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Student Engagement in Aviation Massive Open Online Courses (MOOCs)

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As online training in the aviation industry continues to expand, understanding how learners engage in open online courses may help inform course design. Currently little is known about student engagement in aviation Massive Open Online Courses (MOOCs) and more information is needed about those who utilize, but do not complete them. Datasets from two aviation MOOCs were cluster-analyzed to determine subpopulations based on activity (discussions, videos, quizzes). Differences were examined for days of activity and completion. Survey data revealed differences in demographics and learning goals. Three significantly different subgroups were found for each MOOC. Engagement patterns were similar between corresponding levels across MOOCs for the most and least engaged groups, but differences were noted in the middle groups: MOOC 1 had a broader interest in optional discussions and videos, MOOC 2 had a narrower interest in optional discussions. Notably, significant associations were found between subgroups and days of activity, total quiz scores, and completions. In both MOOCs, significant differences were found between clusters and days of activity, with more highly engaged groups active more days than lower engaged groups. For both MOOCs, significant differences were found between cluster membership and total quiz score and significant associations were found between cluster group and course completion. In both MOOCs, the lower engaged clusters (Low and Moderate Engagers) showed a statistically significantly higher than expected proportion of students not completing the course.

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The aviation industry is currently facing a need to adapt to changes in growth and demand as well as to regulatory issues and constraints on budgets and time (Boeing, 2019; Federal Aviation Administration, 2017). As evidenced by an industry-wide shift to include more computer-based or distance training (Kearns, 2009; Raisinghani et al., 2005) and the relevance of Aviation Accreditation Board International (AABI) programs (Smith et al., 2016), online education delivered by these institutions will be a focus for years to come. Meeting the needs of aviation professionals may be critical in areas beyond traditional, online, for-credit courses, as institutions aim for positive growth and reach out to learners throughout the industry (Iacuzio, 2015). While many universities provide Massive Open Online Courses (MOOCs) with the altruistic aim of extending access to education, a common, secondary institutional goal is that of expanding the university brand for increased recruitment and enrollment in tuition-earning programs (Hollands & Tirthali, 2014).

While a conventional online course experience often consists of admission, limited enrollment, required course materials, and tuition for credit or certificate, MOOCs are different. Often students need only to have access to a computer with an Internet connection and can register for a course in a single click (Wang & Baker, 2015). Unlike a tradition online course, which might have twenty to thirty paying, credit and degree-seeking students, MOOCs are massive in size, hosting sometimes several thousand non-paying, non-credit seeking students at once (Pappano, 2012). For MOOC students, online discussion boards, videos, and assignments are offered freely and with loose timelines. MOOC students can come and go, making use of discussion boards, videos, reading materials, and assessments at-will. While MOOCs may be considered less critical for study compared to traditional for-credit courses, the scale and flexibility of MOOCs offer several key opportunities for instructional designers who recognize how limited throughput of students in traditional courses can cause a lag in research and feedback (Neal & Hampton, 2016). MOOCs allow for instructional experimentation and fine-tuning of learning materials, as well as opportunities for development of adaptive learning, flipped classrooms, and peer-to-peer learning (Haber, 2014; Hollands & Tirthali, 2014; Krause, 2019).

While MOOCs typically have low completion rates (below 10%), the behaviors of many non-completing students suggest students may have other goals (Khalil & Ebner, 2014). This is evident in Tamburri's (2012) description of one machine-learning course where 104,000 students were enrolled. In that MOOC, "46,000 submitted at least one assignment, 20,000 completed a substantial portion of the course" (Khalil & Ebner, 2014, p. 1237). Considering such high numbers and the prevalence of learners who may have goals other than a completion certificate, more research is needed in contexts where success is not binary (e.g., certificate earned versus not earned). Researchers have been urged to make efforts to more appropriately "deconstruct disengagement" (Kizilcec et al., 2013, p. 170) and better consider the needs of these learners who utilize MOOCs but do not complete them.

MOOCs in the Aviation Domain

Currently, little is known about aviation-related MOOCs and respective learners, despite the apparent increasing involvement in online education within the aviation industry (Niemczyk, 2017; Lappas & Kourousis, 2016). Velázquez (2017) conducted a study in the context of a flipped classroom with an aviation MOOC used to augment a course for half of a sample (N = 52). While that study revealed positive outcomes when a MOOC was used to augment a traditional aviation course, the present study aimed to contribute more empirical data on learners in aviation MOOCs in their traditional voluntary, full-scale format. Providing this initial data analysis will fill a knowledge gap, providing the aviation education community a baseline report on engagement patterns and demographics. Such information will allow providers to take advantage of the currently underutilized MOOC format for course design research and improvement of other more formal areas of training and education.

To extend the current understanding of engagement of learners in this aviation-focused, open, online environment, two research questions (RQ) were examined:

- RQ 1. Based on engagement in course discussions, videos, and assessments, what distinct subgroups of students exist within aviation-related MOOCs?
- RQ 2. Based on demographics, days of participation in the course, and achievement, what are the differences among engagement subgroups?

This study took a quantitative, person-centered approach, through cluster analysis, to better understand behaviors of emergent subpopulations (Howard & Hoffman, 2018). This approach aimed to categorize MOOC participants into common subpopulations based on substantive variables and then examined the extent to which these subpopulations were related to other demographic and course variables. The next sections will provide a brief background including other approaches in MOOC research and a theoretical framework for selection of variables.

Background

Research Approaches in MOOC Domain

Within the MOOC domain, searching for distinct subpopulations or profiles of MOOC students via self-reported motivation factors, demographics, and course activity is a common approach (Ezen-Can et al., 2015; Gašević et al., 2014; Kizilcec et al., 2013; Tawfik, 2017). Research highlights student interest in career and educational benefits, with many reporting their primary goal in taking a MOOC was to improve their current job or find a new one (Zhenghao et al., 2015). Beyond motivation, how students vary in engagement patterns is a focus as well. Kizilcec et al. (2013) profiled MOOC participants via cluster analysis and discovered four distinct engagement patterns: Completing, Auditing, Disengaging, and Sampling. It is common for researchers to examine discussion board posts, videos watched, and assessments completed, in search of engagement patterns. Studies utilizing these variables have provided insight into patterns and specific content interests of students who drop-out.

