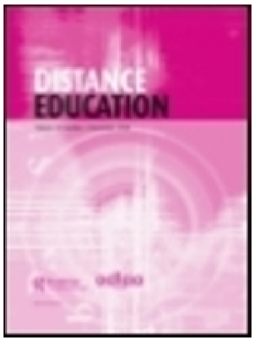

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# Exploring the influences of MOOC design features on student performance and persistence

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**ABSTRACT**

Massive open online courses (MOOCs) face persistent challenges related to student performance, including high rates of attrition and low student achievement scores. Previous studies that have examined the performance of students in MOOCs have done so using qualitative analysis and the quantitative analysis of small samples. This study is the first to examine general course features of MOOCs on a large scale and to quantify the influences of these course features on student performance. Informed by the theory of web-based online instruction, this study used two-stage *K*-means clustering to analyze more than 200 MOOCs that had enrolled about 300,000 students, identifying three patterns of course features among the MOOCs. A MANOVA test and follow-up statistical tests revealed that these patterns of course features influenced the MOOCs' dropout rates and student achievement scores to statistically different degrees. The implications of these findings are discussed.

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MOOC; course feature; student dropout; student performance; large-scale data analytics

## Introduction

Massive open online courses (MOOCs) have gained momentum in recent years as an innovative approach for leveraging technology for educational purposes. The main goal of MOOCs is to provide free and open courses to a global audience. Because they combine open educational resources and online learning, MOOCs have the potential to be an effective, technologically advanced medium for learning in higher education and beyond (Watson, Loizzo, et al., 2016). Although the great potential of MOOCs has been discussed extensively across a variety of media (including text publications and policy forums), MOOCs have faced criticism for unsolved pedagogical problems (Yousef, Chatti, Schroeder, & Wosnitza, 2014). In particular, they have been criticized for unsatisfactory levels of student performance, including low levels of student achievement and high rates of attrition (Crues et al., 2018; Raffaghelli, Cucchiara, & Persico, 2015; Veletsianos & Shepherdson, 2016).

### *Research into student performance and dropout*

Student performance and student retention are long-standing challenges for online courses. A large set of studies have examined how to prevent students from dropping out

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and how to improve their performance. For instance, Lee and Choi (2011) analyzed 159 studies into student dropout from online courses and identified 69 factors that influence students' decisions to drop out. They then divided these factors into three categories: student factors, course/program factors, and environment factors. Bawa (2016) proposed a similar set of categories: social and family factors, motivational factors, cognitive overload, technological constrains, faculty limitations in using technology, instructor difficulties in understanding online students, and institutional limitations in training faculty.

A number of studies have sought to explain the high dropout ratios and low achievement levels of MOOCs in particular. The majority of these studies have examined these issues from the student perspective (Veletsianos & Shepherdson, 2016). For example, by employing various qualitative and quantitative methods, studies have investigated the extent to which students' motivation levels, attitudes, and patterns of behavioral engagement account for their low grades and high likelihood of dropping out (e.g., Halawa, Greene, & Mitchell, 2014; Zheng, Rosson, Shih, & Carroll, 2015). Other studies have found that motivation is one of the strongest predictors of engagement and performance for students in MOOCs (Barba, Kennedy, & Ainley, 2016; Kennedy, Coffrin, de Barba, & Corrin, 2015).

Numerous researchers have used learning analytics and educational data mining to study students' engagement and performance issues. For example, Yang, Sinha, Adamson, and Penstein Rosé (2013) used text mining and social network analysis to study students' social positioning in MOOC discussion forums. They also developed a survival model that can measure the influence of social factors on student dropout. Kizilcec, Piech, and Schneider (2013) used learning analytics to deconstruct patterns of student engagement in MOOCs, identifying four types of engagement trajectories directly related to student achievement and dropout. Many studies have also used data analytics to identify patterns in the behavior of MOOC students and to predict their grades and likelihood of dropping out (e.g., Jiang, Williams, Schenke, Warschauer, & O'Dowd, 2014; Robinson, Yeomans, Reich, Hulleman, & Gehlbach, 2016; Ye et al., 2015).

Other studies have examined students' performance problems from the instructor perspective. For example, Belanger and Thornton (2013) sought to determine how MOOC instructors can engage students to improve their academic performance and prevent them from dropping out. Khalil and Ebner (2013) used a five-step interactivity model to investigate the importance that instructors ascribe to interaction during MOOCs. They suggest that MOOC instructors' perceptions of interaction can influence the behavior and performance levels of their students. Stephens-Martinez, Hearst, and Fox (2014) investigated how MOOC instructors evaluate the usefulness of different sources of information, finding that how an instructor views different sources of information can affect the behavior and performance levels of their students. Watson, Watson, Richardson, and Loizzo (2016) examined how a MOOC instructor's use of social presence, teaching presence, and dissonance influenced the outcomes and attitudes of their students. However, studies examining MOOC course design and its influence on students' performance are limited.

