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Who Will Pass? Analyzing Learner Behaviors in MOOCs

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Abstract: Massive Open Online Courses (MOOCs) have gained worldwide attention recently because of their great potential to reach learners. MOOCs provide a new option for learning, yet the impacts of MOOCs usage on learning still need to be clarified and empirically examined. By collecting data of three MOOCs at Yuan Ze University (YZU), this paper presented a study that classified learning behaviors among 1,230 students on MOOC platform at YZU. In addition, this study examined the impacts of learner behaviors in MOOCs on course completion. The effectiveness of online learning features was examined to expand our knowledge about how students respond to these learning tools. In this study, we used the Ward's and K-means clustering algorithms to determine number of cluster and to classify different types of learners in MOOCs. By cluster analysis, we classified three types of MOOC learners—active learner, passive learner, and bystander. While most students were classified as bystanders (90%), there were only 1% of students labelled as active learner. In these courses, whether a student handed in assignments greatly determined his/her odds of completing course. The results of descriptive analysis indicated that students with various types of learning behaviors in MOOCs did reveal different levels of learning outcome. Active learners who handed in assignments on time and frequently watched videos have significantly shown higher rates of passing the course than the others. Additionally, those who actively participated in online discussion forum received a much higher grade in the class than inactive users.

Keywords: MOOCs, learning behavior, learning outcome, learning analytics

1. Introduction

Massive Open Online Courses (MOOCs) has been one of the disruptive innovations in the field of education. MOOCs are online courses with open registration, a publicly shared curriculum, and open-ended outcomes (Clow, 2013). "A MOOC generally carries no fees, no prerequisites other than Internet access and interest, no predefined expectations for participation, and no formal accreditation" (McAulay et al., 2010). In MOOCs, a collection of video lectures, readings, projects, quizzes, peer-graded assignments, and discussion forums drew learners together. These features were designed to motivate learning and enhance students' learning outcome. Yet whether MOOCs result in a better learning outcome is now needed to be explored in depth. The main purpose of this study is to classify learning behaviors in MOOCs and examine their impacts on learning outcome.

After the first American MOOCs launched by Stanford University in 2011, many of the world's elite universities are now offering some of their best courses for people to learn free online. In Taiwan, Yuan Ze University (YZU) is one of few universities that provide MOOCs. The university has created its own MOOCs platform and provided five MOOCs to students in 2014. We collaborated with the Office of Information Services at campus and collected learner behaviors and their navigation patterns from MOOCs at YZU. In all, we analyzed learning behaviors of 1,230 MOOCs students and examined the relationships of their MOOC usage and course completion.

One of the main objectives in this study is to understand how students use MOOCs and offer insight to what engages or disengages them in MOOC environments. The online learning environments and features were examined to expand our knowledge about how students respond to these learning tools.

2. Literature Review

2.1 Types of MOOCs learners

By counting students' learning behaviors of watching videos and submitting assignments, Anderson et al. (2014) classified MOOCs learners into 5 types: viewers, solvers, all-rounders, collectors and bystanders. In their study, Koller et al. (2013) classified "browsers" and "committed learners" in MOOCs. They further differentiated "committed learners" into passive and active learners. Passive learners were those who frequently watched lecture videos but less submitted assignments, participated in discussion forum and took tests. Active learners completed requirement in the course and contributed to community where they enthusiastically participated in the course, facilitated discussion in forum and assisted in foreign language translation. Kizilcec et al. (2013) labelled four types of learner engagement: "on track" (did assignment on time), "behind" (handed in assignment late), "auditing" (didn't do assignment but watched videos or took tests), and "out" (didn't participate in course at all). In the same vein, they further clustered MOOCs students into "completing", "auditing", "disengaging", and "sampling" groups.

