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Student Engagement in Aviation Moocs: Identifying Subgroups and Their Differences

Jennifer Maddin Edwards

STUDENT ENGAGEMENT IN AVIATION MOOCS: IDENTIFYING SUBGROUPS AND THEIR DIFFERENCES

By

Jennifer Maddin Edwards

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This Dissertation was prepared under the direction of the candidate's Dissertation Committee Chair, Dr. Mark A. Friend, and has been approved by the members of the dissertation committee. It was submitted to the College of Aviation and was accepted in partial fulfillment of the requirements for the
Degree of
Doctor of Philosophy in Aviation

Mark A. Friend

Mark A. Friend, Ed.D.
Committee Chair

Haydee M. Cuevas

Haydee M. Cuevas, Ph.D.
Committee Member

Steven Hampton

Steven Hampton, Ed.D.
Associate Dean for Research and the School of Graduate Studies, College of Aviation

Felix Brito, Ph.D.
Committee Member

Alan J. Stolzer

Alan J. Stolzer, Ph.D.
Dean, College of Aviation

Harry D. Tunnell IV, Ph.D.
Committee Member (External)

Lon D. Moeller, J.D.
Senior Vice President for Academic Affairs and Provost

June 9, 2020
Date

ABSTRACT

Researcher: Jennifer M. Edwards

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The purpose of this study was to expand the current understanding of learner engagement in aviation-related Massive Open Online Courses (MOOCs) through cluster analysis. MOOCs, regarded for their low- or no-cost educational content, often attract thousands of students who are free to engage with the provided content to the extent of their choosing. As online training for pilots, flight attendants, mechanics, and small unmanned aerial system operators continues to expand, understanding how learners engage in optional aviation-focused, online course material may help inform course design and instruction in the aviation industry. In this study, Moore's theory of transactional distance, which posits psychological or communicative distance can impede learning and success, was used as a descriptive framework for analysis. Archived learning analytics datasets from two 2018 iterations of the same small unmanned aerial systems MOOC were cluster-analyzed (N = 1,032 and N = 4,037). The enrolled students included individuals worldwide; some were affiliated with the host institution, but most were not. The data sets were cluster analyzed separately to categorize participants into common subpopulations based on discussion post pages viewed and posts written, video pages viewed, and quiz grades. Subgroup differences were examined in days of activity and record of completion. Pre- and post-course survey data provided additional variables for analysis of subgroup differences in demographics (age, geographic location, education level, employment in the aviation industry) and learning goals. Analysis of engagement variables revealed three significantly different subgroups for each MOOC. Engagement patterns were similar between MOOCs for the most and least engaged groups, but differences were noted in the middle groups; MOOC 1's middle group had a broader interest in optional content (both in discussions and videos); whereas MOOC 2's middle group had a narrower interest in optional discussions. Mandatory items (Mandatory Discussion or Quizzes) were the best predictors in classifying subgroups for both MOOCs. Significant associations were found between subgroups and education levels, days of activity, and total quiz scores. This study addressed two known problems: a lack of information on student engagement in aviation-related MOOCs, and more broadly, a growing imperative to examine learners who utilize MOOCs but do not complete them. This study served as an important first step for course developers and instructors who aim to meet the diverse needs of the aviation-education community.

DEDICATION

To the *Author and Finisher* of my faith: Jesus Christ.
Hebrews 12:2

1 Be thou my vision, O Lord of my heart;
naught be all else to me, save that thou art--
thou my best thought by day or by night,
waking or sleeping, thy presence my light.

4 Riches I heed not, nor man's empty praise,
thou mine inheritance, now and always:
thou and thou only, first in my heart,
High King of heaven, my treasure thou art.

Dallán Forgaill, 6th Century
Hull, 1912

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CHAPTER I

INTRODUCTION

With the proliferation of technology and Internet connectivity over the last two decades, the landscape of online education has changed and continues to change rapidly (Broadbent & Poon, 2015). Considered the fastest-growing sector of higher education today, online education is comprised of degree and non-degree programs, hybrid university courses, and corporate, computer-based training (Protopsaltis & Baum, 2019). The concept of online education, with its host of related terms (e.g., e-learning, distributed learning, distance learning), is defined as education delivered through computer and Internet technology, "where the teacher and students are physically separated" (Kentnor, 2015, p. 22).

Online education is widely applied in formats that are synchronous or asynchronous and can be instructor-led, peer-driven, or self-contained (Keengwe et al., 2014). A conventional online course experience consists of admission, a limited enrollment credit-or certificate course, online compulsory discussion boards, videos, and graded assignments/exams. Students typically work on a set schedule and receive instructor feedback on assignments and online discussion boards (Keengwe et al., 2014). While this conventional design remains prominent, a different format, the Massive Open Online Course (MOOC), has broadened the education landscape since it emerged in the fall of 2011.

Unlike a traditional online course, a MOOC is a course with few enrollment criteria. Also, while a traditional course might have twenty to thirty paying, credit and degree-seeking students, MOOCs are massive in size, sometimes hosting several thousand non-paying, non-credit seeking students at once (Pappano, 2012).

The first MOOC, launched by Stanford University professors Sebastian Thrun and Peter Norvig, offered anyone with an Internet connection the chance to audit an introductory artificial intelligence course online (Grimmelmann, 2014). What started as an experiment for Stanford's professors attracted over 160,000 students and eventually inspired the development of platforms Udacity and Coursera. Soon after, Harvard and Massachusetts Institute of Technology (MIT) founded the non-profit platform edX (Grimmelmann, 2014). In a short time, MOOCs, with their absence of prerequisites or applications, and their free, online video lectures, peer-graded assignments, and lightly monitored discussion boards, transformed higher education for the masses (Pappano, 2012).

Today, MOOC platform corporations are partnered with universities worldwide. Those platforms can be either for-profit or non-profit, and most offer both paid courses (certificates, with some degrees) as well as free courses. MOOC platforms of note are Coursera (37 million users), Goodwill's job training MOOC, called GFCCGlobal (31 million users), edX (18 million users), and Udacity (10 million users) (Busteed, 2019). Not surprisingly, these MOOCs and their masses of eager students have been researched in domains such as motivation and behavior, collaborative learning, educational technology, learner engagement, and self-regulated learning (Gašević et al., 2014).

While an obvious benefit of a MOOC is its ability to reach learners, regardless of their means or location, the MOOC's potential to impact professional development has been a recent focus of various industries and researchers (Dodson et al., 2015; Milligan &

Littlejohn, 2014; Pappano, 2012). Some argue MOOCs offer a potential cost benefit to users and employers (Dodson et al., 2015; Nielson, 2014). Assuming organizations use existing MOOCs instead of formal, in-house, or purchased online training, the organizations could save in the cost of materials, instructors, licenses, and learning management systems (LMS) (Dodson et al., 2015). Additionally, organizations can target education to a particular person and role by selecting different MOOCs for different employees. Corporations, along with aspiring and established professionals, have demonstrated a desire for efficient training and means to collaborate for the advancement of knowledge in a specific domain (Milligan & Littlejohn, 2014).

In the field of aviation, traditional education and training modalities with a flight student and instructor who are face-to-face continue to dominate time and resources for initial entry training programs (Prather, 2007). Nevertheless, collegiate aviation programs have integrated online education opportunities just as their non-aviation university counterparts have, in keeping with the demand for flexible higher education (Mott et al., 2019). Universities with bachelor's degrees that can be earned along with Air Transport Pilot (ATP) certificates now offer a myriad of online courses for both flight and non-flight students (Prather, 2007). This increased online presence, coupled with momentum from research promoting hiring preferences for recent graduates of Aviation Accreditation Board International (AABI) accredited programs (Smith et al., 2016), underscore the relevance and prominence of such institutions in the aviation field.

The field of aviation education has experienced a recent increase in attention surrounding the roles and strategies degree and certificate-granting institutions will serve in filling the need for more aviation professionals in the industry (Lutte & Lovelace, 2016). While traditional online for-credit courses supportive of the aviation professional's education have been a mainstay for years (Newcomer et al., 2014; Prather, 2006), institutions that care about continuing a positive growth trend and fostering their missions of education may offer MOOCs in order to reach many more learners in the industry (Iacuzio, 2015).

Additionally, these institutions may consider the possibility that positive experiences in aviation MOOCs may inspire future aviation professionals to seek enrollment in for-credit courses within their degree programs. While most universities provide MOOCs primarily to extend reach and 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). Thus, to "bind learners" to a "brand rather than charge them for educational experience" (McAuley et al., 2010, p. 33) is considered a worthy return on investment (ROI) for some universities.

MOOC-focused research has included themes of engagement, learner success, motivations, attitudes, learning strategies, social interaction, and learning resources (Gašević et al., 2014). Researchers have been guided by an array of well-established theories of behavior, motivation, and learning, such as planned behavior (Ajzen, 1991), self-determination (Deci, 1971), goal-setting (Locke & Latham, 1994), self-regulated learning (Zimmerman, 1990), social learning (Bandura 1969), constructivism (Piaget, 1971), and connectivism (Siemens, 2005). For the proposed study, Moore's (1973) theory of transactional distance, which posits psychological or communicative distance can impede learning and success, was used as a descriptive framework. In Moore's theory, 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) are considered to be critical dimensions for optimal learning (Falloon, 2011). If students feel reduced transactional distance, it is plausible that engagement will be higher, and outcomes such as persistence, performance, and positive experiences should be as well.

While a comprehensive application of Moore's theory would be ideal, this study utilized only portions of Moore's theory as a descriptive framework. Variables related to the frequency facet of Moore's dialogue factor (e.g., frequency interactions of students with each other and with the content) were used. Although considered inferior to quality, frequency of interaction, as an indicator of engagement in a course, is readily available, and has been used with data mining techniques for early warning systems and immediate course developer feedback (MacFadyen & Dawson, 2010). In MOOC research, traditional methods of data collection (e.g., surveys, structured interviews, grades) are common. While qualitative approaches for comprehensive, theoretical explication (for Moore's theory this would involve quality of interaction) are common, quantitative approaches aimed at more expedient feedback, or unsupervised data exploration, are gaining attention within the fields of learning analytics and educational data mining (Gašević et al., 2014).

Learning analytics involves the "measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Siemens, 2013, p. 1382). Using this approach, researchers analyze navigation patterns, including what features or tools users click on and how long they watch a video or stay on a particular task (Siemens, 2013).

The learning analytics approach is considered ideal for research due to its less obtrusive, more dynamic nature, as well as its ability to reduce the bias of self-selection, compared to survey methods (Gašević et al., 2014).

Statement of the Problem

The aviation industry is currently facing a need to adapt to growth and resulting pilot shortages as well as to regulatory changes 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., 2009) and the relevance of AABI-accredited programs (Smith et al., 2016), online education delivered by these institutions will be a focus for years to come. To date, little is known about learners in aviation-related MOOCs. A considerable number of learners may be outsiders to the industry, who are considering entry. To improve and tailor education to the existing and prospective aviation community, additional knowledge must be collected about MOOC participants with respect to engagement in the open online environment.

Furthermore, in the broader MOOC research community, there has been a call for increased utilization of learning analytics to enable instructors, course developers, and instructional designers to better support the learning process (Gašević et al., 2014; Johnson et al., 2012; Vieira et al., 2018). More research is needed in contexts where success is not considered to be 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) as recent MOOC research has highlighted the need to consider goals and needs of these learners who utilize MOOCs but do not complete them (Breslow et al., 2013; Ferguson & Clow, 2015; Ramesh et al., 2018). An increased understanding of engagement and disengagement, by way of learning analytics, is necessary to enable MOOC designers to add value where users need it most.