## *Design features of online courses*

Studies into the design of online courses are very rich, and according to Jaggars and Xu (2016), they are of four distinct types. Studies of the first type are practitioner-oriented studies, including case studies detailing successful online course designs, studies into best practices, and syntheses of multiple studies (e.g., Grandzol, 2006). Very few of these studies have attempted to empirically validate best practices in the design of online courses. Studies of the second type are surveys on the perceptions of students and instructors regarding which elements of online courses are characteristic of high-quality designs (e.g., Ralston-Berg, 2011). Such studies generally examine a small set of courses or students at a single institution. Studies of the third type are experiments and control studies designed to examine the effects of different online course designs on student learning and achievement. Such studies also tend to use small samples, and for this reason, their rigor is often questionable (see, Means, Toyama, Murphy, Bakia, & Jones, 2009). Studies of the fourth type, which have been conducted by educational associations, propose rubrics and standards with which to gauge the quality of online courses (e.g., Quality Matters Program, 2014). However, different associations have proposed different rubrics and emphasized different features of online courses.

Several studies have investigated the extent to which different course features impact student performance, usually by examining one or a few MOOCs. For example, Admiraal, Huisman, and Van de Ven (2014) compared the impacts of self-assessment and peer assessment on the performance levels of students in three MOOCs. Margaryan, Bianco, and Littlejohn (2015) examined the features of 76 MOOCs, but they did so mainly through qualitative means and did not examine whether these features impacted student performance. According to the literature review conducted by Veletsianos and Shepherdson (2016), some studies into features of course design have examined tools designed to improve social interaction, while others have examined the use of specific types of media in instruction. For instance, Kovacs (2016) studied the effects of students' viewing of videos by embedding in-video quizzes into MOOCs. Sajjadi, Alamgir, and von Luxburg (2016) compared peer grading with grading performed by teaching assistants and suggested ways to automate the grading process. Kim et al. (2017), inspired by psychological reactance theory, restricted the accessibility and repeatability of online courses to prevent students from dropping out of MOOCs.

To date, however, no study has quantitatively examined on a large scale how course features of MOOCs impact student achievement and dropout rates. In fact, according to a review by Bozkurt, Akgün-Özbek, and Zawacki-Richter (2017), only 11% of the studies conducted into MOOCs have examined features of course design. In addition, a review of MOOCs by Zawacki-Richter, Bozkurt, Alturki, and Aldraiweesh (2018) found that most MOOCs suffer from low-quality course designs, and the influence of MOOC design quality on students' performance is also unclear. This study serves as a first step toward the quantitative evaluation of the impact on student performance of basic features in the design of MOOCs.

### *Summary*

Although a large number of studies employing a variety of methods have attempted to explain MOOCs' high dropout rates and low levels of student performance, how design features of MOOCs affect student retention and performance is still unclear. To answer this question, a systematic analysis of a large number of courses will be required. This study offers a first step toward such an analysis, drawing upon the theory of web-based online instruction (Grabowski & Small, 1997) to examine the effects on student retention and performance of basic course features, for example, the number of assignments, the number of grading options, and the duration of the course. The course features were calculated first from more than 200 MOOC courses; two-stage *K*-means clustering analysis was then conducted to reveal the common course feature patterns in MOOCs. Additional statistical analysis was performed to examine how these patterns impacted student achievement and dropout rates. This study had two interrelated goals: to identify patterns of features common to MOOCs and to determine how these patterns affect student achievement and dropout rates.

## Theoretical foundations

A number of theoretical and practice-based frameworks describe design features of online courses. According to Moore's (1973) theory of transactional distance, for instance, courses have three essential features: *structure* (i.e., the extent to which materials and assessments are regulated and sequenced); *dialogue* (i.e., the degree to which student and teacher engage in interactions that promote the development of student knowledge); and *autonomy* (i.e., the degree of freedom students have to choose what, how, and how much they learn). Developed by Garrison, Anderson, and Archer (2001), the community of inquiry framework has also been widely applied to the design of online courses. It consists of three elements: *social presence* is a learner's ability to project themselves socially and emotionally via technology-mediated communication; *cognitive presence* is the extent to which a learner is able to construct meaning through sustained discourse and reflection; and *teaching presence* is the design, facilitation, and direction of social and cognitive processes to achieve learning outcomes.

