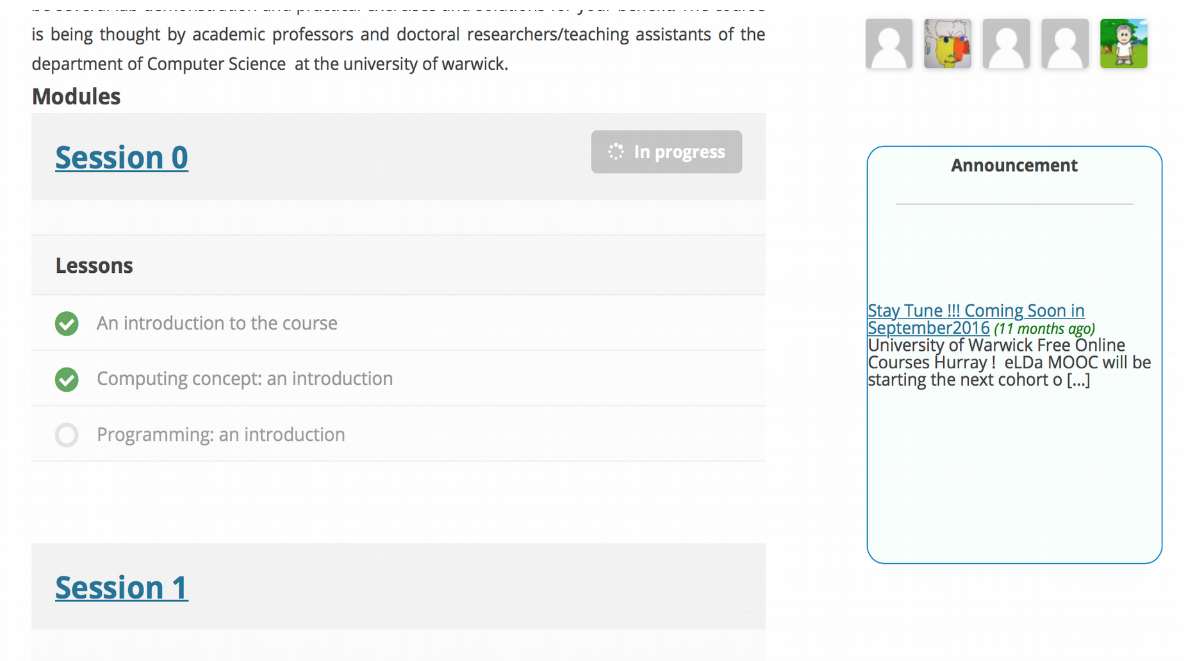

Figure 2. Visualization of course sessions and lessons

4. PROPOSED FRAMEWORK

Learning analytics is the science of using data to build models that lead to better decisions that in turn add value to individual's self-regulated learning skills. The various activities and observation from previous studies could help in improving the present. The following factors help in making learning analytics to be effective in an educational context and as illustrated in Figure 3:

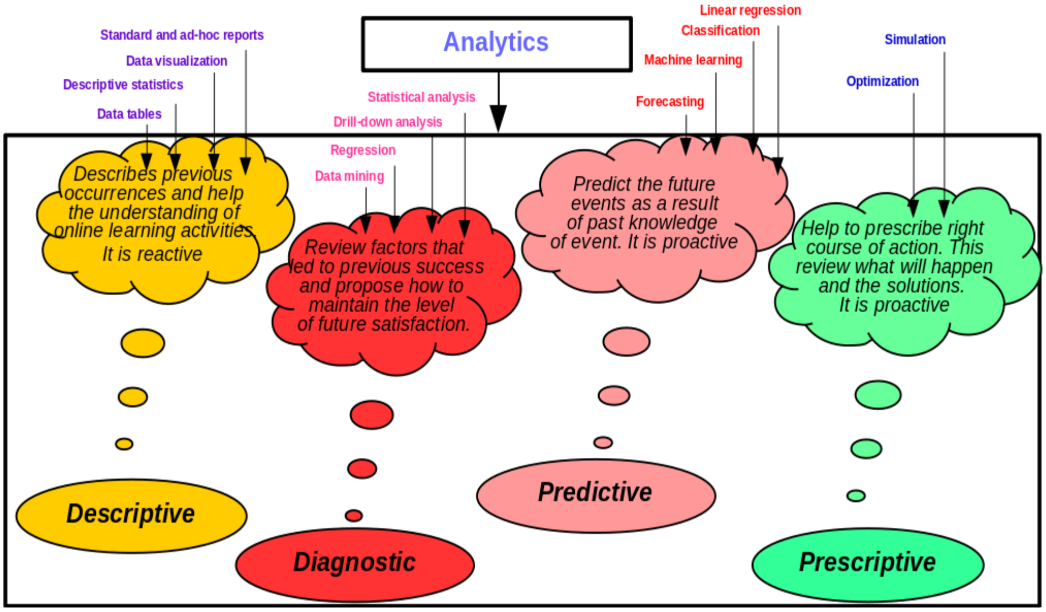

Figure 3. Proposed framework of a learning analytics model

Descriptive Analytics: This is a reactive factor that helps in describing the previous occurrence and understanding of the individual learning activities and habits in a MOOC platform.

Diagnostic Analytics: This review all the factors that led to the previous success of an online course and proposed how to maintain and improve this factors for continuity. This explore the level of satisfaction among the learners with regards to the online course content.

Predictive Analytics: This is a proactive factor which help to predict events as a result of previous observation and knowledge of past learning habits. The previous knowledge obtained as a result of the descriptive analytics and the diagnostic analytics help to support effective prediction of how the new learners could perform in the course based on the knowledge acquired from previous learners' activities and learning habits. This observatory knowledge could help in predicting students at risk of dropping out of the course and this will help in providing support to mitigate dropout among learners.

Prescriptive Analytics: This is a proactive factor which help to prescribe a standard measure that could help to provide effective action among course instructors. This allow the course instructors and coordinators to review possible actions to take in order to resolve the effect of future dropout rate in an online course. The instructor acts based on the knowledge obtained from the predictive analytics and is able to identify areas of the online course that require urgent and adequate review in order to encourage and support self-regulated learning of the participants.

Figure 3 illustrate these four factors and the measure for the four analytic factors proposed in this paper.

5. RESEARCH METHODOLOGY

The overarching approach adopted to be used in this proposed work is derived from the design science research methodology (DSRM), which is a paradigm centered on the development and evaluation of an inventive artefact to investigate a precise problem domain.

5.1 DATA COLLECTION

Previous research conducted using the tool has seen data collected using newly established instrument known as MOOC online self-regulated learning questionnaire (MOSLQ) that was developed to measure and understand self-regulated learning within a novel MOOC platform. Mixed methods of qualitative and quantitative methods was used for the data collection. The data were analysed using statistical package for the social sciences (SPSS). Results based on the activities of students online was presented to illustrate resource management, self-regulated learning and course engagement. The same approach has been proposed in this study to explore learning analytics in the digital course environment.

6 CONCLUSION

This study introduced a proposed framework in applying learning analytics in a novel eLDa-MOOC platform that could be used to penetrate uncertainty around MOOC and how resources are tailored or allocated. With this knowledge captured in a digital learning environment, it could tremendously improve the quality of teaching and learning experience in a MOOC environment. This study presents new methods and results relating to learners' activities in a novel MOOC platform developed for continuing professional development training organised for Computer Science teachers. This further demonstrate the various learning activities, independent learning habits and self-directed learning.

Thus, we explore the effect of learning analytics in mitigating MOOC dropout issues and how we could use the analytics models to support students while engaging with their studies in a self-regulated learning manner in a digital learning environment. This research was conducted on the basis of applying the proposed framework approach in a wider study implemented in eLDa MOOC platform. Several investigations have already been conducted to identify measures that could be used in the analyses of the learning analytics models described in this paper.

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