Purpose Statement

The purpose of the present study was to expand the current understanding of aviation-related MOOCs by determining and examining subpopulations of learners based on common engagement behaviors in the course. A better understanding of the learners may also reveal the extent to which variables of behavior selected for this study are theoretically relevant in overcoming transactional distance (e.g., psychological and communications gaps between instructors and learners), which is common in online learning (Moore, 1973). Additionally, the present study fills a gap in research in its person-centered approach that maximizes the rich data available in learning analytics datasets. A person-centered approach is critical for advancing knowledge on MOOC users because it detects and forms groups of students with common behaviors within the course, without assuming, as in a variable centered approach, that one set of parameters will be sufficient to describe the population. Although less parsimonious than a variable-centered approach, a person-centered approach offers more specificity in how the results describe the subjects (Howard & Hoffman, 2018). An increased understanding of the characteristics and engagement patterns of these groups is an important first step for course developers and instructors who aim to meet the diverse needs of the current and prospective aviation education community.

Research Questions

RQ 1. Based on engagement in course discussions, videos, and assessments, what distinct subgroups of students exist in an aviation-related MOOC?

RQ 2. Based on demographics, days of participation in the course, and achievement, what are the differences among engagement subgroups?

Due to the exploratory and data-driven nature of this study, no hypotheses were made concerning subgroups and the characteristics of these subgroups. While the lack of hypotheses is characteristic of an inductive approach (Lodico et al., 2010), the study examined variables and archived survey questions deemed relevant based upon existing theories and knowledge. It was a secondary aim of this study to provide new knowledge for future hypothesis generation and testing (Kell & Oliver, 2004).

Significance of the Study

Currently, little is known about aviation-related MOOCs and respective learners, despite the aviation industry's apparent increasing involvement in online education (Niemczyk, 2017; Lappas & Kourousis, 2016). The present study aimed to contribute needed empirical data on learner engagement to broaden what is known about this unique education domain, which must sustain and increase knowledge for aviation professionals and enthusiasts. As is typical with action research, generalizability may be limited due to the scope of the data and transferability. The extent to which results can be applied elsewhere will depend upon practitioner assessments in other domains (Dick, 2014). Thus, if findings are deemed transferable by practitioners in other aviation education domains, then understanding how learners engage in optional aviation-focused online course material may inform course design in the aviation industry as online training for pilots, flight attendants, mechanics, and small unmanned aerial system operators continues to expand. It may also aid developers in better design and marketing to increase the interest of those outside the aviation industry who may be considering entry into the industry.

Through the use of learning analytics, employed for developing actionable insights, the processes and results from this study may be instrumental in encouraging course designers and instructors to make more use of the vast amount of information at their disposal (Siemens, 2013). The results of the present study may be useful for identifying at-risk students and for guiding instructional designers who intend to add instructional support (James et al., 2018). Theoretically, the results of the present study may shed light on how a reduction of transactional distance, via increased dialogue and frequency of interaction, may indicate students feel more connected and thus more willing to persist. It may also show how factors of structure and autonomy in a course are related to engagement respective to mandatory and optional content. Finally, demonstrating the utility of learning analytics may reduce what is referred to as the "research and practice gap" that is said to exist when a researcher is far removed from an end-user (or instructor) (Siemens, 2012, p. 5). Thus, the methodology used here may allow others to achieve new insights on how to translate analytic research into practice and enable instructors to scale these methods to their own course data.

Delimitations

Data utilized involved only a single, aviation-related course topic, rather than all available aviation-related course topics. Engagement analysis focused on count measures rather than other temporal measures such as time on task or sequence in which course material was accessed. Archived data selected included only quantitative measures, rather than qualitative content such as quality of discussion content. Additionally, only data recorded during the two-week time period when the MOOC was "live" were analyzed. Finally, archived data were primarily from adult learners instead of all types of learners.

Delimitations related to theory include the use of engagement as a construct following a narrow conceptual definition consistent with the field of learning analytics and MOOC research (Bonafini et al., 2017; Huang et al., 2014; Kahan et al., 2017). Since the construct of engagement varies widely by discipline and context, a brief background of common definitions is necessary to clarify a narrow definition that will delimit the proposed study. In traditional education terminology, student engagement is a broad construct with overlapping cognitive and behavioral dimensions. Definitions vary, but many include descriptions of psychological investment, self-regulation, goal-setting, and persistence (Sinatra et al., 2015).

For the cognitive dimension, student engagement is centered on involvement with activities and conditions that are assumed to be conducive to deep learning or higher-order processing activity (Sinatra et al., 2015). While the behavioral dimension overlaps slightly with the cognitive dimension and has strong ties to achievement, the behavioral dimension is centered on involvement in academic tasks, attention, and information seeking. Despite its strong ties to achievement, behavioral engagement does not necessarily imply strong cognitive or metacognitive activity, which is critical for deep learning (Sinatra et al., 2015). For the present study, it was assumed that the construct of engagement represents the behavioral dimension of engagement. Thus, the use of the term "engagement" and the operationalizations of the number of discussion posts, the amount of video watched, or assessment scores may not represent or imply deep learning or cognitive engagement. Instead, engagement represents behavioral or participative engagement. Operationalization of engagement by measuring active participation in learning activities can be accomplished via direct observation of types and durations of activity (Chapman, 2003) or by analyzing data traces captured by an LMS (Ferguson & Clow, 2015; Kizilcec et al., 2013). These operationalizations are supported by definitions of engagement that speak to "students' cognitive investment in" and "active participation in… their learning" (Zepke & Leach, 2010, p. 168). Thus, in the present study, engagement is narrowly defined as active participation in learning activities. It was assumed that the operationalizations represented active participation in the MOOC course learning activities. Because characterizations of behavioral engagement often implicitly or explicitly include motivation in terms of why students expend effort and persist (Sinatra et al., 2015), the study also included student learning goals and participation intent, which were assumed to represent the motivational aspect of the behavioral engagement.

Limitations and Assumptions

Limitations. While the study offers unique contributions to the aviation and broader education community, some limitations must be acknowledged. First, the archival nature of the data limited what pre- and post-course survey questions were included in the analysis. Targeting motivations and reasons for disengagement may be better accomplished by asking learners why they completed certain portions of the course and not others, or by including more nuanced questions regarding learning goals at the outset or as the course progressed (Yuan & Powell, 2013). The lack of detail available from the post-course survey limited this research to a pre-course survey response on intent and measures of behavior from course activity.

Also related to the archival nature of the data is the limitation of the type of learning analytic data available for analysis. The Canvas LMS does not provide fine-grained detail for video watching within the course. Ideally, research would make use of trace data such as which students watched a video, and how long each student watched the video. Due to constraints of the Canvas LMS, video engagement data for the study was limited to a proxy of video engagement: each student's number of page views for each video.

Another limitation was the low response rate of pre- and post-course surveys and the resulting effect of constrained analysis. Since a greater portion of the learners who completed pre- and post-course survey also completed the course, a selection bias was present. Thus, without complete pre-course surveys, this bias was not fully addressed. While selection bias is common to MOOC research, it must be acknowledged, and care must be taken in generalizing (Hodge, 2016).

Other limitations involved the exploratory use of clustering in the data analysis phase. Because the analysis may not result in meaningful clusters, the results may be difficult to interpret (Antonenko et al., 2012). This was mitigated by choosing the most appropriate algorithm for the variables used, by appropriate validity analyses, and by comparison of results with previous research in the literature.

The scope of research was restricted to data from one-course topic, one platform, one location, and one year-long period. As a result, the generalizability of the study results was a limitation; however, as suggested by the recommendations for future research and the practical implications, some results may transfer to other aviation education settings.

The MOOCs selected for the study were on the subject of small, unmanned aerial systems (sUAS). The MOOCs lasted two weeks; both were held in 2018, and covered topics on the safe integration of sUAS into the national airspace system (NAS), cybersecurity, privacy, and data protection. Even though generalizability is limited, the sUAS course topic, as well as the time frame, during a time when aviation education was growing rapidly, offered data sets with a rich context for this "first" look into aviation-focused MOOCs. While generalizability across the aviation education domain is desirable, it was not the goal in this initial study. The study may serve as the basis for future research, which could establish the extent of generalizability within the broader aviation domain.

Assumptions. Several assumptions (topical, theoretical, methodological, and statistical) were made during the development and execution of this study. These served to inform this study. Three topical and methodological assumptions will be described here, while several statistical assumptions will be described in Chapter III.

The first assumption (topic-specific) was that MOOC enrollment is showing steady growth and will continue to be relevant in the education community (Chuang &

Ho, 2016). The second assumption (theoretical) was that although this study did not assess quality or meaningfulness of dialogue, frequency is a valuable, albeit incomplete, indicator that students may be actively engaging in integrating new information into existing knowledge structures (Garrison, 1993). The third assumption (methodological) was that MOOC participants answered honestly in their pre- and post-course surveys, since these were voluntary surveys that were not shared with classmates.

Definitions of Terms

Asynchronous Discussion	Discussions that do not happen at the same or preset time, pertaining to the online discussion board where students or instructors make posts and reply to other student posts on specified topics or questions.
Comment	A message used to reply to a post in an online discussion board thread (Wong, Pursel, Divinsky, & Jansen, 2015).
Engagement	Student interactivity with typical course content features: assessments, assignments, discussion boards, and videos (Kizilcec et al., 2013).

Extrinsic Motivation	A characterization or driver of behavior that is tied to some purpose beyond the task or to a separable outcome (e.g., certification or pay) (Ryan & Deci, 2000).
Intrinsic Motivation	A characterization or driver of behavior when innate needs are satisfied. This type of motivation involves behavior that occurs because a person derives pleasure or satisfaction from an activity (Ryan & Deci, 2000).
Learner-Content Interaction	"The process of intellectually interacting with content that results in changes in the learner's understanding, the learner's perspective, or the cognitive structures of the learner's mind" (Moore, 1989, p. 2).
Learner-Learner Interaction	Interaction that is synchronous or asynchronous and can occur with or without "real-time presence of an instructor" (Moore, 1989, p. 4).

Learner-Instructor Interaction	Learner and instructor as experiences shared by the instructor, such as providing resolutions to misunderstandings, elaborations, simplifications, analogies, and supplemental readings.
Learning Analytics	“Measurement, collection, optimizing learning and the environments in which it occurs” (Siemens, 2013, p. 1382).
Learning Management System	Web-based system used to distribute and provide access to course materials, resources, and assignments. This system also provides a forum for discussions and a method of tracking assignments, grades, feedback, and extent of student usage of materials.
Massive Open Online Course	Commonly called “MOOC.” Online course characterized by open and often free access, with nearly unlimited enrollment.
Online Learning	Learning enabled by computer or communication technology connected to the internet (Anderson, 2008).

Post	A message for replying to a thread in an online discussion board (Wong, et al., 2015).
Social Presence	A construct explored as a contributor to social climate and learning in classroom; “the degree to which a person is perceived as a “real person” in mediated communication” (Gunawardena, 1995, p. 151).
Thread	Area in online discussion board, created for initiating a new discussion.