2.2 Learner usage of MOOCs and outcome

Kizilcec and colleagues (2013) suggested that we may have a better understanding of students' goals by investigating how students use MOOCs, including features such as video and discussion forums. Two studies (Karpicke & Roediger, 2008; Karpicke & Blunt, 2011) showed that MOOCs leaners who watched videos did have a better learning outcome. In particular, viewing short quizzes in the videos can improve students' learning. Santos et al. (2014) analyzed students' behaviors in MOOCs and found that students who participated more on courses activities have a better chance to pass the course. Students who frequently communicated, discussed, shared and collaborated with others show a better learning outcome. Their study also suggested that those who posted often in discussion forum would have a higher rate of passing the course.

3. Methods

YZU is one of few universities in Taiwan that provides MOOCs. Students' learning data, such as videos watching, assignment submission, forum posting from MOOCs were collected. Totally, we collected learning behavioral data of 1,230 students from the MOOCs platform at YZU.

In this study, two main learning behaviors--assignment submission and video watching—were used for clustering criteria. We used the Ward's and K-means clustering algorithms to determine number of cluster and to classify different types of learners in MOOCs. Descriptive analyses, including Chi-square tests and Mean-difference tests (ANOVA) were conducted to measure learning outcomes among different types of learners. Moreover, participation of discussion forum was examined to explore the impacts of social media usage on learning.

4. Findings

4.1 Learning behaviors in MOOCs

Trends of students' learning behaviors in MOOCs, including login records, video watching, and assignments submitting were analyzed. Figure 1 shows the average numbers of logging in 5 MOOCs. In general, the average numbers of login were low. Only students in "C# Programming" class have closely reached the average number of 1 in the first two weeks, indicated that students in this class might log in the system once in a week during the first two weeks of class. After the second week, the average numbers of login decreased gradually across weeks in this class. Actively watched lecture videos were merely seen in "C# Programming" and "Computer-aided Design and Manufacture" courses (Figure 2). Figure 3 shows that students in "C# Programming" course had higher average numbers of handing in assignments across the whole 9-week course (Figure 3) than the other two courses.