In reviewing a number of studies, Jaggars and Xu (2016) identified four elements in the design of online courses that are critical to student performance: *organization and presentation* (i.e., implementing a clear and consistent structure with intuitive navigation); *learning objectives and assessments* (i.e., emphasizing the importance of clearly presented learning objectives and its close relationship with designed assessments); *interpersonal interaction* (i.e., stressing the significance of interpersonal communication and collaboration in online courses); and *technology* (i.e., regarding the availability of various tools and the ease of use of these tools).

The most fundamental framework for course design is probably Merrill's (2002) first principles of instruction, which offers five prescriptive principles: *problem-centered* (learning is promoted when learners obtain skills in solving real-world problems); *activation* (learning is promoted when learners use prior knowledge as a foundation for new skills); *demonstration* (learning is promoted when learners observe a demonstration of a target skill); *application* (learning is promoted when learners apply the new skills they have obtained); and *integration* (learning is promoted when learners reflect upon and discuss their new skills). A meta-review found that these fundamental principles underlie all contemporary instructional models and theories (Merrill, 2013).

Although the theories reviewed above are all well established in the online learning setting, most of the studies that have been guided by these frameworks have been qualitative or have used traditional methods of small-scale quantitative analysis. One possible reason for this is that these theories are granular in nature; and it is thus relatively difficult to use them to identify and directly quantify the elements in an online course without intensive qualitative coding and/or conducting surveys. For this reason, I chose web-based online instruction (Grabowski & Small, 1997), a more general theory of online learning, to explore the basic course features of MOOCs. According to web-based online instruction, online courses incorporate three overarching types of design elements: *information, instruction*, and *learning* (Grabowski & Small, 1997). A piece of information is any unit of fact or data used for instructional purposes. Instruction is information selected, organized, and sequenced in the direction of a meaningful procedure or activity. Learning engages students in active social cognitive processing to support the development of collaboration and knowledge. A well-designed online course brings together elements of information, instruction, and learning to promote and scaffold learning. Web-based online instruction was chosen as the theoretical grounding of this study because it is flexible enough to accommodate the large-scale quantitative analysis of basic features of MOOCs.

## Methodology

### *Data*

This study examined 211 MOOCs with a total of 284,888 students. These MOOCs covered a wide range of fields: 22 were in business and management; 9 were in computer science; 55 were in education; 29 were in the humanities; 7 were in mathematics and statistics; 5 were in the medical sciences; 5 were in the physical sciences; 60 were in the professional and applied sciences; and 12 were interdisciplinary and other fields. The students also had diverse backgrounds. Of them, 1417 had finished high school; 3936 had completed some college but had not earned a degree; 1970 had earned a degree from a 2-year college; 8041 had earned a degree from a 4-year college; 13,257 had earned a master's degree; 2691 had earned a PhD or the equivalent; 421 had done none of the above; and the rest did not report their academic background. Of the students, 13,324 were in the 19–34 age-group; 15,737 were in 34–54 age-group; and 5283 were 55 or older. The rest did not disclose their age.

In an initial attempt to study features of MOOCs on a large scale, I operationalized the theory of web-based online instruction (which categorizes design elements as information, instruction, or learning) to identify basic features of MOOCs about which every instructor has to make a decision. Table 1 explains the course features and how they were operationalized, in accordance with Koszalka and Ganesan (2004). Once I had identified the course features that I was interested in, 205 MOOCs remained for further analysis.

To determine how these features influenced student achievement and dropout rates, the average student grade and the dropout rate were calculated for each MOOC. Descriptive statistics for the course features, average student grade, and dropout rate are presented in Table 2. The average student grade for each MOOC was obtained by averaging its students' scores on its quizzes and tests.

### *Data analysis*

To identify general patterns in the features of the MOOCs, a two-stage *K*-means clustering analysis was applied to the course features presented in Table 1. *K*-means clustering

**Table 1.** Basic features of MOOCs (adapted from Koszalka & Ganesan, 2004, pp. 246–247).

| Course feature | Definition | Primary type | Value for learning |
|---|---|---|---|
| Number of days | Length of the course | Information, Instruction | Provide information for the materials |
| Number of discussion forums | Discussion forums for students to participate and collaborate | Learning | Engage in social learning activities |
| Number of quizzes | Tools for testing understanding of course information | Instruction, Learning | Identify areas in which additional study is needed and test levels of understanding |
| Number of assignments | Tools for practicing and improving understanding of course information | Instruction, Learning | Improve reflection and understanding of course material |
| Number of peer reviews | Peer assessment used in the course | Learning, Instruction | Use evaluation of others' work to improve student understanding |
| Number of submission types | Various means of submitting assignments, e.g., URL, media recording, file upload | Instruction | Provide different experiences and opportunities for students to practice and digest what they have learned |
| Number of grading types | Various ways to grade assignments, e.g., pass/fail, points, letter grades | Instruction | Provide feedback for learning |