List of Acronyms

AABI	Aviation Accreditation Board International
BIC	Bayesian Information Criterion
FAA	Federal Aviation Administration
LMS	Learning Management System
MOOC	Massive Open Online Course
NAS	National Airspace System
SDT	Social Determination Theory
UAS	Unmanned Aerial Systems
sUAS	Small Unmanned Aerial Systems

CHAPTER II

REVIEW OF THE RELEVANT LITERATURE

In addition to examining the characteristics of learners in an aviation focused MOOC, this study used learning analytics and the descriptive framework of Moore's (1973) theory of transactional distance to better understand student interactions and behaviors during the MOOC. In this section, existing research on personal factors of MOOC learners, including their motivation and engagement in MOOCs, will be reviewed. Next, course design factors will be reviewed. Finally, the theoretical framework, along with additional theories prevalent in the literature will be explained. The additional theories of motivation, social constructs, and interaction in online education will be reviewed to provide a background for motivation components of engagement. Although there is much MOOC research framed upon learning theory, the theoretical scope of this study will be limited to motivation and interaction.

Aviation MOOC Research

Little is currently known about students who enroll in aviation-focused MOOCS. A recent experimental study (Velázquez, 2017) utilized a flipped classroom combined with an aviation MOOC in order to compare final exam scores of MOOC participants in the flipped course format with non-MOOC participants in the traditional course format. In a flipped classroom, lecture-type activities and homework are flipped in terms of what material is covered in class and what is covered out of class. Usually, pre-recorded lectures are viewed outside of class and then homework and active discussion comprise the in-class time. In this case, the *Aviation 101 MOOC* was used to flip the classroom and served as the out-of-class portion of the course for the experimental group, while traditional design of classroom lectures and out-of-class homework were sustained for the control group. This study demonstrated that students in an undergraduate aviation course, *Private Pilot Theory*, who took a MOOC entitled, *Aviation 101*, achieved higher final exam scores than their traditional classroom counterparts in the control group. Because the Velázquez (2017) sample was limited to 52 students and had a combined effect of a traditional and a MOOC course, a more focused study including all MOOC participants in one MOOC, as opposed to just a portion of them, is necessary to better understand aviation MOOC students.

While research is scarce on aviation MOOC learners, research on the non-aviation MOOC community is abundant and growing (Gašević et al., 2014; Milligan & Littlejohn, 2014; Zhu et al., 2018). Growth of MOOCs and online education in general have helped to drive recent advances in LMSs and the features those systems offer in the way of learning analytics (Siemens, 2013). The market of MOOC education has evolved over time, and not surprisingly, universities have also refined their business models for their mission and market (McAuley et al., 2010). Some have increased their offering of MOOCs to expand the university brand for recruitment. This increase is noteworthy for aviation-related MOOCs which are potentially attracting learners who are not already in the aviation field. Research to date has included characteristics of MOOC participants in terms of motivation, enrollment, and engagement (Watted & Barak, 2018). Since MOOC platforms offer education in a form similar to traditional online education, many research themes from the online learning mode are similar and will, thus, be included in the review of relevant literature.

Characteristics of MOOC Participants

The process of determining who participates in MOOCs is fairly straightforward because of the capabilities of the platforms used as LMSs. Most platforms gather demographic data such as age, gender, education level, and location during registration or pre-course surveys, but the extent to which developers and instructors use this data varies widely (Vieira et al., 2018). Self-reported data often includes geographic location, but due to low response rates and a desire to compare sources of information, researchers have also used Internet protocol (IP) addresses to derive approximate physical locations (Christiansen et al., 2013). Most demographic analyses reveal MOOC participants already have high levels of education, are employed, and are predominantly male (Christensen et al., 2013; Chuang & Ho, 2016).

After four years in the MOOC industry, Massachusetts Institute of Technology (MIT) and Harvard released an edX demographic analysis of survey data from users of 290 courses. Those data revealed a median age of 29 and a 2:1 male-to-female ratio (Chuang & Ho, 2016). A study by Zhenghao et al. (2015) that included multiple platforms reported similar demographic data. Approximately 80% of MOOC completers had at least a bachelor's degree prior to the MOOC; almost 60% were employed full-time, and 60% were from developed countries. Demographic reports to date have highlighted the presence of underserved students (e.g., low income, non-white students) (Stich & Reeves, 2017), and some contend the reports have exposed a well-educated and high socioeconomic group of learners who start MOOCs and then quit them (Zhenghao et al., 2015). Despite this negative characterization, other self-reported data to be discussed in the next section offer a more complete, and arguably promising, picture of MOOC users (Zhenghao et al., 2015).

Motivation Factors in MOOCs

While MOOCs typically have low completion rates (below 10%), many students per class complete major portions of the courses (Khalil & Ebner, 2014). The range of engagement in the large scale common to a MOOC is evident in Tamburri's (2012) data from 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, and 13,000, or 12.5% passed (Khalil & Ebner, 2014, p. 1237). Considering such high numbers, and the prevalence of learners who may have goals other than a completion certificate, it is necessary to take a more detailed look at these non-completers (Khalili & Ebner, 2014; Tamburri, 2012). Even non-completers are of interest to the institutions developing MOOCs, because just like completers, they have the potential to return for more courses based on their personal goals or needs. Within the literature, motivation to enroll and motivation to engage are two broad lines of inquiry pursued for an increased understanding of these learners.

Enrollment. In addition to basic demographics, researchers have profiled users by their self-reported motivation factors. The finding that MOOC participants care about both career and educational benefits is widespread. Zhenghao et al. (2015) found that 52% of Coursera survey respondents (classified as "Career Builders") reported their primary goal was to improve their current job or find a new one. Of that group, 87%

reported they achieved a career benefit. In the study including several platforms, 72% of MOOC completers reported career benefits, and 61% reported educational benefits.

In addition to career and education benefits, some argue another motivation factor in MOOCs is personal. Christiansen et al. (2013) describe how, along with career advancement, many people report enrolling out of curiosity. While the factors described thus far are the most common, several other enrollment motivation factors are noted in the literature, such as the general desire to grow in knowledge, to have fun, to connect with others, or to overcome financial or physical (location) challenges (Christiansen et al., 2013; Warusavitarana et al., 2014).

Engagement. In addition to investigating why people enroll in MOOCs, much motivation research is aimed at determining why and how students vary in their engagement in the MOOC (Watted & Barack, 2018). Kizilcec et al. (2013) profiled MOOC participants via cluster analysis, revealing four distinct engagement patterns as shown in Table 1, with labels: *Completing, Auditing, Disengaging*, and *Sampling*. As the table depicts, these researchers examined discussion board posts, videos watched, and assessments completed in search of patterns of participation. Examining these variables using cluster analysis and temporal aspects of the course components allowed them to determine when certain types of students were dropping out and what facets of the course appeared important to these non-completers. Results for the group labeled *Auditing* spurred a call for more research to consider carefully the needs of learners who may not desire to complete the entire course. Suggestions include considering possible course adjustments to the timeline of content accessibility and adjustments to employment of quizzes.

Table 1

MOOC Participant Engagement Patterns

Cluster Name	Description
Completing	Learners who completed the majority of the assessments offered in the class. Though these participants varied in how well they performed on the assessment, they all at least attempted the assignments.
Auditing	Learners who did assessments infrequently if at all and engaged instead by watching video lectures. Students in this cluster followed the course for the majority of its duration. No students in this cluster obtained course credit.
Disengaging	Learners who did assessments at the beginning of the course but then have a marked decrease in engagement (their engagement patterns look like Completing at the beginning of the course but then the student either disappears from the course entirely or sparsely watches video lectures). The moments at which the learners disengage differ, but it is generally in the first third of the class.
Sampling	Learners who watched video lectures for only one or two assessment periods (generally learners in this category watch just a single video). Though many learners “sample” at the beginning of the course, there are many others that briefly explore the material when the class is already fully underway.

Note. Adapted from "Deconstructing disengagement: analyzing learner subpopulations in massive open online courses," by R.F. Kizilcec, C. Piech, E. Schneider. (2013, p. 172). Proceedings of the third international conference on learning analytics and knowledge (pp. 170-179).

Another study focused on profiling engagement of MOOC users (Milligan, Littlejohn, & Margaryan, 2013) classified participants as Active, Lurking, or Passive in participation. While this qualitative study relied on interviews of only twenty-nine participants, results revealed that mediators of engagement were whether or not students had previously participated in a MOOC and confidence. Additionally, the study revealed nearly all students classified as Lurking reported being content with their level of participation. This contentment of lurkers in Milligan et al.'s (2013) study, along with the presence of Auditing and Sampling clusters in Kizilcec et al.'s (2013) study confirm the need for considerations of student success beyond grades.

In a traditional class, grades are an understandable focus, but in a MOOC, grades are less of a focus. It is possible then to define "success" as interaction with peers on a common desired content or to define a level of success as learning one concept of many taught in the MOOC (Pursel et al., 2016). Examining the needs of those whose success definitions may not have included grades can be difficult, however, as many outside factors are assumed to affect completion or engagement as well. Kizilcec et al. (2013) discovered some learners indicated that they did not complete a course due to personal commitments, work conflict, or workload, and thus recommended MOOC designers consider adjusting the pace.

Kizilcec et al. (2013) proposed consideration of a positive feedback loop in the social context, a phenomenon they hypothesized to be influential in high levels of engagement in the Completing group. If such could be fostered for learners who are initially engaged and assessment-oriented, but then are disengaged, persistence may improve. Leach and Hadi (2017), in their study on learner engagement, drew similar attention to the need to evaluate groups who fall short of completion. They argued for consideration of micro-learning, which denotes "smaller portions of learning" or "flexibility for learners to choose what and when to learn" (Leach & Hadi, 2017, p. 149). In calls for future research, these studies hypothesized positive benefits of encouragement from reputation systems, display of participation levels, or other social and community-oriented features (Kizilcec et al., 2013; Leach & Hadi, 2017). Additionally, both urged increased research on intent and supportive designs to raise engagement of learners who take courses for intellectual stimulation rather than a certificate.

In other MOOC-focused cluster research, Anderson et al., (2014) found five subpopulations in styles of engagement with lectures, assignments, and videos: 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 pointed out that even though 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. Echoing others, Anderson et al. (2014) argued that focusing on students "dropping out" of a MOOC or at the other extreme, "completing" an online course yielded superficial distinctions that may be "based on the assumption that there is a single notion of completion" (p. 688).

Other authors have used methodologies of clustering for understanding MOOC engagement with a focus on technology use. Kovanović et al., (2019) report research on student differences in this domain have adopted K-means clustering, hierarchical clustering, and model-based clustering, with interpretations guided by an assortment of relevant theories. Since analysis procedures, as well as course context, are known to impact study findings, it is not surprising to observe wide variation in number of profiles and characteristics within the profiles in these studies.

Although many studies report three profiles, the challenge to determine a generalizable profile is distinctly noted as variables can differ drastically between courses (Kovanović et al., 2019; Milligan et a., 2013; Pursel et al., 2016). Even in studies where methodology is more controlled, researchers have struggled to find consistent numbers of profiles among courses. Ferguson et al. (2015) identified a range of differing number of profiles even when course context was similar. Only very broad clusters of Sampling and Completing were robust throughout all courses they studied and matched up with two of Kizilcec et al.'s (2013) four clusters.

The important implication from these studies is that researchers cannot assume a clustering approach in one learning context will be validated in another context. Additionally, Ferguson et al. (2015) admit their use of the k-means clustering technique may not have been the best methodology due to the challenge of determining how many clusters to extract. A hierarchical clustering approach was suggested as potentially more effective. The hierarchical clustering method has been successfully employed for determining learner profiles in MOOCs (Cobo et al., 2011; del Valle & Duffy, 2009; Kovanović et al., 2019; Tseng et al., 2016; Wise et al., 2013).

