Do the Same Rules Apply? Transferring MOOC Success Behaviors to University Online Learning

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Abstract: In this paper, we replicated the methods and findings of a study on successful completion of massive open online courses (MOOCs) in the context of online learning in a university in Metro Manila, Philippines. Specifically, we examine whether discussion forum behaviors associated with completion in MOOCs also resulted in better outcomes in university online learning courses. To this end, we collected logs from the university's learning management system. The Mann-Whitney U test was used to compare the average scores of those who conformed to these behaviors and those who did not. Pearson's r correlation was then used to determine if a significant relationship exists between each of the measured behaviors and the average scores of the students for each course. The same analyses were then performed for each of the five schools in the same university. The study failed to replicate the results of the MOOC study in all cases. The difference in means was not far apart for all rules. This could be attributed to the difference in pacing and demographic between universities and MOOCs. Despite these, the study still demonstrates that techniques used to study MOOCs can be used to study the behaviors and success indicators of students.

Keywords: MOOC, university online learning, academic success

1. Introduction

Massively Open Online Courses (MOOCs) are Internet-based classes offered at minimal to no cost. They are available to any participant with Internet access, anytime, anywhere (Cagiltay, Cagiltay, & Celik, 2020). Because barriers to entry are low, millions of people enroll in these courses. The top 5 MOOC providers—Coursera, edX, XuetangX, Udacity, and FutureLearn—account for a collective population of 90 million learners.

Completion rates for these MOOCs, though, tend to be low, typically between 5 and 15% (Ahern, 2018). Researchers have therefore tried to study the relationship between student in-course behaviors and their course completion. Typically, these studies examined students within a single course, raising questions about replicability. Which of these findings generalize across MOOCs and which do not? Andres and colleagues (2018) addressed the issue of replicability by testing prior findings against data from multiple MOOCs. They found that students who were likely to complete a course tended to spend more time in forums and on assignments, make longer posts, post, and respond more frequently, and so on.

The question that we pose in this paper is whether these findings transfer beyond MOOCs, to online learning during the COVID-19 pandemic. Transferring these findings could provide an alternative method of studying success indicators beyond the usual surveys done for online learning. This study investigates the following behaviors associated with earning a certificate in MOOCs studied by Andres et al. (2017):

- Rule 1. Number of posts in discussion forums is greater than average.
- Rule 2. Length of posts in discussion forums is longer than average.
- Rule 3. Number of responses to others in discussion forums is greater than average.
- Rule 4. Number of respondents to threads in discussion forums is greater than average.

More specifically, the study aims to answer the following research questions:

- RQ1: Is there a significant difference between the average scores of students that fall under the behaviors listed and those that do not?
- RQ2: Is there a correlation between the average word count per discussion post, the average number of posts, the average number of replies received, and the average number of replies to others, and the average score of each student?
- RQ3: Are these correlations present within the courses offered by the different schools of the university?

2. Background Literature

2.1 MOOCs and Universities

MOOCs have often been compared to on-campus university courses, especially given that some universities also offer MOOCs. On-campus university courses consist of students who are closer to one another while MOOCs have a wider reach across different countries. University courses also follow a directed learning curriculum with a pre-defined course outline. MOOCs mostly follow self-directed learning with a more flexible timeline. (Begiu & Strobl, 2015). Even educators have a difference in their approach and roles between the two. Educators in MOOCs those courses cited managing the course, creating resources, and guiding students as part of their roles. On the other hand, on-campus university educators cited that guiding and accompanying students formed the bulk of their work while providing feedback carried a lesser weight (Cabrera & Fernández-Ferrer, 2017).

2.2 Student Success in MOOCs and University Online Learning

Research into MOOCs has focused on behaviors associated with completing the course as most MOOCs have a low completion rate (Crossley et al., 2016). The present study focuses on data collected from discussion forums which have similarly been the subject of several studies into MOOC completion. Andres et al. (2017) investigated 21 findings or rules from previous studies to identify if these held true for their dataset. Out of the 21 rules, 14 involved behaviors in discussion forums, but the present study focuses on the four rules mentioned earlier. Out of the four, the study failed to replicate the second rule since the analysis was not statistically significant.

On the other hand, studies into the performance of university students in online learning primarily focus on survey-based questions. A survey of undergraduate nursing students in South Korea by Kim et al. (2022) found that self-directed learning behavior and satisfaction with their course were found to be predictors of academic achievement. Other studies (Basith et al., 2020; Gopal et al., 2021) similarly made use of surveys and explored the relationship between online learning satisfaction and academic performance. It is evident that previous studies have focused on data collection through surveys. As such, the present study aims to investigate the use of techniques in MOOC researchers to understand the behaviors associated with academic success in university online learning.