In other MOOC-focused cluster research, the search for distinct subpopulations moves beyond the limiting binary metric of completion and attempts to classify students more fully, in terms of how they interact or engage with the content. For example, Anderson et al. (2014) found five subpopulations: Viewers, Solvers, All-Rounders, Collectors, and Bystanders. Viewers were known for watching lectures and handing in almost no assignments. Solvers were known for handing in assignments but watching almost no lectures. All-Rounders were known for balancing both lecture and assignment categories. Collectors were known for their effort to download lecture videos but not hand in many assignments. The final group, Bystanders, represented those who registered but did not participate. Reinforcing the call to consider students who are not traditionally engaged, the authors argued that while most students earned a grade of zero, the finding that Viewers spent a non-trivial amount of time watching lectures demonstrated many students were invested in the course even if they did not complete it. Anderson et al. (2014) argued that focusing on only drop-outs and finishers presumes a superficial "single notion of completion" (p. 688). Where online learners are categorized as "lurkers" or invisible participants, an effort to better understand those who are difficult to study is important for allowing developers to better meet the needs of these "legitimate peripheral participants" (Honeychurch et al., 2017, p. 197).

With cluster analytic methodologies prevalent in student engagement research, student differences have been reported using k-means clustering, hierarchical clustering, and model-based clustering (Kovanović et al., 2019). Analysis procedures, as well as course context, are known to impact study findings, thus, a wide variation in the number of profiles and characteristics in these studies, make it difficult to generalize results. Even in studies where methodology is controlled, researchers have struggled to find consistent numbers of profiles among courses. In a comparison of courses, Ferguson and Clow (2015) identified a range of different profiles (in type and number) even when course context was similar, noting only very broad clusters of Sampling and Completing were robust throughout all courses they studied. The important implication here is that researchers cannot assume a clustering approach in one learning context will be validated in another context. Given Ferguson and Clow's (2015) noted difficulty with k-means in determining how many clusters to extract, and given the lack of theoretical rationale for predicting the number of clusters, a hierarchical clustering approach was selected for this study.

Theoretical Framework and Engagement Variables

Within distance education literature, one particularly relevant theory employed has been Moore's (1973) theory of transactional distance, which posits: psychological or communicative distance can impede learning and success. It is argued that decreasing transactional distance helps to overcome physical distance and positively influences learning. To manage transactional distance, Moore (1997) asserts one must consider factors of dialogue (e.g., frequency and quality), structure (e.g., course rigidity or flexibility), and learner autonomy (e.g., the extent to which a learner feels independence in the course). Moore (1997) defines interaction in the three main categories: learner-instructor, learner-learner, and learner-content. A fourth mediating category, learner-interface was proposed later by Hillman et al. (1995).

With respect to distinguishing the types of interaction subsumed in the dialogue construct, Moore (1989) described interaction between learner and instructor as experiences shared by the instructor, such as providing resolutions to misunderstandings, elaborations, simplifications, analogies, and supplemental readings. Learner to learner interaction is described as synchronous or asynchronous and occurring with or without an instructor readily present. Finally, interaction between learner and content is described as learner-content interactions, where ideas (text, audio, or video) are internalized and wrestled with by the learner, thus shaping learner understanding or perspectives (Moore, 1989). Under Moore's typology, low distance and high interaction are reported to yield positive achievement effects in distance education (Bernard et al., 2009; Bolliger & Halupa, 2018; Picciano, 2002). Interactions between learner and interface or learner and instructor have been associated with greater perceived learning and satisfaction (Kara, 2021), retention (Hone & El Said, 2016), and determination of at-risk students (Shelton et al., 2017).

Moore's theory served as a framework for this study's variables of engagement that relate primarily to the dialogue construct. Assumptions as to the flexible structure and high autonomy of the course were considered in terms of mandatory and optional content. Using the dialogue construct, this study operationalized Moore's three types of interaction to frequency count data available within the learning management system (LMS). This method is consistent with other research that has employed data mining techniques for early warning systems and immediate developer feedback (Jokhan et al., 2018; MacFadyen & Dawson, 2010). While qualitative approaches for a more comprehensive, theoretical explication (e.g., quality of interaction) are common, quantitative approaches aimed at more expedient feedback, or unsupervised data exploration, are accepted.

Method

This study used archival course data from two iterations of one aviation-focused MOOC, with data taken only from the two weeks when the courses were "live." The aviation-focused MOOC was hosted by an Aviation Accreditation Board International (AABI)-accredited university in the southeast United States on the Canvas Network LMS by Instructure. The MOOC was advertised via Twitter, Facebook, and the university website. It had no prerequisites or cost and offered only a record of completion. The aviation-focused MOOC covered topics for small unmanned aerial systems (sUAS) including safe integration of sUAS into the national airspace system (NAS) with private, commercial, and public applications. It also covered topics on UASs cybersecurity, privacy, and data protection. The course contained two modules, recommended for completion at the rate of one module per week. Each module contained discussion boards, videos, course readings, and a quiz. In order to have earned a record of completion, a student needed to have reviewed all main content pages with readings and recorded lectures, posted in specified key topic discussions, and have scored at least 80 out of 100 points on module quizzes. MOOCs were analyzed separately due to slight differences in course content.