In summary, motivation factors in MOOCs, with respect to enrollment and engagement, are considered to be personal factors and have been the focus of much MOOC research to date. With respect to engagement in MOOCs, profile research using hierarchical clustering methods offers promising ways of better understanding subpopulations of students based on key variables. In addition to personal factors, other course-specific design factors are integral to understanding MOOC behavior as well. Several course design factors will be explained in the following section, then a theoretical framework and justification for the variables selected for analysis will conclude the chapter.

Course Design Factors

Models: cMOOC and xMOOC. MOOCs can be considered one of two main formats, cMOOC or xMOOC, which differ in both style and theoretical underpinnings. The first type, cMOOC, is built upon connectivist principles and aims to foster learning through experiences that are networked, open, and decentralized. The cMOOC's connectivist and emergent learning principles, based upon Siemens' (2005) connectivism learning theory, decreases the focus on the educator as the central source of information, and instead focuses more on learners who construct knowledge through social or relational negotiation with course material (Anders, 2015). cMOOCs are known for flexible course structure with instructors who serve as facilitators (Anders, 2015). This style of MOOC boasts self-organized patterns of collaboration in learning through social media accounts or blogs, with postings, videos, and other collaborative content aggregated by hashtags into shared content that can be referenced by all participants (Anders, 2015).

A more prevalent model referred to simply as "MOOC" in this study is the xMOOC. An xMOOC is based upon cognitive-behaviorist or instructivist principles of pedagogy, whereby content-based training or instruction is offered on an LMS, which usually hosts video lectures, integrated quizzes, readings, practice work, and a final exam

(Anders, 2015). xMOOCs were originally content-based and prescriptive in nature, with learning paths pre-charted in formalized bodies of knowledge. However, over the years, social and collaborative theories and techniques have been applied to enhance the learning process and complement the instructivist pedagogy (Anders, 2015). Although criticized for being rooted in pedagogies and methods of large-scale lecturing, which some argue offer little support for learner understanding, the xMOOCs offer a structure that can be important for inexperienced learners (Anders, 2015). This structure contrasts with what some consider an overwhelming information flow and lack of structure in the cMOOC and offers a format that is conducive to a broadening agenda of both universities and users.

Cost and Credentials

When MOOCs emerged, their original format was a cost-free model with an altruistic aim to extend open and high-quality education globally (Hollands & Tirthali, 2014). Considering the soaring cost of higher education, this goal seemed worthy of such efforts (Bulfin et al., 2014), and some thought it might “democratize” education (Hollands & Tirthali, 2014, p. 7). Over time, however, the idea of bringing high-quality, cost-free education to potentially underserved populations became less pronounced, as demographic data showed that most MOOC participants were already well-educated and well-employed learners (Stich & Reeves, 2017). As the typical MOOC population was of high socioeconomic background, with interests in niche education qualifications or advanced degrees, the MOOC model was adjusted for this market (Hollands & Tirthali, 2014).

As such, cost-based, certificate-granting MOOCs emerged, with the marketing message that learners could use these to enhance their career training portfolio (Friedman, 2016). An example of a post-degree certificate option is a MOOC certificate on agile project management which costs $562 and involves five courses (Schaffhauser, 2019). Such a course serves as an expedient, and some would deem necessary, professional development option for a program manager who is already established in the workforce (Schaffhauser, 2019). Recently, credential options have expanded dramatically, and cost-free MOOCs often act as gateway courses to cost-based MOOCs and cheaper master's degrees. One example of this is MIT's MITx MicroMasters in Supply Chain Management, which involves five required MOOCs, graded assignments, and a capstone exam. Certificates are granted for each MOOC and build credit toward what is dubbed a MicroMasters degree (EdX, 2016). Learners in this mode get a chance to try out the program before deciding, and the cost-savings of completing a portion (up to a semester's worth) of the master's degree in the MOOC format before finishing with a traditional format is attractive to many (Friedman, 2016). Indeed, this newer strategy for MOOCs as career advancers or gateways to degree programs has caught on with several universities worldwide.

An example is Georgia Tech's edX-hosted Master of Science degree in Analytics which costs $9,900 and takes one to three years to complete. Such a price tag is relatively inexpensive when one considers the residential version of this program costs $36,000 (in-state) or $49,000 (out-of-state) (McKenzie, 2018). Georgia Tech (2019) reports there is no difference in how the degree is reported on the diploma as there is no reference to the online nature of the less expensive version. However, as one might expect, differences do exist in amount of support and options available between the two. The online version has fewer options, with only the most popular electives offered, while the more expensive version, termed the "premium tuition program" offers boot camps, dedicated placement professionals, and other features not available to the online cohort.

Although course design characteristics of cost and credentials vary, both have emerged as consistent factors related to motivation for enrollment (Christiansen et al., 2013; Zhenghao et al., 2015). Nevertheless, continued research across the industry, as well as within institutions, is required as the market evolves. Additionally, other course-design factors are important to consider in order to shed light on motivation factors related to engagement and completion (Watted & Barak, 2018). These course design factors include discussion boards, video content, and support to learners. As the following sections will describe, each factor has been examined using various operationalizations, specific to different modes of analysis and course designs.

Discussion Board Role

In traditional online classrooms, the discussion boards have played a prominent role in fostering interactions between students, teachers, and content (Dailey-Hebert, 2015). Discussion boards often consist of guided topics, where students make a primary post about a topic related to the week's module content and respond constructively with a specified number of peer replies. Most online courses have asynchronous discussion boards where students can pace themselves throughout the week, making contributions within the constraints of the module's scheduled requirements, but not at a precise, common time. Sometimes the required number of posts are simply due by the end of the module, but structured timeframes and rubrics can be employed to encourage a pattern of interactive conversation, rather than cursory and last-minute transmissions (Woods & Bliss, 2016). While adherence to etiquette (netiquette) of online discussions is necessary to bridge the physical distance inherent in the online classroom and keep the discussion moving in a productive direction, the widespread acceptance for the role of an online discussion rests in its unique role to promote content knowledge, writing, and critical thinking skills all from the luxury and relative safety of a personal workspace (Aloni & Harrington, 2018).

Discussion board benefits and challenges. Benefits of discussion boards in online learning span topics of student comfort, connectedness, improved writing, critical thinking, and course satisfaction. Indeed, the satisfaction users report with discussion boards includes increased comfort with participation. Specifically, users report that they appreciate feeling less awkward and having more time to think, reflect, and research answers (Woods & Bliss, 2016). They also note the asynchronous format allows more time for many viewpoints to be considered (Dailey-Hebert, 2015; Hill et al., 2009; Sun et al., 2008). Additionally, the asynchronous discussion board has been shown to foster deeper comprehension and critical thinking (Aloni & Harrington, 2018; Hawkes, 2006) and to draw in students who project introverted personalities or low self-confidence in traditional classroom settings (Chen & Caropreso, 2004; Xie, 2013).

Although not all online courses use discussion board rubrics, it is notable that those that are structured with rubric or guidance as to format, frequency, and timing have demonstrated some positive effects (de Brito Neto, 2017; Woods & Bliss, 2016). This is important, because often reported challenges to discussion boards include confusion over purpose or instructor expectations and difficulty tracking long discussion threads (Aloni & Harrington, 2018). Rubrics or mechanics criteria have been shown to influence meaningful discourse of interpretation of content through analysis, synthesis, and creating inferences (Woods & Bliss, 2016) and to promote higher grades (de Brito Neto, 2017). Rubric guidance can move students past another common challenge to low-structure discussion boards, low-quality postings. With adequate rubrics, students can be guided to produce more than surface-level expositions of personal ideas, since rubrics often aim to elicit discussion posts substantiated with scholarly sources and relevant applications (Gao et al., 2013).

Discussion board operationalizations in the literature. Online discussion boards are a common focus in studies of MOOC engagement and interaction. Through various operationalizations, such as discussion board content quality, quantity, and temporal aspects such as timing throughout the module or course, researchers have aimed to better understand how to foster engagement and how engagement affects course outcomes (Cheung, 2014; Clow, 2013; Tang et al., 2018). To be sure, choices of variables and methods depend on research goals and resources. From theoretical validation to intervention to better understanding behavior, researchers have declared a myriad of operationalizations useful and have employed both mixed and quantitative methods of analysis.

Mixed methods for quality of postings. In mixed qualitative and quantitative approaches aimed at content quality, engagement has been operationalized with various content analysis frameworks. For example, one framework focuses on the learning process of distance learners in five categories: 1) level of learner participation, 2) pattern of interaction in terms of direct or indirect interpretation, 3) social comments present in the discussion post, 4) evidence of cognitive skill, such as deep analysis versus shallow repeating, and 5) meta-cognitive skill (evidence that one is evaluating and managing his or her own thoughts) (Cohen et al., 2019). Content analyses can also include categories not directly linked to a specific theoretical framework. Examples include coding a discussion post using other content categories, such as: content is specific to the topic (Cohen et al., 2019) or to technical or logistical aspects of the course (Wise et al., 2017), content reflects giving/seeking clarification on a topic (Gütl et al., 2014), or content contains agreement/disagreement or positive/negative sentiments (Ramesh et al., 2013; Wen et al., 2014).

Investigating content, in search of specific higher-order thinking behaviors, provides a challenge for MOOC research because rule-based algorithms needed for such large-scale data are not compatible with the aim of research (Wang et al., 2015). As such, much content analysis research must be accomplished via hand-coding, which is costly in both time and effort (Chandrasekaran et al., 2015). Occasionally, a proxy for quality is employed by utilizing the number of up-votes a post receives compared to the average number of votes for any contribution in a thread (Huang et al., 2014). Up or down votes are features provided in the discussion board of some LMSs and offer students a chance to up- or down-vote any other post in the thread. This feature is sometimes accompanied by a reputation score which is computed automatically using a sum of square roots of votes and represents quantity and quality (Huang et al., 2014). While limitations of inference accompany use of peer voting as a proxy for quality of course, it is a practical option some researchers consider. In sum, while hand-coding is necessary and some would consider worthwhile for theoretical development and validation, it may be impractical for monitoring and intervention goals of practitioners (Wang et al., 2015). Although automatic extraction of discussion structure for better insight on student discussions is a desired goal for some in the learning analytics community, unsupervised machine learning to this end requires topic modeling and qualitative evaluation of clusters, the benefits of which are still being explored (Ezen-Can et al., 2015). If one requires more feasible variables for operationalizing engagement, count measures and temporal measures are often employed.

Quantitative methods for quantity and time. In quantitative approaches, summed discussion board measures (number of posts, number of replies, number of positive or negative votes, and number of thread views) as well as summed page or video views have been used to better understand engagement and course outcomes (Crossley et al., 2016). Frequency of posting has been shown to predict higher grades (Wang et al., 2015), higher completion rates (Crossley et al., 2016), and higher course satisfaction (Tawfik et al., 2017). More active participants, some spurred on by earning virtual badges for non-grade related achievements (like authoring strong posts or reading certain amounts of posts) are known to excel in both assignments and quizzes (Anderson et al., 2014; Engle et al., 2015).