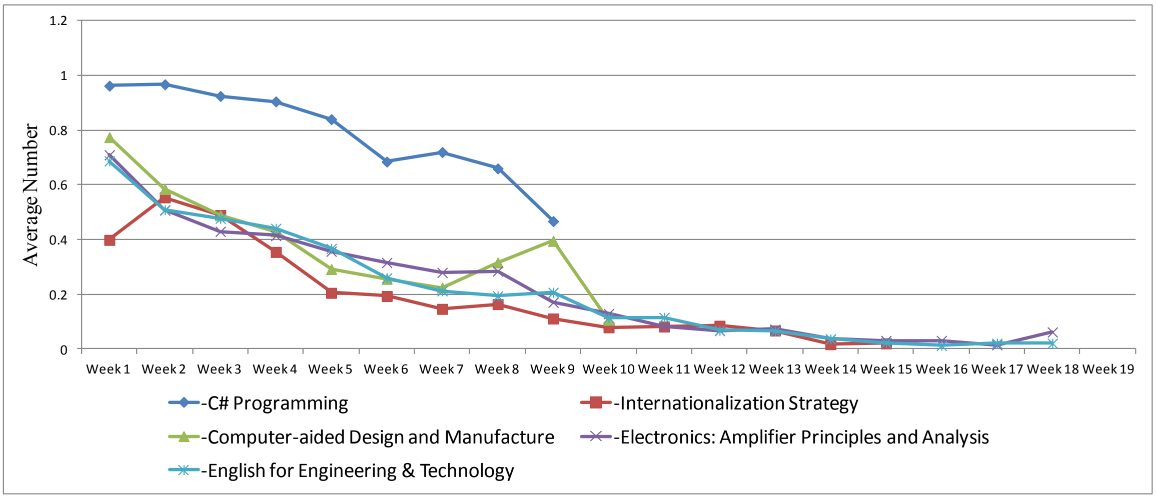

Figure 1. The average number of logging in MOOCs

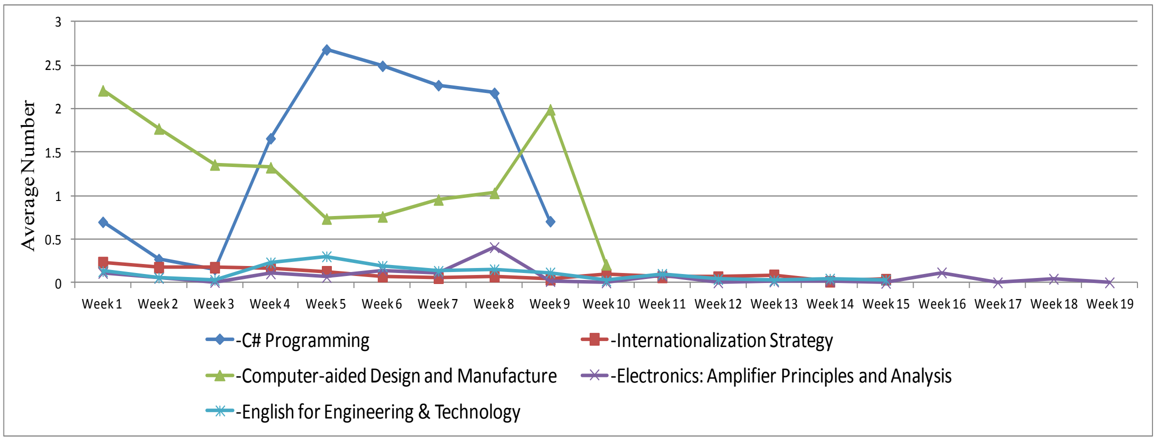

Figure 2. The average number of video watching

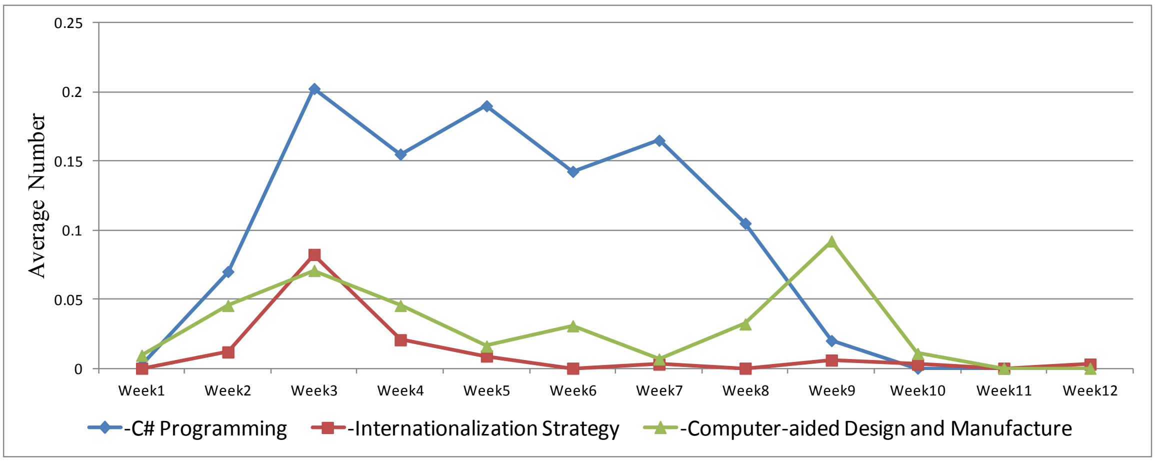

Figure 3. The average number of assignment submission

4.2 Classify learners by Cluster analysis

We employed the Ward's and the K-means clustering algorithms to determine number of cluster and to classify 1,230 students into different types of leaners. Based on behavioral patterns of watching video and submitting assignment, three groups of learners were clustered: active learner, passive learner and bystander. Figure 4 shows the proportions of different types of leaners. In three MOOCs, most students were bystanders (90%), only 1% of students were active learner and 9% of them were passive leaners. While "C# Programming" course had the higher proportions of active (2%) and passive (13%) learners, students in "Internationalization Strategy" composed most of bystanders (97%).