Research Question 1 Method

To answer the first question, "What distinct subgroups of students exist in an aviation-related MOOC, based on engagement in course discussions, videos, and assessments?" a clustering algorithm was employed to assign learners into different clusters. Cluster analysis was selected due to its demonstrated effectiveness in prior engagement research (Anderson et al., 2014; Ferguson & Clow, 2015; Kovanović et al., 2019). Noted weaknesses for cluster analysis are: "(a) Clustering algorithms will sometimes find structure in a dataset, even where none exists, and (b) results are sensitive to the algorithm used. It is not uncommon to obtain completely different results depending on the method chosen" (Antonenko et al., 2012, p. 395). Weaknesses can be mitigated when researchers use the most appropriate algorithm respective to variable type, when cluster validity analyses are conducted by examining group means across clusters, when clusters are compared or aligned with other similar examples in the literature, and when split-samples yield cluster solutions similar in size and characteristics to the final solution obtained with the full sample (Antonenko et al., 2012; Hair et al., 2015).

Archived datasets from the platform Instructure were obtained for two iterations of a Small Unmanned Aerial Systems MOOC offered in 2018 (MOOC 1, *N* = 1,032; MOOC 2, *N* = 4,037). MOOCs were given artificial numbers, ordered by size, not date. MOOCs were analyzed separately due to slight differences in content, which prevented combination of the two datasets.

Demographic data were analyzed from pre-and post-course surveys that yielded considerable missing data. Not surprisingly, the most engaged groups had the highest participation in surveys. Overall, the MOOCs were slightly different in median age category, with MOOC 1 at 35 to 44 years of age and MOOC 2 at 45-54 years of age. Both MOOCs had almost 60% of survey respondents report education level of a bachelor's degree or higher. Both MOOCs also had the same most-reported geographic location, with MOOC 1 at 57% and MOOC 2 at 81% of responders located in North America. The MOOCs were similar in gender composition, with 84% male and 16% female in MOOC 1, and 87% male and 13% female in MOOC 2. As for employment in the aviation industry, most were not; 52% (MOOC 1) and 63% (MOOC 2) reported not being employed in the aviation industry. In MOOC 1, 43% of survey responders reported no prior experience in a MOOC, while in MOOC 2, 79% of responders reported no prior MOOC experience. On the question of affiliation with the host institution, most responders reported no affiliation (83% in MOOC 1 and 88% in MOOC 2).

The first research question, aimed at determining subgroups of engagement, was addressed through two-step cluster analysis in Statistical Package for Social Sciences (SPSS). Final clustering variables, after pre-cluster checks on correlation and variance, were: Mandatory Discussion Posts, Optional Discussion Views, Video Page Views, Quiz 1 Attempts, and Quiz 2 Attempts as shown in Table 1.

Table 1

Variable Details for Determining Engagement Subgroups (RQ1)

Variable Name	Details: sUAS MOOC Course Content
Mandatory Discussion Posts	Planning Considerations National Airspace System (NAS)
Optional Discussion Views	Introduction Ask the Expert - Miscellaneous Ask the Expert - Operations Ask the Expert - Systems Ask the Expert - Regulations
Video Page Views	Webinar 1 AUVSI Trusted Operator Program (TOP) Webinar 2 Canberra Unmanned Aerial Vehicles Webinar 3 Systems Engineering
Quiz Attempts	Module 1 Quiz Module 2 Quiz

Note. AUVSI = Association for Unmanned Vehicle Systems International (AUVSI, 2019).

Research Question 1 Results

Some iterations of cluster analysis yielded two-cluster solutions that were not interpretable, given the aims of this research to learn more about the students who engaged but did not complete the course. Thus, these auto-cluster solutions were not retained, and 3, 4, and 5-cluster solutions were compared to "explore alternative cluster solutions… in an effort to best represent the underlying data patterns" (Hair et al., 2015, p. 432). The final solution was determined by selecting the solution that came as close as possible to optimal quality criterion of silhouette (cohesion and separation) > 0.6 and ratio of sizes (largest to smallest cluster) < 3, while still being interpretable in that it provided more than just a two-cluster solution of completers and non-completers.

MOOC 1 Results

In MOOC 1, out of 1,032 students who enrolled, 532 were deemed active (engaged in course content for more than one day), and 457 cases were retained for analysis after outlier removal. For MOOC 1, the 4- and 5-cluster solutions were discarded due to sub-optimal quality criterion. The 4-cluster solution had a "fair" 0.4 silhouette measure and a large ratio of size (25.7). The 5-cluster had a "good" silhouette of 0.6 but was also discarded due to its high ratio of size (102.33). MOOC 1's optimal cluster solution was thus obtained using Log-likelihood and a specified, fixed 3-cluster setting. The 3-cluster solution had an acceptable quality criterion with the "good" silhouette measure of 0.6 and a ratio of sizes of 3.0.

MOOC 2 Results

In MOOC 2, of the initial 4,037 who enrolled, 1,796 were deemed active, and 1,691 cases remained after outlier removal. For MOOC 2, the 4- and 5-cluster solutions were also discarded due to sub-optimal quality criterion. The 4-cluster solution had a "good" silhouette of 0.7 but had a high ratio of size (23.33). The 5-cluster solution also had a "good" silhouette of 0.8 but had a high ratio of size (24.86). The optimal solution was obtained using Log-likelihood and a specified fixed 3-cluster setting. The 3-cluster solution had acceptable quality criterion with a "fair" silhouette measure of 0.5 and a ratio of sizes of 2.90.

MOOC 1 Cluster Descriptions

A graphical presentation of each cluster's average *Z*-scores across each clustering variable are shown in Figure 1. The most important predictor for determining cluster assignment was Mandatory Discussions, followed by Quiz 1 Attempts, Quiz 2 Attempts, Webinar Views, and Optional Discussion Views.