Temporal considerations are also important to researchers (Tang et al., 2018). Citing low interaction, poor feedback, and poor communication, researchers agree that MOOCs are often challenged in the area of student-student and student-instructor communication (Hone & El Said, 2016). Thus, other methods of analysis have been employed to delve deeper into discussion board engagement in MOOCs. Moving past simple quantitative measures (number of posts and views), some have examined patterns of discussion board engagement. Tang et al. (2018) found increased performance for those who maintain activity in the discussion board over the entire course and noted 47% of learners were in a group that was seldom engaging, 36.2% were in a group that was gradually disengaging, and 16.5% of the learners were in a group that was persistently engaging. Key findings by Tang et al. (2018) were that discussion forum participation was important for better performance and that a constant trajectory of regular participation outperformed initial high participation or last-minute high participation in the several weeks before the exam.

Other more advanced considerations of the temporal dimension of discussion boards involve time-on-task measures, such as total time spent writing or reading a discussion message (Kovanović et al., 2019). Although time on task has been a desired source of information for those who are probing facets of cognitive engagement and effort, it can pose challenges in its need for manual estimation during extraction from the LMS and in its effect on generalizability (Kovanović et al., 2015; Kovanović et al., 2019).

As grades are not the only positive outcome of interest, engagement researchers have also examined highly active users for positive or negative effects on other less-engaged students (Huang et al., 2014; Wong et al., 2015). Huang et al. (2014) examined what they called “superposters” or “students who post most frequently on the forum, and typically disproportionately more often than their peers” (p. 117). The aim in this investigation was to determine whether or not these prolific posters were posting quality content and what, if any, effect they had on the engagement of the group. The researchers wanted to know if they would drown out other activity, flood the discussion board with low-quality posts, or alienate the rest of the class. Not surprisingly, Huang et al. (2014) found “superposters” wrote longer than average posts and achieved above-average performance and above-average enrollment in other courses.

Less surprising were the findings that “superposters” were not always the fastest or most upvoted, and their human-coded discussion board content was rated useful. Furthermore, correlation analysis showed high “superposter” activity contributed value to the course overall. This high activity showed positive and significant correlations with higher overall activity and forum health with respect to volume, upvotes, and orphaned threads (Huang et al., 2014). Although no causal effect was claimed, since a latent factor such as instructor activity or incentives may have influenced engagement too, the authors stressed the key finding was that “superposters” did not suppress activity or drown it out. Also, given that MOOC instructors and teaching assistants are far outnumbered, the researchers suggested that active students could potentially be used to positively influence these collaborative learning environments.

Video

Just as discussion board activity has been operationalized to study engagement, video usage has as well and has gained attention over the years (Bonafini, 2017; Guo, Kim, & Rubin, 2014; Koedinger et al., 2015). This growth is due in part to more accessible learning analytic features in LMSs that capture data on frequency of access, playback, and pauses (Siemens, 2013). Video-watching behavior can be classified as session-level user characteristics, by way of clickstream data for percentage of video watched or length of a pause during a video (Brinton et al., 2016). Patterns in video watching enabled Li et al. (2015) to identify possible time points where students found content in the video difficult. Li et al. (2015) examined MOOC video interaction patterns in two MOOCs, one course on programming and one on electrical engineering. In this study the researchers noted key patterns such as video replay, frequent pause, and long pause which allowed them to make several practical recommendations to improve course design. In video sessions with high drop-out rates, replays, and pauses, they discovered a correlation with difficulty level and recommended side bars with easy re-access points for students. For the videos with frequent or long pauses, Li et al. (2015) recommended redesigns to reduce information overload, or auxiliary overlays to help students break down the complex material (e.g., coding blocks) that was presented right before students paused the video. They contend this information may be useful for planning interventions.

Other researchers have analyzed patterns of playback behavior for relationships with performance in video-embedded quizzes (Brinton & Chiang, 2015). Variables in Brinton and Chiang's (2015) study included amount of video played, pausing behavior, rate of playback, and jumping or rewinding the video. In this investigation, use of early video-watching data allowed prediction of performance within the first few weeks of the course. To be sure, studies on video usage do not always indicate strong positive effects on course outcomes. In a study comparing the causal relations of assignment activity, reading activity, and video activity with performance, Koedinger et al. (2015) found that higher assignment activity had a relationship with higher quiz scores. The effect of assignment activity on quiz scores was six times stronger than that of individual factors of reading or video activity and more than three times stronger than the impact of combined factors of watching and reading (Koedinger et al., 2015).

Other areas of research in the domain of MOOC video usage have included determining most popular video positions (Kim et al., 2014) and specific patterns in plays, skips, and pauses (Sinha et al., 2014). These attempts to better understand engagement through video usage are guided in part by the assumptions that video watching is voluntary and enhances student autonomy in MOOCs (Bonafini, 2017). Considered an essential element of the MOOC format, videos are of interest to researchers because they are highly relied upon by students (Bonafini, 2017) and because they are known to increase satisfaction and connectedness in realms of student-instructor interaction (Dailey-Hebert, 2015).

With video production capabilities as advanced as they are, it is not difficult for an instructor to make personal videos that include both the professor and presentation slides combined, both of which are shown to enhance learning and feelings of connectedness (Dailey-Hebert, 2015). The assumption that video-watching reflects increased engagement, and the evidence that watching more videos correlates positively with completion rates, explains why some researchers use video data to identify points of disengagement and trigger support mechanisms that might encourage re-engagement (Pursel et al., 2016).

Pre-course survey. Although not all MOOCs survey students in the beginning of the course, some do capture important demographic and motivation data at the outset (Bergner et al., 2015; Kizilcec et al., 2013). As described earlier, analysis of this type of data commonly characterizes MOOC participants as well-educated and employed learners (Stich & Reeves, 2017). Pursel et al. (2016) found pre-course surveys useful in predicting completion as students who indicated intent to watch all course videos or indicated their intent was to be active or complete the course were indeed more likely to complete the course.

While some find prior experience in MOOCs or online learning to be important in predicting completion (Milligan et al., 2013), relationships are not always present (Pursel et al., 2016). Demographic variables have also been used in examining engagement profiles, not just completion. Significant differences have been noted between engagement profile and answers to pre-course survey questions on interest, intent, professional needs, and prior experience in MOOCs (Kovanović et al., 2019).

Engagement profile differences were also found for learners from countries with a high human development index (Kizilcec et al., 2013). Understanding how such survey items relate to engagement is important because MOOC designers want to know how to better support individuals and help them achieve career and education benefits regardless of whether or not they earn a certificate (Zhenghao et al., 2015). While this may be best discerned via post-course surveys delivered well after the course, at the minimum, pre-course survey data is useful in revealing some prospective benefits.

In summary, both personal and course design factors are essential considerations in MOOC research. The proposed study aims to examine aviation MOOC students through the personal factors of engagement and motivation and course design factors of discussion board, assessments, videos, and pre-course surveys. Although relevant learning theories have been used to study MOOCs, the proposed theoretical framework for this study was limited to motivation and interaction domain as described next.

Theoretical Framework

In order to better understand learning engagement within an aviation-focused MOOC, variables relevant to key motivation and learning theories were examined for their relations with engagement metrics. These will be described and justified by a review of the theoretical literature. While portions of Moore's (1973) theory of transactional distance serve as the primary descriptive framework, additional theories prevalent in the literature are explained to provide a background for motivation components of engagement. After Moore's theory is described, a brief discussion of how self-determination theory's (Ryan & Deci, 2000) intrinsic and extrinsic motivation relate to study constructs will follow. Finally, construct relevance will be demonstrated through the theoretical lenses of social context (Deci et al., 1991), social goals (Wentzel, 1999), and social presence (Gunawardena, 1995). Although not primary to the framework in this study, the theories shown in Table 2 are important for understanding the student engagement literature.

Table 2

Summary of Relevant Theories in Student Engagement Literature

Self-Determined Motivation **Self-Determination Theory (SDT)** **Intrinsic vs. Extrinsic Motivation**	・Posits better learning when students are interested in learning, value the education, and are confident in their own abilities. ・Intrinsically motivated behavior—when pleasure or satisfaction is achieved from performance causing willing (versus forced) engagement in activities without the requirement of material rewards. An intrinsically motivated activity is fully endorsed by the student. ・Extrinsically motivated behaviors are tied to some outside reward or consequence. Many of these outside rewards are not thought to be self-determined, but some can be (e.g., for an academic certificate or degree: a student shows both when she loves the course content and needs the course to get better at her job).
Social Context **Social Goals**	・Feelings of competence and relatedness (necessary for self-determined action) can be bolstered by positive feedback and interaction from peers or an instructor. ・Can center around goals like being seen as successful, dependable, or responsible. ・Social goals may include gaining approval from others, cooperating with others, and fostering friendships.
Social Presence Theory	・Posits that students can overcome the lack of non-verbal cues by projecting their identities and engaging in quality interactions. ・Can be affected by frequency, type, and quality of interactions between instructors and students, and can increase student satisfaction, perceived learning, and retention.
Social Presence Definition	"A student's sense of being in and belonging in a course and the ability to interact with other students and an instructor" (Picciano, 2002, p. 22).

Note. Self-Determined Motivation, SDT (Ames, 1992; Deci, Vallerand, Pelletier, & Ryan, 1991; Miltiadou & Savenye, 2003); Social Context and Social Goals (Deci et al., 1991;Wentzel, 1999); Social Presence Theory (Gunawardena, 1995); Social Presence Definition (Picciano, 2002), Social presence research (Shelton, Hung & Lowenthal, 2017).

Moore's theory of transactional distance. Interest in the construct of student engagement has been sustained over the years, and much of it has been framed and refined by Moore's (1973) theory of transactional distance. Moore's theory defines "transactional distance" as the "psychological and communications space" (Moore, 1997, p. 22) between instructors and learners that is common in distance-learning scenarios. In this context, such psychological or communicative gaps are posited to affect engagement and impede learning. 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) (Falloon, 2011). 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, Willis, and Gunawardena (1994).

With respect to distinguishing the types of interaction subsumed in the dialogue construct, Moore (1989) sought to bring clarity to a field of research, which until then, he argued, had been muddled by many different definitions. To present clearer constructs, Moore described interaction between learner and instructor as experiences shared by the instructor, such as providing resolutions to misunderstandings, elaborations, simplifications, analogies, and supplemental readings. He asserted learner-to-learner interaction can be synchronous or asynchronous and can occur with or without "real-time presence of an instructor" (Moore, 1989, p. 4). Finally, he defined "interaction" between learner and content as "the process of intellectually interacting with content that results in changes in the learner's understanding, the learner's perspective, or the cognitive structures of the learner's mind” (Moore, 1989, p. 2). Research under this typology offers empirical support for the construct of interactions being related to positive learning (Picciano, 2002), course outcomes (Zimmerman, 2012), perceptions of higher course quality (Abrami et al., 2011), satisfaction (Dennen et al., 2007), retention (Hone & El Said, 2016), and determination of at-risk students (Shelton et al., 2017).

Theoretical assumptions for this study. Theoretically, it was assumed that increased engagement in discussion boards and videos decrease transactional distance and increase feelings of social connectedness, consistent with Moore’s (1997) theory of transactional distance. Based on previous research in this domain, an increase in engagement and reduction in transactional distance was assumed to be related to increased persistence, performance, and positive experience in the course (Falloon, 2011). Additionally, it was assumed that frequent and meaningful dialogue in the discussion board, while often limited in a MOOC, is an important ideal to strive for in the pursuit of maximizing learning. Although this study did not assess quality or meaningfulness of dialogue, it assumed that frequency is a valuable, albeit incomplete, indicator that students may be actively engaging in integrating new information into existing knowledge structures (Garrison, 1993). In Figure 1 the components of Moore’s theory are depicted as a framework for the proposed study variables.