**Table 2.** Descriptive statistics for course features and student performance for 205 MOOCs.

| Course feature | Mean | SD |
|---|---|---|
| Number of days | 56.76 | 30.53 |
| Number of discussion forums | 17.28 | 14.36 |
| Number of quizzes | 10.20 | 7.83 |
| Number of assignments | 15.92 | 10.53 |
| Number of peer reviews | 0.53 | 1.66 |
| Number of submission types | 2.16 | 1.46 |
| Number of grading types | 1.35 | 0.55 |
| Grade | 0.30 | 0.24 |
| Dropout rate | 0.97 | 0.07 |

is an established method for separating multivariate data into groups that are internally homogenous and collectively heterogeneous (Guo & Zhang, 2014). Because the clustering process is sensitive to the scale between variables (Jain, 2010), the course features were standardized to prevent large values from disproportionately affecting the centroid calculations. The *K*-means algorithm also requires that the number of clustering centers be prespecified, and it iterates case allocation to the nearest center point. A two-stage clustering analysis was therefore performed: the first stage removed outliers, and the second stage identified patterns of course features.

The first stage was applied across a range of possible cluster numbers *K*. When a large number of cluster partitions is selected ($K > 20$), the minimum membership is very small and may indicate the existence of extreme outliers. In this study, cluster solutions for $K = 21, 22, 23, 24, 25$ were selected to find possible outliers. Before I could conduct the second stage of the clustering analysis, in which patterns in course features would be identified, I had to find the optimum number of clusters. The aim was to minimize the differences between the members (i.e., the courses) of each group and to maximize the differences between the members of different groups. The Ball statistic (Ball & Hall, 1965) was calculated to identify the optimum number of clusters for the study, which suggested that the average distance between a data point and its corresponding cluster centroid could serve as an effective measure of the number of clusters in the data. After the optimum number of clusters had been determined, the second stage of the clustering was performed to identify common patterns of MOOC features.

Additional statistical tests were conducted to determine how different patterns of MOOC features influenced average student grade and dropout rate. Since there was a statistically significant correlation between average student grade and dropout rate ($r = 0.28$, $p < 0.000$), a one-way MANOVA test was applied to determine the influences of patterns of course features on average student grade and dropout rate. A univariate ANOVA and a Tukey's HSD *post hoc* test were then used to reveal detailed effects of patterns of MOOC features on average student grade and dropout rate.

## Results

### *Two-stage K-means clustering to identify patterns of MOOC features*

A two-stage *K*-means clustering analysis was used to identify general patterns in MOOC features. The first stage of the clustering was performed to remove any possible outliers. After a high number of clusters was selected for $K$ = 21, 22, 23, 24, 25, the clustering solution selected most of the same outliers in the respective low-membership clusters, as Table 3 shows. This result suggests that the selected outliers were robust for high values of $K$. As a result, the two courses that appeared most frequently in these low-membership clusters for the different values of $K$ were removed from the dataset.

Since there was no definitive number of patterns of MOOC features, the Ball statistic was calculated to determine the optimum number of clusters for the second stage of the *K*-means clustering. The optimum number of clusters is found at the elbow of the Ball-statistic curve, where the maximum difference between the hierarchy levels of the index is located. The decreasing Ball statistic has a maximum at the elbow of the curve (at $K = 3$ in Figure 1). For this reason, 3 was set as the predefined value for $K$ in the second stage of the clustering analysis.

The second stage of the *K*-means clustering analysis was then conducted. Three distinct patterns of MOOC features were discovered, as Figure 2 shows. Table 4 shows the statistics for each cluster, which explains the characteristics of the MOOC features. These statistics revealed three patterns of MOOC design features, which are named and described below.