3. Methods

3.1 Description and Preparation of Dataset

The study made use of students' log data from the Canvas LMS of a university in Metro Manila, Philippines, collected during one semester from August 25, 2021, to December 18, 2021. During this time, all classes at the university were held online. There were a total of 3,429 classes offered and 6,439 students enrolled in the university. The university was divided into 5 schools: education, humanities, management, science and engineering, and social sciences. Many courses within each school can be taken by students from any field of specialization, i.e., a student specializing in management can take a social science course,

and a student specializing in science can take a humanities course. The discussion forum logs from each course were used to compute the average word count, average number of replies to others, and average number of replies received for each of the students.

In the study of Andres and colleagues (2017), success was defined as the earning of a certificate. In our dataset, though, students earned grades that ranged from 0 to 100, so success had more variation. Hence, we used the grade logs for all graded assignments and computed the average score percentage of each student for each course.

3.2 Comparison of Means for each Rule

Since the success indicator (average score across all graded assignments) is no longer binary (completed or did not complete the course), a comparison of means was used instead of the chi-square test used by Andres et al. (2017). For each course, a course average for each of the four rules was obtained to split the students into two groups for each rule: those who are above average and those who are below average. A test was then used to compare the means of each group for all four rules. In choosing the test, the normality of the data was first assessed using Q-Q plots (Das & Imon, 2016). Q-Q analysis for all four rules showed that all four data are not normal. Thus, the Mann-Whitney U test (McKnight & Najab, 2010) was used to test if there is a significant difference in the average score percentage of those who are above average and those who are below average for each rule. The same analysis was done for the data after being divided by school.

3.3 Analysis using Correlation for each Rule

Given that both the rules and the success indicator are continuous variables, it is possible to identify if there exists a correlation between each rule and the average score percentages. For this, Person's r correlation (Akoglu, 2018) was used. This analysis provides more insights for courses in the university where academic success is dependent on numerical grades and not a binary variable (pass or fail).

4. Results and Discussion

4.1 Analysis Across the Entire Population

Table 1 presents the median and interquartile range for the two groups under each rule. The results of the Mann-Whitney U test show that there is a significant difference ($p \leq 0.05$) between the mean score percentage of the above and below-average groups for Rules 2–4. This seems to follow the findings of Andres et al. (2017), but the median and interquartile range of the average score percentage per group doesn't support the replication. The two median average score percentages of the two groups under Rules 2–4 only differ by at most 1%. Similarly, the interquartile ranges of both groups are mostly overlapping.

Table 1. *Median and IQR for the average score percentage of the groups in each rule.*

#	Rule		Median	IQR
1	Average number of posts	Above average	91.00	83.69 – 96.66
		Below average	90.67	83.78 – 96.07
2	Average word count*	Above average	91.60	82.94 – 95.83
		Below average	90.00	84.80 – 96.67
3	Average number of replies given*	Above average	91.18	84.27 – 96.67
		Below average	90.65	83.67 – 96.09
4	Average number of replies received*	Above average	91.34	84.76 – 96.43
		Below average	90.63	83.54 – 96.18

*statistically significant ($p \leq 0.05$)

The results of the Pearson's r Correlation in Table 2 provide more insights into the data. Only the correlation coefficients for Rules 1 and 2 were found to be statistically significant ($p \leq 0.05$). For Rule 1, the result shows that there exists a negligible correlation between the students' average number of posts and their average score percentage. Similarly, for Rule 2, the result shows that there exists a negligible correlation between the students' average word count per post and their average score percentage. These results show that students with a higher average number of posts and word counts did not necessarily have higher average scores.

Table 2. *Results of Pearson's r Correlation across all four rules.*

#		Pearson's r coefficient	p-value
1	Average number of posts	-0.041	0.00*
2	Average word count	0.060	0.00*
3	Average number of replies given	0.01	0.25
4	Average number of replies received	0.00	0.99*

*statistically significant ($p \leq 0.05$)

Overall, the results suggest that the study failed to replicate the results of Andres et al. (2017). Although the Mann-Whitney U test showed a statistically significant difference with the means for Rules 2–4, the difference turned out to be at most 1%. For Rule 2, this point was confirmed by the Person's r Correlation which showed negligible correlation. Moreover, the Person's r Correlation also showed that Rule 1 may not hold true as well given the negligible correlation. These results could be explained by how university instructors often give more rigid guidelines—such as requiring only one post—compared to those in MOOCs. Similarly, results show that the length of these responses don't have a significant relationship with the students' performance. It might be more insightful, then, to analyze the content of responses. Aside from instructor guidelines following the directed learning approach (Belgiu & Strobl, 2015), the failure to replicate could also be attributed to the difference in demographic between universities and MOOCs.