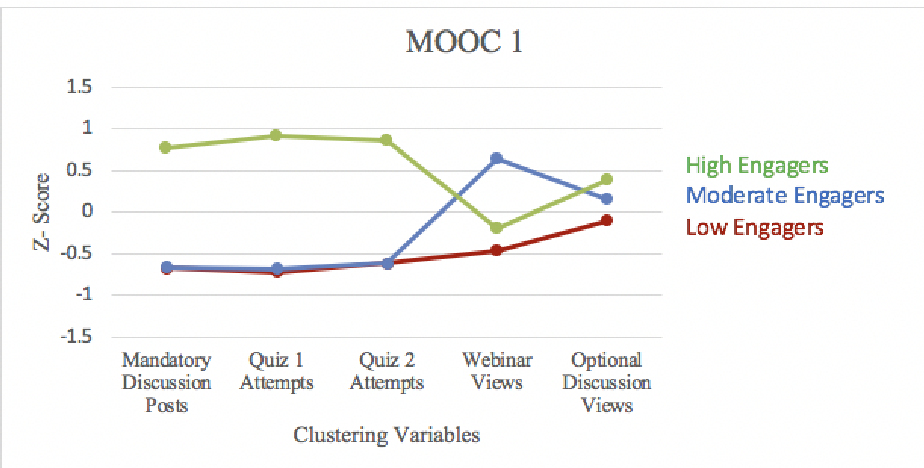
Low Engagers. This cluster represented 48.6% of the cases analyzed. None of the students in this cluster completed the course. Low Engagers were below the mean on all engagement variables and had the lowest mean days of activity (three days) of all the clusters.

Moderate Engagers. This cluster represented 16.2% of the cases analyzed. None of the students in this cluster completed the course. Moderate Engagers were below the overall sample mean of Mandatory Discussion Posts, Quiz 1 Attempts, and Quiz 2 Attempts, which is consistent with this group's zero course completions. This group showed moderate engagement in optional content; Optional Discussion Views were slightly above the mean, and Webinar Views were well above the mean. Students in this cluster were active on average only four days, which was slightly above the mean of Low Engagers (three days) but well below the mean of the High Engagers (nine days).

High Engagers. This cluster represented 35.2% of the cases analyzed and had a completion rate of 62%. High Engagers were highest on all mandatory engagement variables, but were not the highest on one optional variable, Webinar Views (Moderate Engagers had more Webinar Views). This group had the highest mean days of activity (9 days) and the only course completers (N = 101).

Figure 1

Z-scores of clustering variables for MOOC 1 clusters



MOOC 2 Cluster Descriptions

A graphical presentation of each cluster's average Z-scores across each clustering variable are shown in Figure 2. The most important predictor for determining cluster assignment was Quiz 2 Attempts, followed by Mandatory Discussion Posts, Quiz 1 Attempts, Webinar Views, and finally, Optional Discussion Views. Similar to MOOC 1, mandatory content items were the best predictors for group membership.

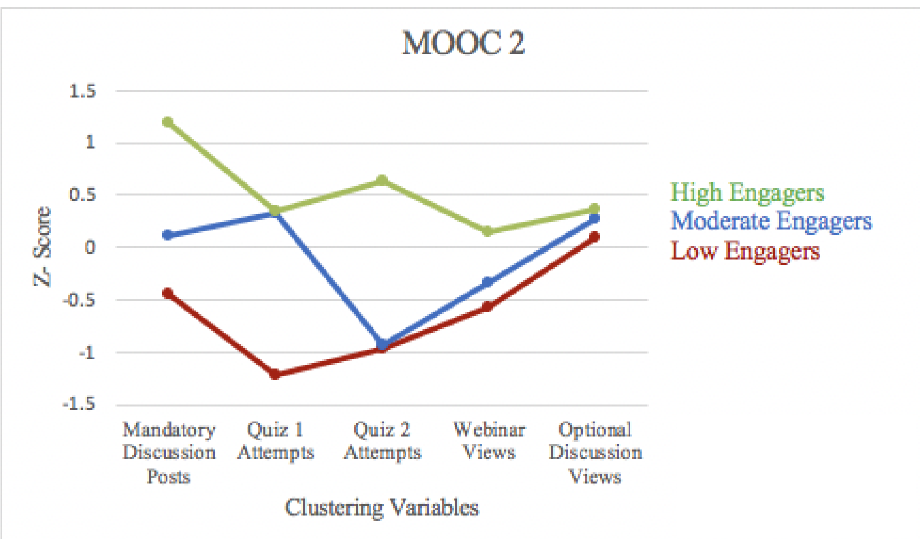
Low Engagers. This cluster represented 25.1% of the cases analyzed. None of the students in this cluster completed the course. Low Engagers had the lowest means on all engagement variables as well as days of activity (five days).

Moderate Engagers. This cluster represented 19.2% of the cases analyzed and had 324 (99.7%) students who did not complete the course and one (0.3%) student complete the course, which was almost identical to MOOC 1's middle group. Moderate Engagers were below the mean on Mandatory Discussion Posts, above the mean on Quiz 1 Attempts, and well below the mean on Quiz 2 Attempts. Similar to MOOC 1, this group showed interest in optional content, but it was isolated to Webinar Views where they were close to the mean. Differing slightly from MOOC 1, this group was below the mean on Optional Discussion Views. Moderate Engagers had a mean of seven days of activity.

High Engagers. This cluster represented 55.6% of the cases analyzed and had 764 (81.2%) students finish the course. High Engagers were above the mean on Quiz 1 Attempts, well above the mean on Quiz 2 Attempts and Mandatory Discussion Posts, and above the mean on Webinar Views and Optional Discussion Views. MOOC 2's High Engagers, were similar to MOOC 1's High Engagers on everything, except they were higher above the mean on optional content, not just mandatory content. Students in this cluster had a mean of almost 10 days of activity.

Figure 2

Z-scores of clustering variables for MOOC 2 clusters



MOOC 1 Cluster Differences on Engagement Variables

Cluster solution quality was confirmed by comparing the clusters across the engagement variables used to form the cluster solution and noting significant differences. A series of five individual, univariate, one-way ANOVAs were conducted on the subgroups as independent variables, one for each of the clustering engagement variables as dependent variables (Table 2). The assumption for homogeneity of variance could not be met; therefore, Welch's test was used.