Cluster 1 contained 63 MOOC courses and had the highest values of the three clusters for number of assignments ($M$ = 20.08, SD = 10.86), number of peer reviews ($M$ = 1.03, SD = 2.38), number of submission types ($M$ = 3.46, SD = 1.69), and number of grading types ($M$ = 2.11, SD = 0.32). These course features reflect various ways for students to learn

**Table 3.** Stage one of the *K*-means clustering.

| K number | Minimum membership | Maximum membership |
|---|---|---|
| 21 | 3 | 24 |
| 22 | 1 | 25 |
| 23 | 3 | 27 |
| 24 | 1 | 24 |
| 25 | 2 | 27 |

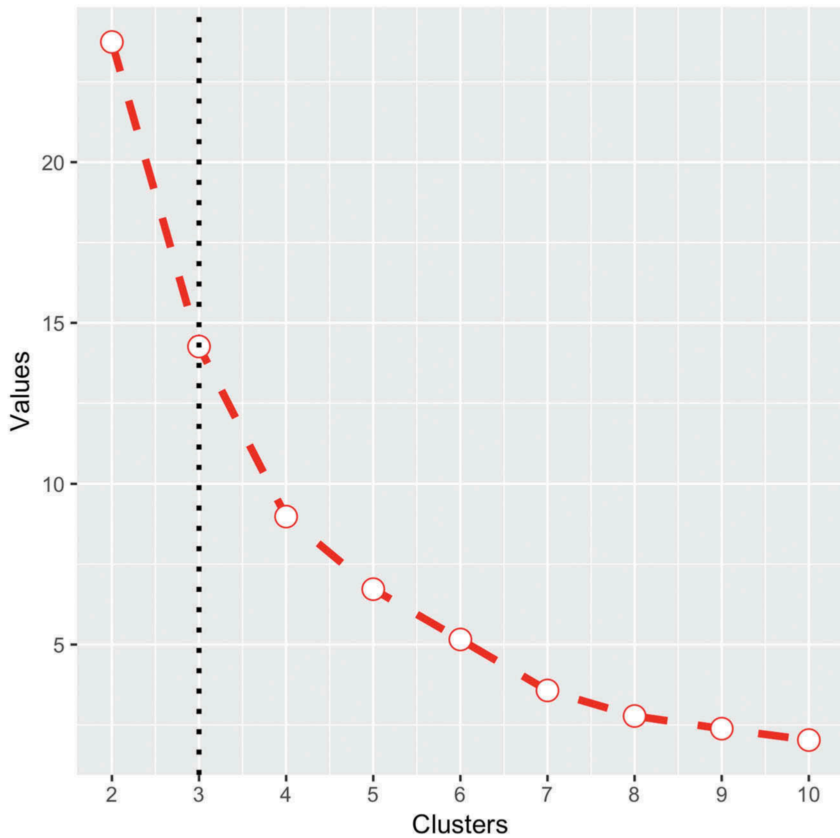



**Figure 1.** Ball statistic.

and reflect on course materials as well as different ways to provide feedback to students. Since cluster 1 had the lowest values for number of days ($M$ = 55.81, SD = 30.17) and number of quizzes ($M$ = 8.95, SD = 7.59), the MOOCs in this cluster had the shortest durations and the fewest number of assessments. Because this cluster's value for number of discussion forums ($M$ = 17.65, SD = 13.38) fell between those of the other two clusters, the MOOCs in this cluster also demonstrated a moderate emphasis on collaboration and social learning.

Cluster 2 contained 41 MOOCs and had the highest values for number of days ($M$ = 59.29, SD = 25.15) and number of discussion forums ($M$ = 36.02, SD = 10.75). In contrast, it had the lowest value of the three clusters for number of submission types ($M$ = 1.51, SD = 0.68). These course features showed that students worked collaboratively and engaged in various social learning activities, but the designs of the courses in this cluster were relatively loose because the courses in this cluster were relatively limited in creating different learning experiences for students. This limitation was also reflected in the values of this cluster for number of quizzes ($M$ = 10.22, SD = 8.28), number of assignments ($M$ = 15.05, SD = 10.11), number of peer reviews ($M$ = 0.27, SD = 0.90), and number of grading types ($M$ = 1.05, SD = 0.22), all of which fell between those of the other two clusters.