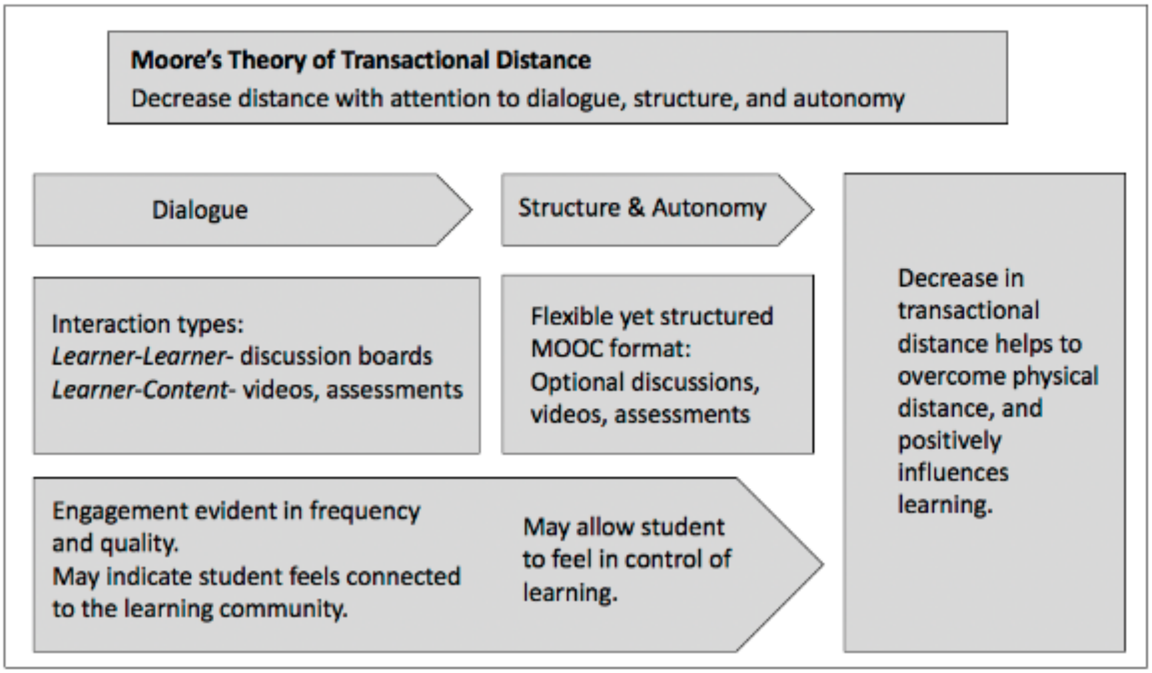


Figure 1. Theoretical framework using Moore's theory of transactional distance.

Self-Determined Motivation. Also critical to understanding student learning and engagement are the theories explaining motivation, which are well established in education literature (Ames, 1992; Deci et al., 1991). In pursuit of a better understanding as to why students engage and persist in academic settings, researchers have used theories that incorporate intrinsic versus extrinsic motivation and goals (Miltiadou & Savenye, 2003). Along these lines, self-determination theory (SDT) posits other factors either facilitate or forestall learning and development (Ryan & Deci, 2000). Intrinsic motivation is present when innate needs for competence, autonomy, and relatedness are satisfied. That type of motivation involves behavior that occurs because a person derives pleasure or satisfaction from an activity. An intrinsically motivated person is not constrained by obligation or rewards.

In contrast, extrinsic motivation is present in contexts that involve pressure and control, which reduce one's feelings of autonomy and connectedness (Ryan & Deci, 2000). Extrinsic motivation characterizes behavior that is tied to some purpose beyond the task, or to a separable outcome, such as a certification or pay (Ryan & Deci, 2000). In early applications of self-determination theory, extrinsic motivation was assumed to conflict with the characterization of being self-determined. However, in more recent research, the two, in certain forms, are able to complement each other. For instance, a MOOC learner could exhibit intrinsic motivation in her love or passion for the subject and material of the course she is taking, but she could also exhibit an extrinsic motivation to take the course because she knows she needs the knowledge for her everyday job. In this case, an extrinsic motivation (work-necessity) is self-endorsed and, thus, becomes additive to her volition to engage (Ryan & Deci, 2000).

Social context. Another important construct in the discourse of self-determined motivation is social context. One of SDT's main hypotheses is that social contexts can facilitate how competent, related, and autonomous a person feels and can lead to self-determined action (Deci et al., 1991). In the social context, feelings of competence and relatedness can be bolstered by positive feedback and interaction from peers or an instructor (Deci et al., 1991). With respect to group work, feelings of autonomy can be bolstered when a learner has choice of group or feels workloads within the group are equitable.

Social goals. The social realities of online course designs are evident in the prevalent use of discussion board, group projects, peer review, and peer grading. As such, one must consider theories that address social goals and social motivations. Wentzel (1999) is often cited for her research addressing social motivation in academic settings. In this domain, goals include being seen as successful, dependable, or responsible. Other social goals include gaining approval from others, cooperating with others, and fostering friendships (Wentzel, 1999). As noted by Xiong et al. (2015), the MOOC environment must also consider social motivation to include “students’ feelings of relatedness with peers” (p. 26).

Social presence. Using much of the same language, researchers have utilized the construct of “social presence” as described by Gunawardena (1995) to study participants in text-based learning environments. Social presence theory posits that students can overcome the lack of non-verbal cues by projecting their identities and engaging in quality interactions (Gunawardena, 1995). Picciano (2002) defines “social presence” as “a student's sense of being in and belonging in a course and the ability to interact with other students and an instructor” (p. 22). Notably, Picciano (2002) distinguishes between two facets, interaction and sense of belonging, and argues they may affect student outcomes independently. Interaction, such as posting in a discussion board, may indicate a degree of presence, but interaction does not necessarily mean an individual feels like part of the group. Social presence can be affected by frequency, type, and quality of interactions between instructors and students, and can increase student satisfaction, perceived learning, and retention (Shelton et al., 2017).

Summary of Framework and Variables

Guided by theory and previous research, key variables were selected for determining learning engagement subgroups in an aviation-focused MOOC as well as for determining how these engagement subgroups differ on key demographic and pre-course survey data. First, variables of engagement, as depicted in Table 3, were linked with supporting theories and research. Those variables were used in the cluster analysis to form subgroups of engagement. Next, variables to characterize the determined subgroups of engagement were linked with justification from relevant research and were then used to further understand the characteristics of the determined engagement subgroups.

Variables of engagement. Moore's theory of transactional distance, where distance in interactions are posited to create psychological or communicative gaps and impede learning, provided a framework for the focus on engagement as a function of interactions. 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) (Falloon, 2011). Consistent with Moore's theory, and specifically his three types of interaction, low distance and high interaction are reported to yield positive achievement effects in distance education (Bernard et al., 2009). Moore's theory is a useful framework for this study and for its empirical support in the literature, as such interactions are related to positive learning (Picciano, 2002), course outcomes (Zimmerman, 2012), perceptions of higher course quality (Abrami et al., 2011), satisfaction (Dennen et al., 2007), retention (Hone & El Said, 2016), and determination of at-risk students (Shelton et al., 2017).

The variables in this study relate primarily to the dialogue construct of Moore's theory as the study design was based on an archived dataset, limiting the variability necessary to examine structure and autonomy. Nevertheless, assumptions as to the course's flexible structure (same for all MOOC participants) and high autonomy (all MOOC participants could choose what portions to participate in) were made. Using the dialogue construct, this study operationalized Moore's three types of interaction to data available within the LMS. Moore's learner-learner interaction construct is aligned with variables that relate to the discussion board data traces, and Moore's learner-content interaction is aligned with variables that relate to video and assessment data traces. While very limited, Moore's third category of interaction, learner-instructor interaction, is aligned with video data traces for video content, which includes instructors presenting course material. These engagement variables, described in Table 3, were used in the clustering algorithm to determine what type of engagement subgroups were present in an aviation-focused MOOC. The remaining analyses aimed to characterize those engagement clusters further.

Table 3

Engagement Variables for Subgroup Formation

Discussion engagement	Posts viewed Posts written	Moore's (1997) Theory: Learner-Learner Interaction; Social context (Deci et al., 1991) Social goals (Wentzel, 1999; Xiong et al., 2015); Social presence (Gunawardena, 1995; Picciano, 2002; Shelton et al., 2017)
Video engagement	Video pages viewed	Moore's (1997) Theory: Learner-Content Interaction and Learner-Instructor Interaction; Social presence (Gunawardena, 1995; Picciano, 2002; Shelton et al., 2017)
Assessment engagement	Quizzes submitted	Moore's (1997) Theory: Learner-Content Interaction; Self-Determined Motivation (Deci et al., 1991

Attributes or Variables for Characterizing Engagement Subgroups. As depicted in the right half of Table 4, variables drawn from pre-course survey data and performance and trace data within the LMS were used to further characterize the subgroups of engagement. Age, geographic location, and education level are common variables used in research on MOOC populations (Pursel et al., 2016). While age is often somewhat linearly associated with completion and performance, it has been found to taper off at a certain point (Pursel et al., 2016).

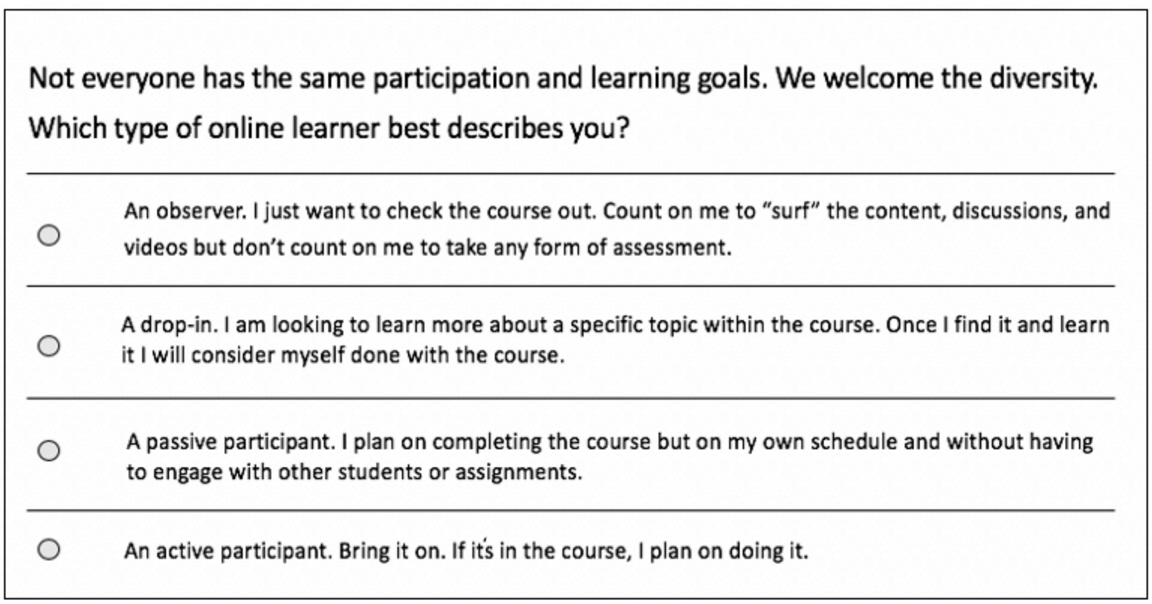
Table 4

Research Questions and Variables

RQ 1: Cluster Analysis Variables for determining engagement subgroups		RQ 2: ANOVA, Chi-Square Analysis Variables (attributes) for characterizing engagement subgroups	
Discussion engagement	Discussion board views	Demographics	Age
	Posts written		Location
Video engagement	Video page views		Education level
Assessment engagement	Quizzes submitted		Employment in aviation industry
			Intent
		Participation	Days of activity
		Achievement	Total quiz score
			Record of completion

Geographic location is examined based on its empirical relevance to factors in this study (Liu et al., 2016). Evidence is found in studies where completion and certification in MOOCs have been shown to be higher for non-American students (Nesterko et al., 2013) and where amount of content covered and time spent were found to be significantly predicted by country of origin (Guo & Reinecke, 2014). While some research focuses on fine indices of geographic origin, such as how developed student origin countries are (Kizilcec et al., 2013) or Hofstede’s or other cultural dimensions (Liu et al., 2016), this study utilized a simple geographic variable consistent with the scope and aim of this research. Analysis of group attributes in the second research question requires only either the country or continent of origin. Continent of origin was collected in the pre-course welcome survey, and country of origin was collected in the post-course demographic survey. When origin data were missing from the pre-course survey but available in the post-course survey, country data were coded by continent, consistent with common practices in MOOC research (Nesterko et al., 2013).