Table 2

Characteristics of Three Cluster Subgroups for MOOC 1

	Low Engagers $N = 222$		Moderate Engagers $N = 74$		High Engagers $N = 161$			
Dependent Variables	Mean	SD	Mean	SD	Mean	SD	F_w	p
Mand. Disc. Posts	0.04	0.19	0.05	0.23	2.27	0.88	$F_w(2, 454) = 502.28$	< .001
Opt. Disc. Views	1.94	1.81	3.57	3.78	5.16	3.09	$F_w(2, 454) = 72.11$	< .001
Webinar Views *	0.00	0.00	1.55	0.91	0.37	0.72	$F_w(1, 233) = 97.97$	< .001
Quiz 1 Attempts	0.02	0.13	0.07	0.30	1.84	0.74	$F_w(2, 454) = 472.90$	< .001
Quiz 2 Attempts	0.00	0.00	0.00	0.00	1.20	0.85	N/A	N/A

Note. * Webinar ANOVA between Moderate and High Engagers only. Mand. = Mandatory, Disc.= Discussion, Opt. = Optional.

Significant and not-significant differences, shown in Table 3, were observed between clusters for all engagement variables, except in Quiz 2 attempts where no variance was observed for Low and Moderate Engagers who made no attempts. Significant differences between cluster pairs were as follows: High Engagers had more Mandatory Discussion Posts, Quiz 1 Attempts, and Optional Discussion Views than Low Engagers. High Engagers had more Mandatory Discussion Posts, Quiz 1 Attempts, fewer Webinar Views, and more Optional Discussion Views than Moderate Engagers. Finally, Moderate Engagers had more Optional Discussion Views than Low Engagers.

Table 3

MOOC 1 Group Mean Differences (ANOVA)

	Mandatory Discussions	Quiz 1 Attempts	Quiz 2 Attempts	Webinar Views	Optional Discussions
High - Low Engagers	$p < .001$	$p < .001$	H = 1.2, L = 0	H = .37, L = 0	$p < .001$
High – Moderate Engagers	$p < .001$	$p < .001$	H = 1.2, M = 0	$p < .001$	$p < .005$
Moderate - Low	$p = .812$	$p = 0.363$	M = 0, L = 0	M = 1.2, L = 0	$p = .002$

Note. When a group had no variance, group means were reported instead of ANOVA p values. H = High Engager group mean, M = Moderate Engager group mean, L = Low Engager group mean.

MOOC 2 Cluster Differences on Engagement Variables

As in MOOC 1, a series of five individual, univariate, one-way ANOVAs were conducted on the three subgroups as independent variables, one for each of the clustering engagement variables as dependent variables. The assumption for homogeneity of variance was not met; therefore, Welch’s test was used. Results are reported in Table 4.

Table 4

Characteristics of Three Cluster Subgroups for MOOC 2

	Low Engagers $N = 425$		Moderate Engagers $N = 325$		High Engagers $N = 941$			
Dependent Variables	Mean	SD	Mean	SD	Mean	SD	F_w	p
Mand. Disc. Posts	0.07	0.25	0.79	0.65	2.18	0.63	$F_w(2, 1688) = 3947.04$	< .001
Opt. Disc. Views	2.97	2.03	4.01	3.07	4.64	3.88	$F_w(2, 1688) = 56.81$	< .001
Webinar Views	0.01	0.10	0.45	0.74	1.36	0.99	$F_w(2, 1688) = 914.26$	< .001
Quiz 1 Attempts	0.10	0.30	1.82	0.89	1.83	0.84	$F_w(2, 1688) = 1931.77$	< .001
Quiz 2 Attempts *	0.00	0.00	0.02	0.14	1.23	0.48	$F_w(1, 1264) = 4873.19$	< .001

Note. * Quiz 2 ANOVA between Moderate and High Engagers only. Mand. = Mandatory, Disc.= Discussion, Opt. = Optional.

Significant and not-significant differences, shown in Table 5, were observed between clusters for all engagement variables, except in Quiz 2 attempts where no variance was observed for Low Engagers who made no attempts. Significant differences between cluster pairs were as follows: High Engagers had more Mandatory Discussion Posts, Quiz 1 Attempts, Webinar Views, and Optional Discussion Views than Low Engagers. High Engagers had more Mandatory Discussion Posts, Quiz 2 Attempts, Webinar Views, and Optional Discussion Views than Moderate Engagers. Moderate Engagers had more Mandatory Discussion Posts, Quiz 1 Attempts, Webinar Views, and Optional Discussion Views than Low Engagers.

Table 5

MOOC 2 Group Mean Differences (ANOVA)

	Mandatory Discussions	Quiz 1 Attempts	Quiz 2 Attempts	Webinar Views	Optional Discussions
High - Low Engagers	$p < .001$	$p < .001$	H = 1.23, L = 0	$p < .001$	$p < .001$
High – Moderate Engagers	$p < .001$	$p = .963$	$p < .001$	$p < .001$	$p < .001$
Moderate - Low	$p < .002$	$p < .001$	M = 0.02, L = 0	$p < .001$	$p < .001$

Notes. When a group had no variance, group means were reported instead of ANOVA p values. H = High Engager group mean, M = Moderate Engager group mean, L = Low Engager group mean.

Research Question 2 Method

The second research question, "What are the differences among engagement subgroups based on demographics, days of participation, and course achievement?" was answered using Chi-Square analysis for categorical data (demographics, record of completion) and ANOVA for continuous data (grades, days of activity).