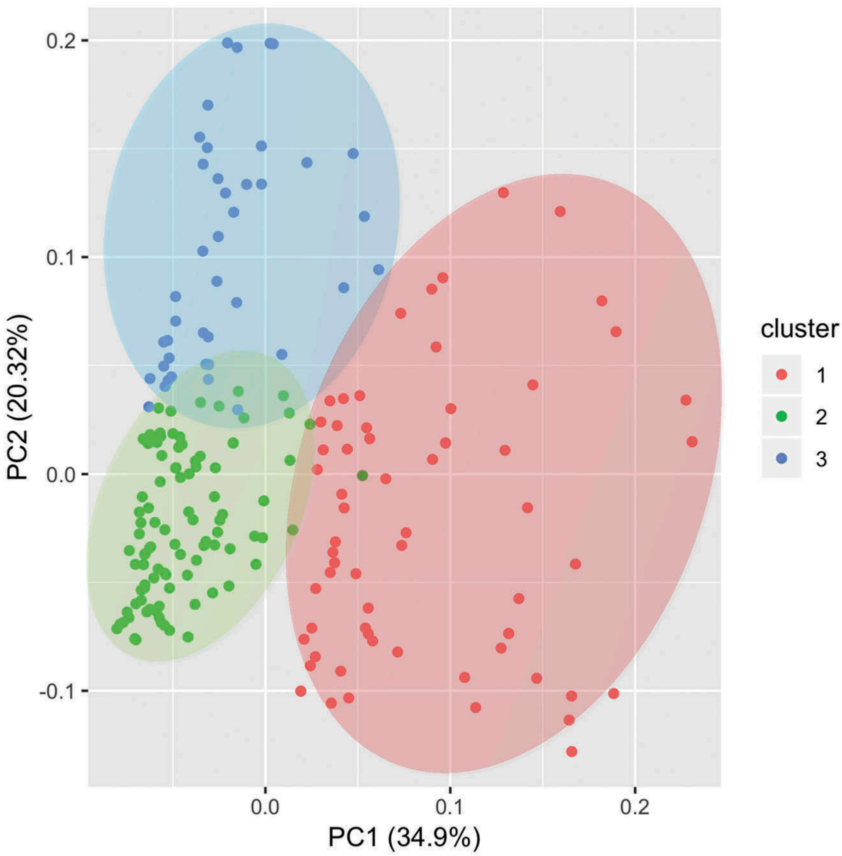



**Figure 2.** Results for the second stage of the *K*-means clustering.

**Table 4.** Cluster statistics.

| Course feature | Cluster 1 (*N* = 63) Mean | Cluster 1 (*N* = 63) SD | Cluster 2 (*N* = 41) Mean | Cluster 2 (*N* = 41) SD | Cluster 3 (*N* = 99) Mean | Cluster 3 (*N* = 99) SD |
|---|---|---|---|---|---|---|
| Number of days | 55.81 | 30.17 | 59.29 | 25.15 | 57.56 | 33.21 |
| Number of discussion forums | 17.65 | 13.38 | 36.02 | 10.75 | 8.75 | 6.68 |
| Number of quizzes | 8.95 | 7.59 | 10.22 | 8.28 | 11.15 | 7.76 |
| Number of assignments | 20.08 | 10.86 | 15.05 | 10.11 | 13.6 | 9.84 |
| Number of peer reviews | 1.03 | 2.38 | 0.27 | 0.90 | 0.19 | 0.80 |
| Number of submission types | 3.46 | 1.69 | 1.51 | 0.68 | 1.58 | 0.90 |
| Number of grading types | 2.11 | 0.32 | 1.05 | 0.22 | 1.0 | 0.24 |

Cluster 3 contained 99 MOOCs and had the highest value for number of quizzes (*M* = 11.15, SD = 7.76), but the lowest values for most of the other dimensions, including number of discussion forums (*M* = 8.75, SD = 6.68), number of assignments (*M* = 13.6, SD = 9.84), number of peer reviews (*M* = 0.19, SD = 0.80), and number of grading types (*M* = 1.0, SD = 0.24). This cluster's values for number of days and number of submission types also fell between those of the other clusters because the courses in this cluster tended to have many quizzes and tests but to score low in the other dimensions.

### Influence of patterns of MOOC features on average student grade and dropout rate

Descriptive statistics were calculated to determine how the identified patterns of course features influenced average student grade and dropout rate. The results (shown in Table 5) indicate that cluster 1 had the highest value for average student grade ($M$ = 0.314, SD = 0.26), and cluster 2 had the lowest value for average student grade ($M$ = 0.254, SD = 0.23). Cluster 1 had the highest value for dropout rate ($M$ = 0.980, SD = 0.07), and cluster 3 had the lowest value for dropout rate ($M$ = 0.972, SD = 0.07). While the absolute differences between these values are not large, their actual, practical influence could be huge, given the enrollment sizes of MOOCs. To illustrate, a typical MOOC can easily have over 10,000 students, and some large MOOCs can enroll over 100,000 students. Thus, the difference of 1–10% difference in dropout rate between the clusters can result in 100–1000 students in course retention. A 5% difference in average student grade between two clusters is not trivial, either.