Education level, employment, and intent are key variables in MOOC research as well. Most MOOC enrollers and completers are found to be highly educated and employed (Stich & Reeves, 2017), but the inclusion of a pre-course survey item capturing whether or not the student is employed in the aviation industry could provide more information than a simple employment question. A final demographic variable, intent (for participation), taken from the pre-course survey, represented the user's intent and motivation. The question and answer choices are shown in Figure 2.



Not everyone has the same participation and learning goals. We welcome the diversity. Which type of online learner best describes you?

- 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.
- 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.
- A passive participant. I plan on completing the course but on my own schedule and without having to engage with other students or assignments.
- An active participant. Bring it on. If it's in the course, I plan on doing it.

Figure 2. Pre-course survey intent for participation question.

Both the employment and intent variables relate to the self-determination theory factors of intrinsic and extrinsic motivation (Deci et al., 1991) and are useful for contextualizing MOOC engagement motivation broadly in the domain of professional learning (Milligan & Littlejohn, 2014) and specifically in the domain of aviation professional learning (Lappas & Kourousis, 2016).

The final two constructs used to form variables for characterizing the determined engagement subgroups were participation and achievement. Participation was measured in days of activity throughout the duration of the course. This variable has been used in MOOC research consistently with varied findings. Kovanović et al. (2016) found a social cluster which included students with the most days active in the course, while Hone and El Said (2016) noted that most students were active for only the first half of the entire course. In a different study, Kahan et al. (2017) found that four out of seven engagement clusters were all very similar in their number of days active yet were markedly different from the remaining groups. As a basic characterization of participation, this variable was calculated from the difference in days between course start and last date of activity prior to or on the course end date.

Two achievement variables, final grade and record of completion were included as well. These variables are metrics commonly used in education engagement research (Kahan et al., 2017) and were employed to further characterize the determined engagement groups. Use of these variables meets the call by other researchers to include variables that provide more evidence of MOOC achievement and interaction, beyond the superficial completion certificate (Anderson et al., 2014).

Research Gaps

This dissertation aimed to examine student engagement in aviation-related MOOCs through the lens of learning analytics. In design of the study, multiple gaps in the existing literature were identified:

- Prior to this study, little information on student engagement in aviation-related MOOC was available. Only one study (Velázquez, 2017) on a small ($N = 52$) flipped classroom that used an aviation MOOC to augment a course had been conducted.
- In the general domain of MOOCs, existing engagement research lacks information on middle groups of students who engage in MOOCs but do not complete them. A call to further "deconstruct disengagement" has been made (Kizilcec et al., 2013, p. 170).
- A key step in learning analytics is "closing the loop" by feeding an intervention back to learners (Clow, 2012, p. 134). To date, no aviation-MOOC data have been analyzed to feed back interventions to students. This study aims to fill that gap locally (for the host institution) as its person-centered approach allowed for the detection and formation of groups of students with common behaviors within the course, without assuming, as in a variable centered approach, that one set of parameters would be sufficient to describe the population.
- This study aimed to reduce what is referred to as the "research and practice gap" said to exist when a researcher is far removed from an end-user (or instructor) (Siemens, 2012, p. 5). While systems that make use of learning analytics data have been employed to provide expedient feedback to users (e.g., Purdue's

system to alert students when they are on or off-track) more actionable insights on expedient methodologies involving learning analytics are needed for instructors of MOOCs or other online courses. The use of simple quantitative metrics available in the LMS, with little coding and no qualitative analysis, may provide an example of a methodology that is feasible to scale to other course types and data.

Summary

The relevant literature on personal factors of MOOC learners, motivation and engagement in MOOCs, and critical online course design factors were reviewed. Additionally, the theoretical framework of Moore's theory of transactional distance, where distance in interactions are posited to create psychological or communicative gaps and impede learning, provided a framework for the focus on engagement as a function of interactions. This theory, along with additional motivation and interaction theories prevalent in the literature were explained. The studies and theories covered here guided selection of key variables for determining learning engagement subgroups in an aviation-focused MOOC as well as for determining how these engagement subgroups differ on key demographic and pre-course survey data. Chapter III will include the methodology and provide further detail on how the engagement variables were analyzed.

CHAPTER III

METHODOLOGY

This study used archival course data from two iterations of one aviation-focused MOOC. 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 with discussion boards, videos, course readings, and quizzes at the end of each module. 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 points on module quizzes.

Research Approach

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. This approach differs from variable-centered approaches as explained by Morin, Gagne, and Bujacz (2016):

> Variable-centered approaches… assume that all individuals from a sample are drawn from a single population for which a single set of "averaged" parameters can be estimated. In contrast, person-centered approaches... relax this assumption and consider the possibility that the sample might include multiple subpopulations characterized by different sets of parameters. (p. 8)

Cluster analysis was selected as the method of analysis due to its demonstrated effectiveness in prior engagement and learning analytics research (Anderson et al., 2014; Cobo et al., 2011; del Valle & Duffy, 2009; Ferguson & Clow, 2015; Huberty et al., 2005; Howard et al., 2018; Kizilcec et al., 2013; Kovanović et al., 2019; Tseng et al., 2016; Wise et al., 2013). As an exploratory method, cluster analysis has proven useful for data mining and organizing large data sets in domains beyond the education field, such as in fields of bioinformatics, industrial engineering, and marketing (Antonenko et al., 2012). Clustering is noted as useful when categories within the data are not known in advance, and the methodology is effective at grouping students and their actions (Baker & Inventado, 2014). For online learning environments, clustering is regarded as an advantageous method due to its ability to provide insights utilizing large amounts of click-stream data collected automatically, rather than self-reported data which requires an overt collection method that could compromise the student's learning process (Antonenko et al., 2012).

Design and Procedures

As summarized in Figure 3, in order to answer the first research question: "What distinct subgroups of students exist in an aviation-related MOOC, based on engagement in course discussions, videos, and assessments?" a quantitative approach using a clustering algorithm was employed to assign learners into different clusters. The second research question, "What are the differences between engagement subgroups based on demographics, days of participation, and course achievement?" was answered by a series of statistical procedures (Analysis of Variance (ANOVA), and Chi-Square analysis).

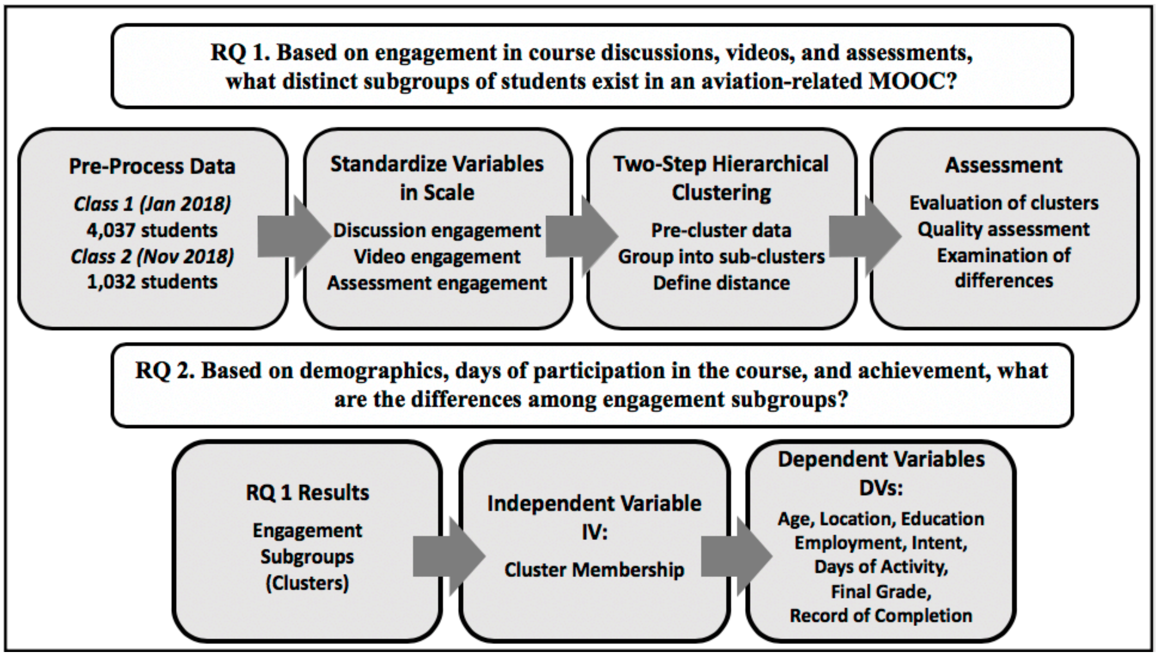


Figure 3. Research design.

Hierarchical and non-hierarchical clustering. Clustering is a process that divides a population into a number of groups that have similarity among specified traits (Kaushik, 2016). Common in education research, cluster analysis is used for data exploration to determine meaningful clusters based on given variables to test hypotheses regarding cluster structure and to confirm previously reported cluster results (Huberty et al., 2005). Hierarchical clustering is one of many different kinds of clustering algorithms. Agglomerative hierarchical clustering starts at the bottom of the hierarchy, with every observation as a separate cluster, then repeatedly identifies clusters that are closest together and merges them until all the clusters are merged together at the top. Agglomerative clustering is known as the bottom-up method. Hierarchical clustering can be accomplished in reverse direction also, in what is called divisive hierarchical clustering, where separate clusters are built from a single starting cluster in a top-down manner. Either method results in a dendogram or hierarchical tree as the final output which visually shows the hierarchical relationship between the clusters (Battaglia et al., 2015).

Although non-hierarchical algorithms (e.g., *k*-means) are often used when the data set is large, they are recommended for use in cases where there is a theoretical rationale for predicting the number of clusters (Antonenko et al., 2012). The hierarchical clustering method was selected based on the lack of a theoretical rationale for predicting the number of clusters and based on strong recommendation from Ferguson et al. (2015). Hierarchical clustering has been conducted successfully in education profile research as well (Wise et al., 2013; Kovanović et al., 2019). Noted weaknesses for cluster analysis in education research are reported by Antonenko et al. (2012): “(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” (p. 395). These 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 (Antonenko et al., 2012), and when split-samples yield cluster solutions similar in size and characteristics to the final solution obtained with the full sample (Hair, et al., 2015).