Demographics

Data were obtained via archived pre-course survey responses for Age, Education, Location, and Intent. Employment in the aviation industry data was obtained from an archived post-course survey, but since response rates were very low (13% and 37%), this attribute was omitted from Chi-Square analyses. When necessary, cells were consolidated to meet the expected frequencies assumption, and the analyses were run separately for each MOOC. Within each MOOC, the null hypothesis (H_0) was that there were no significant associations among the cluster groups across the question categories. Significant and non-significant associations were found as summarized in Table 6.

Table 6

Chi-Square Results for Pre-Course Survey Responses

MOOC 1		MOOC 2	
Age not significant	$\chi^2(8, N = 296) = 3.1$ $p = .928$	Age not significant	$\chi^2(12, N = 1015) = 20.43$ $p = .059$
Education not significant	$\chi^2(4, N = 297) = 0.65$ $p = .957$	**Education** **significant**	$\boldsymbol{\chi^2(14, N = 1083) = 31.04}$ $\boldsymbol{p = .005}$
Location not significant	$\chi^2(6, N = 298) = 5.9$ $p = .432$	Location not significant	$\chi^2(6, N = 1081) = 12.10$ $p = .060$
Intent not significant	$\chi^2(6, N = 298) = 11.1$ $p = .087$	Intent not significant	$\chi^2(6, N = 838) = 10.21$ $p = .116$

A significant association was found between cluster group and education ($N = 1083$; $\chi^2(14) = 31.04$, $p = 0.005$, Cramer's V = 0.12). To determine the strength of this association, because the table was greater than 2 x 2, Cramer's V (an extension of Phi φ) was evaluated (Hair et al., 2015; Liebetrau, 1983). Effect sizes were modified based on degrees of freedom (*df*) by dividing Phi φ by the square root of *df*. This resulted in effect size evaluation guidelines for *df* = 14 of small (0.03), medium (0.08), and large (0.13). Thus, the effect size for the association between cluster group and education was considered medium (0.12).

In a post-hoc analysis, adjusted, standardized residuals were examined in contingency table cells (Agresti, 2002). Low Engagers showed a statistically significantly higher than expected proportion of students with some graduate education, and High Engagers showed a statistically significantly lower than expected proportion of students with some graduate education.

Participation and Achievement

Table 7 and Table 8 show descriptive statistics for MOOC 1 and MOOC 2 on Days of Activity and Total Quiz Score. Days of Activity (1-14) was calculated by taking the difference in days between course start and last date of activity prior to or on the course-end date. Total quiz score (0 to 200) was calculated by taking the sum of scores from two quizzes.

Table 7

Descriptive Statistics for MOOC 1 Clusters on Days of Activity, Total Quiz Score

		N	Mean	Median	*SD*	Min	Max
Days of Activity	Low Engagers	222	3.23	1.00	3.325	1	14
	Moderate Engagers	74	4.16	2.00	3.811	1	14
	High Engagers	161	9.21	11.00	4.294	1	14
Total Quiz Score	Low Engagers	222	1.58	0.00	11.718	0	100
	Moderate Engagers	74	4.59	0.00	19.458	0	100
	High Engagers	161	163.7	190.00	50.888	0	200

Note. *N* = Number of respondents, *SD* = Standard Deviation, Min = Minimum, Max = Maximum.

Table 8

Descriptive Statistics for MOOC 2 Clusters on Days of Activity, Total Quiz Score

		N	Mean	Median	*SD*	Min	Max
Days of Activity	Low Engagers	425	5.66	5.00	3.50	2	14
	Moderate Engagers	325	7.58	8.00	3.80	1	14
	High Engagers	941	9.86	10.00	3.29	1	14
Total Quiz Score	Low Engagers	425	6.35	0.00	22.30	0	100
	Moderate Engagers	325	86.15	100.00	32.14	0	200
	High Engagers	941	190.33	200.00	20.30	0	200

Note. *N* = Number of respondents, *SD* = Standard Deviation, Min = Minimum, Max = Maximum.

MOOC 1 Cluster Differences on Days of Activity

To find cluster differences on the continuous variable of days of activity (1-14), a one-way ANOVA was conducted. Significant differences were found between clusters and days of activity ($F_w(2, 454) = 110.29$, $p < .001$). Post-hoc comparisons using the Games Howell test revealed significant differences between High and Moderate Engagers ($p < .001$), with High Engagers active on average 5.05 days more than Moderate Engagers. There were significant differences between High and Low Engagers ($p < .001$), with High Engagers active on average 5.99 days more than Low Engagers. No significant differences were found between Moderate Engagers and Low Engagers ($p = .147$), with Moderate Engagers active on average 0.94 days more than Low Engagers.

MOOC 2 Cluster Differences on Days of Activity

Just as for MOOC 1, a one-way ANOVA was conducted to determine cluster differences on the variable of days of activity. Since the assumption for homogeneity of variance was not met, Welch's statistic was used. Significant differences were found between clusters and days of activity ($F_w(2,1688) = 229.34$, $p < .001$). Post-hoc comparisons using the Games Howell test revealed significant differences between High and Moderate Engagers ($p < .001$) with High Engagers active on average 2.28 more days than Moderate Engagers. Significant differences were found between High and Low Engagers ($p < .001$) with High Engagers active on average 4.19 more days than Low Engagers. Significant differences were found between Moderate and Low Engagers ($p < .001$) with Moderate Engagers active on average 1.91 days more than Low Engagers.

MOOC Cluster Differences on Total Quiz Score

To find cluster differences on total quiz score, a one-way ANOVA was conducted for each MOOC. Since the assumption of equal variances was not met, Welch's statistic was used. Significant differences were found between Cluster membership and Total Quiz score in MOOC 1 ($F_w(2, 454) = 783.92$, $p < .001$) and in MOOC 2 ($F_w(2,1688) = 10931.43$, $p < .001$).