4.2 Analysis per School

Tables 3 and 4 show the results of the same analyses conducted on the dataset divided by the school that offers each course. The results of the Mann-Whitney U test for all schools show that, among those with a statistically significant difference in means, the difference in the medians is at most 1%, and the interquartile ranges are mostly overlapping. The only exceptions are Rules 3 and 4 for the science and engineering courses where a difference of 3% was observed. However, the interquartile ranges for the two groups under both rules are still mostly overlapping. Moreover, the Pearson's r correlation for Rules 3 and 4 of the science and engineering courses show negligible correlations for both rules. Thus, we are unable to conclude that these courses adhere to Rules 3 and 4. The remaining statistically significant results for the Pearson's r correlation show negligible. Therefore, even when divided by school, the study fails to replicate the results of Andres et al. (2017), and the results are similar to the results of the analysis done across the entire population. This could indicate that instructors across schools provide the same rigid guidelines described earlier.

Table 3. *Median and IQR for the average score percentage of the groups in each rule divided by school.*

School	Rule	Below Average		Above Average	
		Median	IQR	Median	IQR
education	1	96.25	93.45 – 99.57	96.19	92.50 – 98.88

	2	96.38	93.57 – 99.33	96.08	92.92 – 99.89
	3	96.19	93.45 – 99.58	96.19	90.62 – 98.64
	4	96.15	93.33 – 99.56	97.62	93.41 – 98.90
management	1*	89.00	82.92 – 94.00	88.27	78.34 – 92.75
	2*	88.00	81.15 – 92.76	89.17	83.33 – 94.38
	3*	89.00	82.45 – 93.82	87.64	78.53 – 91.98
	4	88.67	82.00 – 93.80	89.22	80.83 – 92.94
social sciences	1*	91.0	84.92 – 96.06	92.5	85.71 – 97.14
	2*	90.64	84.21 – 96.00	92.00	86.21 – 97.00
	3*	91.11	85.00 – 96.00	92.79	85.54 – 97.96
	4	91.32	85.00 – 96.19	91.43	84.45 – 98.00
science and engineering	1	90.63	82.24 – 96.00	91.38	79.49 – 96.67
	2	90.15	81.41 – 96.24	91.24	82.18 – 96.03
	3*	90.28	81.24 – 95.94	93.35	82.61 – 97.01
	4*	90.00	81.02 – 96.00	93.62	87.55 – 96.73

*statistically significant ($p \leq 0.05$)

Table 4. *Results of Pearson's r Correlation across all four rules per school.*

Rule	education		management	
	Pearson's r coefficient	p-value	Pearson's r coefficient	p-value
1	-0.09878	0.34352	-0.05855	0.04901*
2	0.15506	0.13563	0.09572	0.00127*
3	-0.06646	0.52451	-0.06733	0.02354*
4	0.01456	0.88923	0.01896	0.52403

Rule	social sciences		science and engineering	
	Pearson's r coefficient	p-value	Pearson's r coefficient	p-value
1	0.02430	0.17346	-0.03003	0.19286
2	0.03352	0.06042	0.00179	0.93821
3	0.05577	0.00177*	0.08993	0.00009*
4	-0.04601	0.00993*	0.05730	0.01290*

*statistically significant ($p \leq 0.05$)

5. Conclusion and Further Studies

Overall, the study failed to replicate the results found by Andres et al. (2017). There are several possible reasons why the MOOC results did not transfer to our population. First, the students enrolled in MOOCs and those enrolled in traditional college courses differ in fundamental ways. MOOC students tend to be between 25 and 65 years old (Cagiltay, Cagiltay, & Celik, 2020). Most already have a higher education degree and are male. They enroll in a MOOC because (1) they want to retool or explore new professional areas, (2) they have a personal interest in the course content, or (3) the course is important for career advancement (Baturay, 2015; Williams, Stafford, Corliss, & Reilly, 2018). Guided by their own motivations, most learners tend to navigate the course in a non-linear fashion, studying what they need and skipping the rest (Cagiltay, Cagiltay, & Celik, 2020). MOOCs enable this type of behavior because students are minimally supervised—it is rare for a student to receive direct and timely feedback from course instructors.

On the other hand, the students in our population were enrolled in traditional courses that were forced online by COVID-19. Hence, students received direct supervision from

teachers, including psycho-social support (see Moreno et al, 2021). Furthermore, culturally, Filipinos place a high value on education (Galang & Reyes, 2009). They see education as a solution to poverty and ignorance, as a means towards better life opportunities. Finally, Filipinos are motivated to persevere in their studies by social cues from parents, teachers, classmates, and friends. These factors may have driven students to succeed in their courses, despite the difficulties brought on by the pandemic.

Although the study was unable to replicate the results, it was still able to demonstrate how techniques used to study MOOCs can be used to study the behaviors and success indicators of students. This deviates from the usual surveys to study student behavior and makes use of data collected from a learning management system. Moreover, future studies can still consider replicating the other rules that the current study was not able to consider.

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