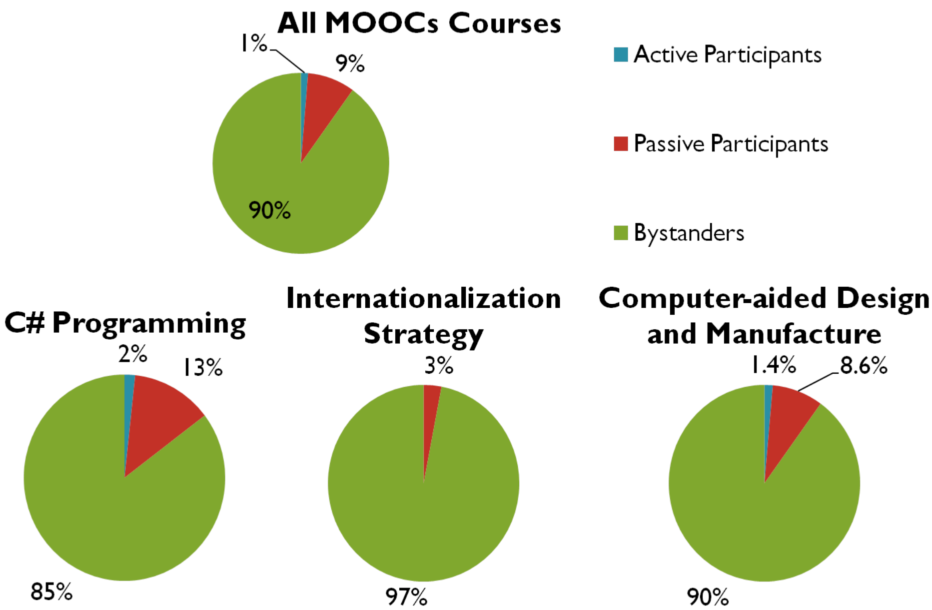

Figure 4. The proportions of different types of learners in MOOCs

4.3 *Learning outcome of different clusters*

Chi-square and ANOVA tests were conducted to measure learning outcomes among different types of learners. The results indicated that students with various types of learning behaviors in MOOCs did reveal different levels of learning outcome. Active learners who handed in assignments and watched videos more often have significantly shown higher rates of passing the course than the others. In all three courses, while 42% of active learners passed the course, only 33% of passive learners and 3% of bystanders completed the course. The pass rate was highest in "C# Programming" course. There was a rate of 85% among active leaners in "C# Programming" course who passed the course, in compared to only 27% of active learners passed "Computer-aided Design and Manufacture" course.