Post-hoc comparisons using the Games Howell test revealed significant differences ($p < .001$) were between High Engagers and Moderate Engagers, with High Engagers achieving total quiz scores on average 159.07 points higher than Moderate Engagers in MOOC 1 and 183.98 points higher in MOOC 2. Significant differences ($p < .001$) were found between High and Low Engagers, with High Engagers achieving total quiz scores on average 162.09 points higher than Low Engagers in MOOC 1, and 104.18 points higher in MOOC 2. For MOOC 1, no significant differences ($p = .421$) were found between Moderate and Low Engagers, with Moderate Engagers achieving total quiz scores on average 3.01 points higher than Low Engagers. For MOOC 2, significant differences were found between Moderate and Low Engagers ($p < .001$), with Moderate Engagers achieving total quiz scores on average 79.80 points higher than Low Engagers.

MOOC Cluster Differences on Course Completion

Course completion rates for the clusters in MOOC 1 were 0% for Low Engagers, 0% for Moderate Engagers, and 62.7% for High Engagers. In MOOC 2 completion rates were 0% for Low Engagers, 0.3% for Moderate Engagers, and 81.2% for High Engagers. To find cluster differences across Course Completion, a Chi-Square analysis was conducted in each MOOC. The null hypothesis (H_0) was that there were no significant associations among the cluster groups and course completion. Associations were found between cluster group and course completion in MOOC 1 ($N = 457$; $\chi^2(2) = 238.37$; $p < .001$) and in MOOC 2, ($N = 1691$; $\chi^2(2) = 1106.89$; $p < .001$).

To determine the strength of this association, Cramer's *V* was evaluated (Hair et al., 2015; Liebetrau, 1983). Effect sizes were modified by dividing Phi φ by the square root of *df*. The effect size was large for both MOOCs (0.72 and 0.81). In a post-hoc analysis, adjusted, standardized residuals were examined in contingency table cells (Agresti, 2002). Low and Moderate Engager clusters show a statistically significantly higher than expected proportion of students did not complete the course. The High Engager cluster showed a statistically significantly higher than expected proportion of students did complete the course.

Discussion

Discussion of Engagement Subgroups (RQ 1)

The cluster solutions for both MOOCs were deemed of sufficient quality based upon silhouette measures and analysis of cluster structures. To examine structure, means were compared to show significant differences between MOOC clusters among clustering variables. Reliability was deemed sufficient in that split samples in each MOOC yielded cluster solutions accurately representing the final solution in each MOOC. External validity was deemed sufficient with noted limitations in that no other aviation-related MOOC research was available for comparison. Both MOOCs had results consistent with other findings in the literature.

For example, in MOOC 1, the progressively higher number of mandatory discussion posts and quiz attempts from the lowest engagement group to the highest engagement group matches what is reported in the literature regarding graded or mandatory content as a differentiator among engagement clusters (Kovanović et al., 2019). For optional content, which consisted of webinar and optional discussion views, the results were notable for both MOOCs, as the moderately engaged cluster was differentiated from the low-engaged cluster by an optional content variable. In MOOC 1, the moderate group was above the mean in viewing both optional discussions and video (Webinar) and even had higher Webinar views than the highest engaged cluster. In MOOC 2, the moderate group was similarly differentiated from the lowest engaged group in optional content but was only interested in the optional discussion content.

Consistent with what is already known about video content consumption and engagement, the highest engagement clusters in both MOOCs had high levels of video views. Anderson et al.'s (2014) engagement study noted higher video content activity was a characteristic of those who had high achievement, while Sinha et al. (2014) found video lecture involvement characteristic of those with high motivation and persistence in the course. This study differed from such findings only in MOOC 1 where the highest engaged cluster, which had the highest course completions, did not have the highest mean for viewing video content. This may be due to the unique nature of the *optional* webinars in this study that differed from *mandatory* videos in other studies. In the larger sample of MOOC 2, however, the results for video viewing were similar to findings in the literature. For both MOOCs, webinars were not lecture-based; they were designed with an expert-interview and question-and-answer format. This format is noted as a way to reduce distance common to the formal lecture hall style common in recorded lectures (Haber, 2014).

Discussion of Subgroup Attributes (RQ 2)

RQ 2 aimed to determine cluster differences on seven attributes within each MOOC. No significant associations were found between cluster and attribute for age, location, or intent categories. The top two age categories for MOOC 1 were 25-34 (29%) and 35-44 (23%), and for MOOC 2 they were a little older at 45-54 (20%) and 55-64 (19%). For geographic location, both MOOCs had North America as the top reported location with 57% in MOOC 1 and 81% in MOOC 2, followed by Asia (13%) and Latin America (7%) respectively. For Intent to Participate, the most-selected categories in every cluster were either active or passive participant and there were no significant associations found between intent categories and cluster. Question choices were as follows:

- An **active participant**. Bring it on. If it's in the course, I plan on doing it.
- A **passive participant**. I plan on completing the course, but on my own schedule and without having to engage with other students or assignments.
- A **drop-in**. I am looking to learn more about a specific topic within the course. Once I find it and learn it, I will consider myself done with the course.
- An **observer**. I just want to check the course out. Count on me to "surf" the content, discussions, and videos, but don't count on me to take any form of assessment.

As noted, significant associations were found between the "Some Graduate" education category and the clustering for MOOC 2. In this MOOC overall, 29.4% of students reported some graduate education or higher (39% for Low Engagers, 33.1% for Moderate Engagers, and 26.8% for High Engagers). A posthoc analysis revealed Low Engagers had a higher proportion of students reporting some graduate education [than what would be expected if there were no differences among the three clusters]. Conversely, High Engagers had a lower than expected proportion of students report some graduate education.