Since average student grade and dropout rate were highly correlated, a MANOVA test was applied to determine the influences of the patterns of course features on these values. The observations were quite different for the three clusters, however, and this may have significantly affected the results of the statistical tests. A total of 41 courses were randomly selected from cluster 1 and cluster 3 so that each cluster had the same number of observations. The MANOVA test revealed a statistically significant difference in the levels of student performance (average student grade and dropout rate) between the three patterns of MOOC features, $F(2, 122) = 12.578$, $p < 0.0001$; Wilk's $\Lambda = 0.827$, partial $\eta^2 = .173$. A follow-up univariate ANOVA revealed a significant difference in average student grade between the three clusters, $F(2, 122) = 9.622$, $p < 0.001$; $\eta^2 = .138$ and a significance difference in dropout rate, $F(2, 122) = 9.656$, $p < 0.001$; $\eta^2 = .139$.

Tukey's HSD tests were then performed on all possible pairwise contrasts, as is shown in Table 6 and Figure 3. The following pairs of clusters were found to differ significantly in average student grade: cluster 1 ($M$ = 0.314, SD = 0.259) and cluster 2 ($M$ = 0.254, SD = 0.225) and cluster 1 and cluster 3 ($M$ = 0.294, SD = 0.239). In other words, the students enrolled in the MOOCs in cluster 1 had statistically superior grades than the students enrolled in the MOOCs in cluster 2 and cluster 3. The range of the effect size was 0.02–0.25, as Figure 3 shows.

The Tukey's HSD tests revealed that the following pairs of clusters differed in their dropout rates to a statistically significant degree: cluster 1 ($M$ = 0.980, SD = 0.069) and cluster 3 ($M$ = 0.972, SD = 0.069) and cluster 2 ($M$ = 0.974, SD = 0.073) and cluster 3. These results indicate that the students enrolled in the MOOCs in cluster 3 were less likely to drop out than the students enrolled in the MOOCS in cluster 1 and cluster 2. The range of the effect size was 0.02–0.06, as Figure 3 shows.

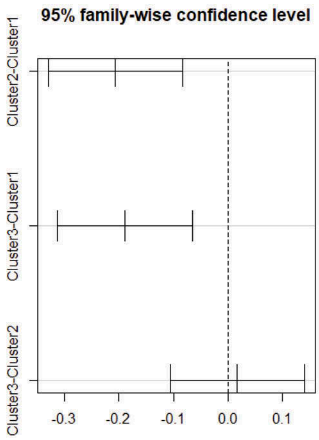
**Table 5.** Descriptive statistics for the average student grade and dropout rate for each cluster.

| | Cluster 1 | | Cluster 2 | | Cluster 3 | |
|---|---|---|---|---|---|---|
| Student performance | Mean | SD | Mean | SD | Mean | SD |
| Grade | 0.314 | 0.259 | 0.254 | 0.225 | 0.294 | 0.239 |
| Dropout rate | 0.980 | 0.069 | 0.974 | 0.073 | 0.972 | 0.069 |

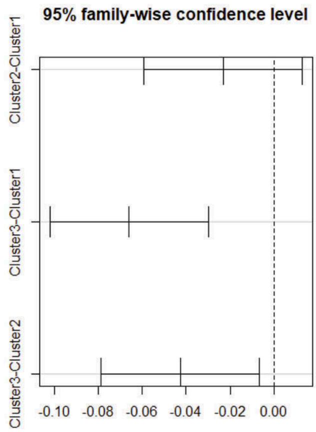
**Table 6.** Results of the Tukey's HSD tests.

| | | Difference | 95% confidence level | | Significance |
|---|---|---|---|---|---|
| Grade | Cluster 2–Cluster 1 | −0.207 | −0.331 | 0.083 | 0.000*** |
| | Cluster 3–Cluster 1 | −0.189 | −0.312 | −0.065 | 0.001** |
| | Cluster 3–Cluster 2 | 0.018 | −0.106 | 0.141 | 0.940 |
| Drop | Cluster 2–Cluster 1 | −0.023 | −0.059 | 0.129 | 0.283 |
| | Cluster 3–Cluster 1 | −0.069 | −0.102 | −0.030 | 0.000*** |
| | Cluster 3–Cluster 2 | −0.043 | −0.079 | −0.007 | 0.016* |

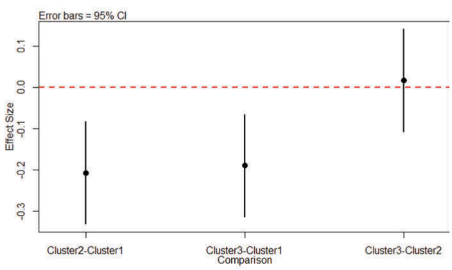
***$p < 0.001$, **$p < 0.01$, *$p < 0.05$