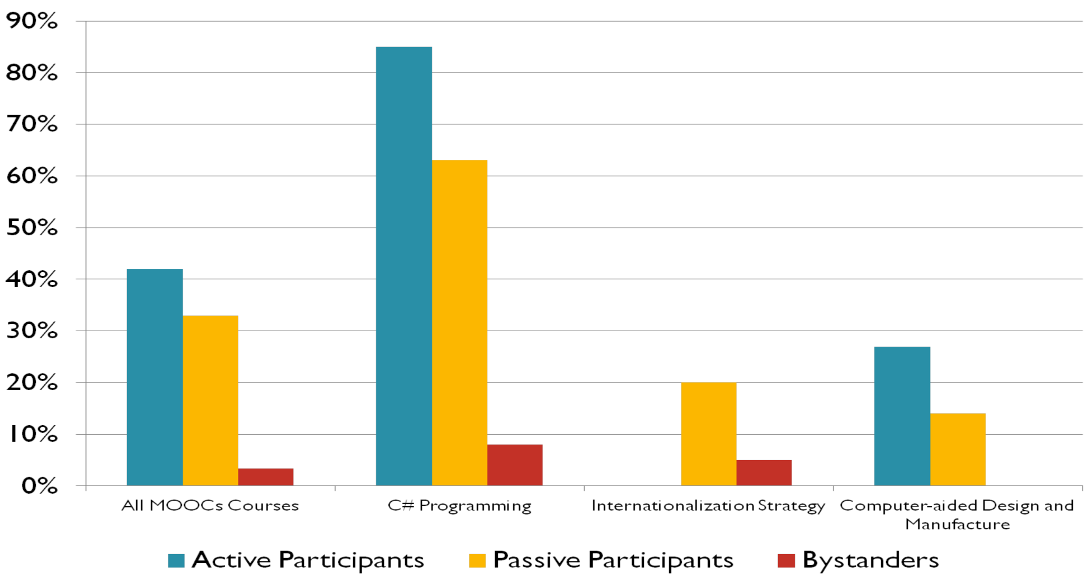

Figure 5. The different types of learners passed the course in MOOCs.

4.4 Impact of discussion forum

In this section, we examined the impact of discussion forum on learning outcome. There was only one course-"C# Programming"-applied this tool on MOOC platform at YZU. A discussion forum was provided for students to discuss and collaborate with each other while they undertake their learning in the course. Chi-square test and mean difference test were employed to explore the effects of forum usage in MOOCs. First, we classified two groups of students: active and inactive users of discussion forum. Active users accounted for about 8% in this class. Then, course pass rates of these two groups and their average grades of this course were calculated. The results indicated there was a 68% pass rate among active users compared to only 11% of inactive users who passed the course. Chi-square test showed a significant difference between these two groups. The test of mean difference also revealed a much higher score among active users (mean score of 72.1) than inactive users (mean score of 12.5) in their final grades. Those who participated more often in discussion forum show a better learning outcome than the others. In all, this result suggested featuring discussion forum in MOOCs was needed to facilitate learning outcome in online environment.

5. Discussion

In this study, we first described trends of usage behaviors in MOOCs. Then, K-means cluster analysis was employed to group students by their learning behaviors. Further, we examined the relationship of MOOC usage and learning outcome. The first part of results suggested that login frequencies among students started to show a dropping trend in the second week of the courses. Except for two courses, students in most courses show a low rate of logging in system and few number of video watching. Assignment submission varied by section design in each of the courses. Secondly, learners in MOOCs at YZU can be classified into three groups: active learner, passive learner, and bystander. In three courses, only 1% of students counted as active learners, while 9% and 90% of them were passive learners and bystanders respectively. Those active learners did show a better course complete rate of 42% than that of passive learners (33%) and bystanders (3%). These results suggested that types of learners played a determined factor on learning outcome. In addition, statistical tests showed that active use of discussion forum in MOOCS did enhance students' learning outcome.

The trends of learning curve in MOOCs at YZU indicated the first two weeks was a critical point of time to retain students in MOOCs. For students' retention, MOOCs instructors need to carefully design course sections and pay more attention on students' feedbacks in early of the classes. The results of cluster analysis suggested most students fell into the "bystander" category. The course complete rate was merely 3% in this group. To motivate this group to engage in MOOCs is a great challenge. Researchers need to examine these "bystanders" further and explore how different patterns of behavior and engagement in these MOOC learners reflect different motivations. In terms of learner activities within discussion forum, this study found that actively participate in discussion forum influence course completion. The presence of forum discussion is correlated with higher course retention and students' performance. Recently, Sharif and Magrill (2015) have suggested discussion forums in MOOCs represent a unique opportunity for insight into the formation of learning communities. It is essential for instructors to effectively use the features of discussion forum and facilitate active forum discussion in MOOCs.

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