Although the significant association of cluster membership and education was small, just as with age, the descriptive findings on education can be used for more informed marketing and course-design decisions. For instance, the finding that more-than-expected, highly educated students were present in the low engagement group may indicate those students were at that time also enrolled in graduate study and potentially too busy to engage more. Admittedly, the constraint of not enough time available may apply to other groups as well. For either scenario, designers may consider creating MOOCs that require less daily time commitment. Alternatively, the finding that more than expected highly educated students were present in the low engagement group may mean it takes a different kind of content to engage those users. Christensen et al.'s (2013) Coursera study ($N \approx 52{,}000$) reported that benefits from taking MOOCs are more frequently reported by students with lower socioeconomic status and lower education levels attained. While the present study did not focus on socioeconomic status, the education findings may indicate steps need to be taken in course design to ensure benefits of the course are experienced at the higher education levels as well lower ones.

For participation and achievement attributes, within each MOOC, significant differences ($p < .001$) were found between clusters and the attributes days of activity and quiz scores, with more highly engaged groups active more days, and with higher scores than the lesser engaged groups. Also, significant associations were found between course completion and cluster. Overall MOOC 1 had a 10% completion rate, while MOOC 2 had a 19% completion rate. In both, post-hoc analyses showed statistically significant, higher than expected proportions of Low and Moderate Engagers did not complete the course, while a statistically significant, higher than expected proportion of High Engagers did complete the course.

MOOC 1's completion rate of 10% is consistent with other studies which report relatively small completion rates (average around 7%) (Jordan, 2014). Surprisingly however, MOOC 2's rate was well above the average, with 19% (765 of the initial 4,037) of registrants completing the course. The disparity between the two MOOCs in this study, may be attributed to MOOC 2 occurring first and depleting the pool of likely participants. However, why MOOC 2 had an above average completion rate, independent of its comparison to MOOC 1, warrants further investigation. It could be attributed to course length which is reported by Jordan (2014) as having a significant negative correlation with course completion (shorter courses tend to have higher completion rates). It could also be due in part to the topic, and the need at the time the course was offered. Since it is possible that higher MOOC completion rates may be attributed to course topics that are more practical or vocational (Auyeung, 2015), in cases where practical or professional-focused courses are needed immediately for work, students may persist out of necessity.

The MOOCs in this study did not offer a traditional certificate of completion but offered only a record of completion, in an attempt to avoid any confusion with certifications regulated by the FAA. The absence of this extrinsic reward of a certificate could indicate that many people truly wanted or needed the information offered by the MOOC to help them with their daily job. In developing countries, where workplace training and education are not available, MOOCs may serve as a stopgap. Although not every learner has specific goals for professional learning, many cite goals related to filling gaps in professional knowledge or conversing with other domain professionals (Milligan & Littlejohn, 2014). Since research shows that persistence and certificate attainment is found to be higher for international students than for Americans (Nesterko et al., 2013), investigating hypotheses about professional necessity may be worthwhile.

Study Limitations

This study was limited in scope by topic, location, and time. More analysis including other topic types (e.g., vocational topics related to a person's everyday job versus traditional-academic topics, related to a person's degree program or area of academic study) should be made. Also, the short duration of the MOOC, at only two weeks, and the delimitation of the study to examine activity when the course was live instead of after the course, when students still had access to course content, may have contributed to the finding of only one middle subgroup rather than two as some studies have found. If so, this delimitation may have prevented discovery of a distinct subgroup of students who benefitted from course content long after the end date.

Finally, this study was limited by the nature of variables selected. Measuring engagement with the number of posts written or viewed or by the number of times a student views a video page is common and expedient, especially for learning analytics research using large data sets. Even so, such metrics reveal much less about engagement than more fine-grained data such as length or quality of post, or video viewing patterns including pauses, fast-forwards, and replays.

Study Implications and Future Research

As the first comprehensive descriptive statistics presented on a large sample of the Aviation MOOC population, this study offers a few practical contributions for course developers who are now armed with profile knowledge of their audience. This set of demographic data allows for further analysis of behaviors of groups that are deemed to be underrepresented or underserved in the MOOC, including perhaps the high school sector or an international cohort.

Additionally, course developers may use findings from this study to guide positioning of survey questions in future MOOCs. For instance, instead of risking very low response rates in a post-course survey, one or two survey questions could be embedded in the optional content (discussions and webinars) to explore the nature and degree of interest the student has in the MOOC.

Since demographics in this study revealed most MOOC students were older and not already students in the host institution—it may be helpful to continue to tailor design to non-traditional students who attend out of personal interest or planning for future career paths. It may also be helpful to consider that many students may not consider MOOCS as a replacement to a traditional credit bearing course. This study's findings of optional content as a differentiator among the lower and moderately engaged students, aligns with the trend reported in the broader MOOC community, and emphasizing or expanding this type of content may be a valuable endeavor.

Unlike traditional online courses, MOOCs offer students great flexibility in how they can interact in a course with other learners or course content, all of which result in varied engagement patterns among students. The way in which clustering variables in this study differentiated the middle clusters serves as a practical contribution and an immediate starting point for research into why this specific content was relevant and engaging enough to attract students who did not care about completing the course.

Conclusion

The goal of this research was to expand upon what little was known of students in aviation-related MOOCs and to make use of learning analytics to uncover course-specific behavior insights about the different subpopulations. Both MOOCs revealed three distinct subgroups of students that were significantly different in four of the seven attributes analyzed (Education, Days of Activity, Total Quiz Score, and Course Completion). The way in which clustering variables in this study differentiated the middle clusters, specifically in webinars and optional discussion engagement, offered practical implications for course developers to utilize.

MOOCs are of interest to students for professional reasons and for life-long learning. The optional webinars in these MOOCs were not just a "sage on stage" delivering a lecture—but were interactive and discussion-focused, and ultimately not testable material. The value in this virtual community of learning and networking is highlighted in this study's results. MOOCs and other non-traditional modes of learning, such as flipped classrooms or courses using mixed modes of delivery are of increasing interest to those concerned with fostering positive and active learning experiences (Velázquez, 2017, 2020). The data-driven recommendations emerging from this study serve in a small, but important, role, to develop a clearer picture of engagement and learning in the aviation domain and help educators meet the needs of the growing aviation community.

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