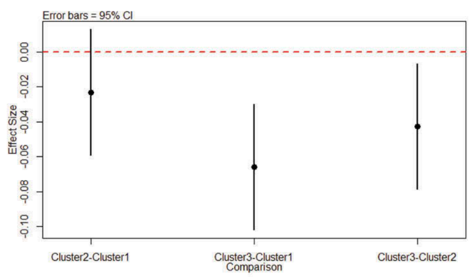

Grade comparison




Dropout comparison




Grade comparison effect size




Dropout comparison size

**Figure 3.** Tukey's HSD tests.

## Discussion

This study was the first to use large-scale data analytics to quantitatively characterize basic features of MOOCs and to examine their relationships with student performance. It offers three main contributions to the field: it identifies common patterns of MOOC features; it quantifies the extent to which different patterns of MOOC features influence students' grades and dropout rates; it offers a new methodological lens through which to study features of online courses, one that allows these features to be studied on a large scale and thus promises more systematic results. The implications of these contributions are discussed more specifically below.

First, previous studies have focused on one or a few characteristics of MOOCs and have generally employed qualitative descriptions or quantitative analyses of small samples (Admiraal et al., 2014). As a result, the basic characteristics of MOOCs are unknown. Specific principles are unable to offer practical guidelines for designing and developing a course. Examining one or a few MOOCs also does not provide a solid foundation and information for the instructors to design a course. Because it quantitatively analyzed a large number of MOOCs, this study is able to provide concrete numbers describing what most MOOCs look like and common patterns of MOOC features. These numbers and patterns can serve as a baseline in reference to which any MOOC designer can determine whether their course is way above the common range in terms of course length, number of assignments or not, as well as which specific pattern it belongs to (cluster 1, cluster 2, or cluster 3). This awareness could prevent MOOC designers (and especially new MOOC instructors) from flying blind. With this baseline, MOOC designers can refer to Merrill's (2002, 2013) first principles of instruction or to the community of inquiry framework (Garrison et al., 2001) in designing their courses at a more granular level.

Second, because it reveals the relationships between different patterns of MOOC features and student performance, this study also has practical implications for designing MOOCs. We can use discriminant analysis (Jain, 2010) to help an instructor decide which pattern of course design their MOOC belongs to, enabling them to forecast what might happen in their course and thus to be better prepared to plan their instruction. For example, if a course falls in cluster 1, its instructor can expect that students will have high grades but be at greater risk of dropping out. With this knowledge, the instructor can be more careful and devote more attention to students at risk of dropping out. If a course falls into cluster 2, in contrast, its instructor can expect that students will be relatively unlikely to drop out but that academic performance will be a serious concern. The instructor can then pay more attention to and provide more support for struggling students.

Third, this study presents a new methodological framework with which to study features of online courses at a large scale. Previous studies into design features of online courses have generally been qualitative, although a few studies have been experimental (Jaggars & Bailey, 2010). In addition, previous studies have generally examined one or a few classes and produced qualitative findings, evaluated the overall effectiveness of a design, or described a specific design feature of an online course. The two-stage clustering analysis I employed can be used to simultaneously consider every feature of an online course and to identify distinct patterns among these features. The results of this type of analysis can serve as a foundation for examining the effects of course features as a whole. In addition, large-scale clustering analytics can abstract away from individual differences and can thus produce results that are more generalizable than those of case studies (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2010).

Nevertheless, this study has several limitations. First, it considered only seven basic features of online courses, leaving out of its analysis many other features, including course goals and objectives as well learner characteristics that influence learning achievement. Second, course features are much more than the type of numeric values given in this study. Considering course features only quantitatively and not considering their quality (e.g., the quality of online interaction that they offer) may not provide a comprehensive picture of patterns of MOOC features. Third, the analysis of the relationships between course features and student performance was only correlational (not causal). Additional control experiments could determine how specific patterns of course features influence the performance levels of students in MOOCs. Fourth, this study used only MOOCs from the Canvas platform, so its results may have limited generalizability to MOOC courses on other platforms.

## Conclusion

This exploratory study used large-scale data analytics to identify basic features of MOOCs and to determine their relationships to student performance and persistence. We discovered three distinct patterns of MOOC features and determined the extent to which they correlated with a MOOCs average student grade and dropout rate. The results of this study have practical implications for the design of future MOOCs, and the study itself has methodological implications for future research into online courses. Future studies could analyze additional MOOC features to obtain a more comprehensive picture of the features of MOOCs. In addition, a future study could design a MOOC to fit one of the patterns of features that this study identified and then evaluate the effectiveness of this MOOC by measuring the performance of its students. Finally, future studies could apply the methodology used in this study to online courses generally, establishing the transferability of this study.

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No potential conflict of interest was reported by the author.

## Notes on contributor

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