Apparatus and Materials.

An archived dataset of two MOOC courses was obtained from the course platform host, Instructure. Each course contained one file for all survey questions, one file for grades, and one file for every activity in the Canvas course module areas and help areas. Clickstream data and Canvas application programming interface (API) data were accessed to retrieve data on key variables.

Population/Sample

The population of this study was comprised of learners in aviation-related MOOCs. The sample was comprised of two groups of learners who enrolled in an aviation-focused MOOC, Small Unmanned Aerial Systems, during two iterations offered in 2018. The decision to select a sample that was active during only one year and in one course topic of sUAS offered data sets with a controlled (in terms of format and duration) yet rich context for this "first" look into aviation-focused MOOCs. Registrations for the sUAS MOOC were higher than any other aviation-related MOOC, which ensured a large sample could be analyzed. Analysis was initially conducted on the most recent MOOC, which was the smaller of the two MOOCs. This group included learners from a MOOC offered from November 19, 2018, to December 2, 2018, and consisted of 1,032 students. Next, analysis was conducted on the second, larger MOOC that was offered January 22, 2018, to February 4, 2018, and consisted of 4,037 students. Artificial numbering ("MOOC 1" and "MOOC 2") labeled and ordered the MOOCs by increasing size. The students enrolled in these courses included individuals worldwide; some were affiliated with the host institution, but most were not. Cluster analysis sample size guidelines, similar to those of linear regression, set forth an acceptable range of 10 to 20 cases for each variable (Wise et al., 2013). Five clustering variables require 50 to 100 cases. Thus, the archived dataset (*N*= 4,000) exceeded the minimum range for the analysis proposed.

Treatment of the Data

Data were extracted from the Canvas Network LMS activity log and de-identified. Data cleaning was conducted to omit data that was not useful to the study such as entries beyond the dates of the course or entries with errors. Next, data for the following learner engagement variables were collected and associated with an appropriate individual identifier: discussion posts viewed and written, videos pages viewed, assessment submitted. Similarly, pertinent data from pre-course and post-course surveys were collected and associated with an appropriate individual identifier. Finally, data were transformed into aggregated variables for analysis (Hung, Rice, & Saba, 2012) in IBM Statistical Package for Social Sciences (SPSS) (SPSS, 2019) Premium GradPack 26 for Windows. Prior to the clustering process, variables shown in Table 5 were standardized in scale. Due to the size of the data set and nature of the variables, a two-step hierarchical clustering was employed. The two-step method is useful for a large data set, as it can handle continuous or nominal data. Limitations of the two-step method include sensitivity to order effects, thus order of cases must be randomized (Antonenko et al., 2012).

Table 5

Variable Details for Determining Engagement Subgroups (RQ 1)

Variable Name	Details
Mandatory Discussion Views and Posts	Planning Considerations National Airspace System (NAS)
Optional Discussion Views and Posts	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).

RQ 1. The first research question "Based on engagement in course discussions, videos, and assessments, what distinct subgroups of students exist in an aviation-related MOOC?" was explored through two-step cluster analysis in SPSS. The procedure for two-step clustering first required variables to be standardized to Z scores. The hierarchical algorithm used to divide the pre-clusters into subgroups was the distance measure, Log-likelihood, which determines cluster distance or similarity. Although often the Log-likelihood measure is advised for analyzing both continuous or categorical variables or when allowing the number of clusters to be determined automatically, the Euclidian distance, normally employed when specifying fixed number of clusters, did not yield an interpretable solution. Some iterations of cluster analysis returned unclear subgroups or two cluster results that were and were not interpretable given the aims of this research to learn more about the students who did not complete the course. Thus, some cluster solutions using auto-cluster were not retained, and one of the variables was removed. The five final clustering variables were: Mandatory Discussion Posts, Optional Discussion Views, Video Page Views (Webinar 1 Views), Quiz 1 Attempts, and Quiz 2 Attempts. Several analyses were conducted with data sorted in different orders since the cluster analysis is sensitive to case order. Since auto-clustering yielded two-cluster solutions that were not interpretable based upon the "conceptual aspects" of the research question (Hair et al., 2015, p. 448), which aimed to uncover more about non-completers, a closer examination of Schwarz's Bayesian Information Criterion (BIC) was conducted as the initial step in exploratory clustering. Although SPSS two-step in auto-clustering mode uses a combination of lowest BIC and highest ratio of distance measures in selecting its optimal solution, that solution may not agree with a cluster-by-cluster rule of thumb assessment which involves selecting cluster solutions that display relatively lower BICs and higher ratio of distance measures (Garson, 2012). Figures 4 and 5 below, show that both MOOC's auto-cluster results yielded lowest BICs at cluster solutions beyond that of a 2-cluster solution and that both demonstrated marginal drops in BIC between 3 and 5 clusters (MOOC 1: 2-cluster BIC = 4.191, 3 cluster BIC= 1.667, 4-cluster BIC = 1.474, 5 cluster BIC = 1.285 and MOOC 2: 2-cluster BIC = 4.418, 3 cluster BIC= 1.143, 4-cluster BIC = 1.3295, 5-cluster BIC = 1.643). The ratio of loglikelihood distance measures were highest for both MOOCs in the 2 cluster solution (at 4.191 and 4.418 respectively), but since that 2-cluster solution was rejected, the next three ratios of loglikelihood distance measures were examined (MOOC 1: 3 cluster = 1.667, 4-cluster =

1.474, 5 cluster = 1.285 and MOOC 2: 3 cluster = 1.143, 4-cluster = 1.3295, 5-cluster = 1.643). The next highest was noted in the 3-cluster solution for MOOC 1 and the 5-cluster solution for MOOC 2, but minimal differences were shown between the 3, 4, and 5 cluster solutions.

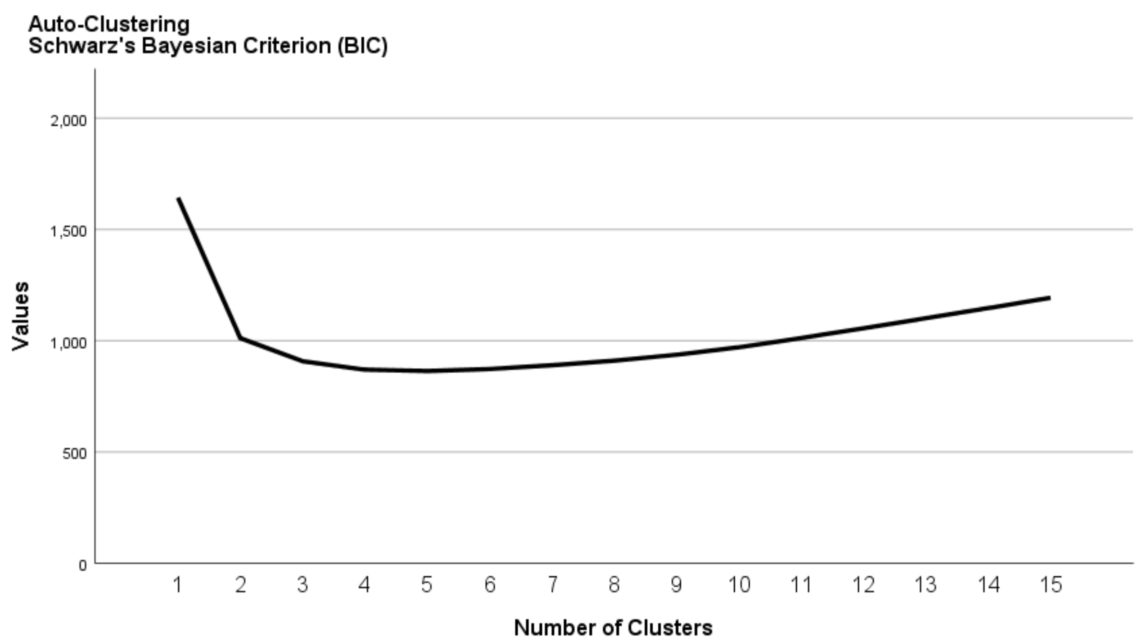


Figure 4. MOOC 1's BIC values for different cluster solutions.

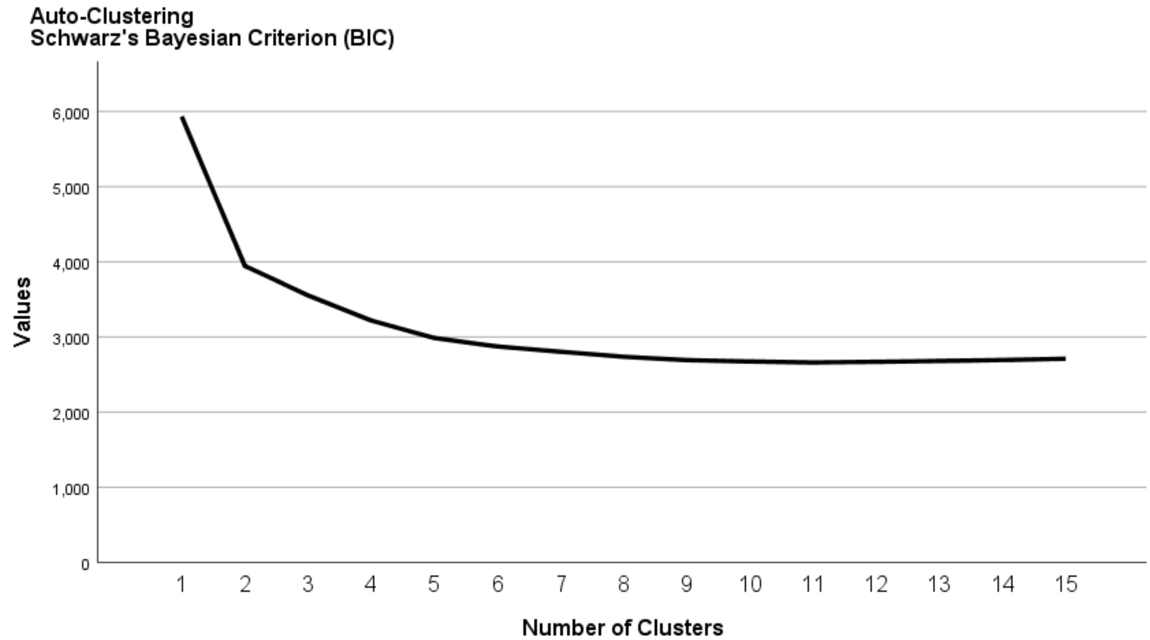


Figure 5. MOOC 2's BIC values for different cluster solutions.

Thus, both MOOCs were examined with the fixed cluster setting at 3,4, and 5 clusters after determining the evidence of minimal differences in distance and after considering the argument that lower BIC alone was "not worth the increased complexity (diminution of parsimony)" (Garson, 2012, p.81). The final cluster 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 cluster to smallest cluster) < 3, while still being interpretable in that it provided more than just a two-cluster solution of completers and non-completers. For MOOC 1, the 4- and 5-cluster solutions were discarded due to sub-optimal quality criterion. The 4-cluster solution had a "fair" .4 silhouette measure (optimal would be >6) and a large ratio of 25.7 (optimal would be <3). The 5-cluster had a "good" silhouette of .6 but was also discarded due to its high ratio of 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 acceptable quality criterion with the "good" silhouette measure of .6 and a ratio of sizes (largest cluster to smallest cluster) of 3.0. 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 .7 but had a high ratio of 23.33. The 5-cluster solution also had a "good" silhouette of .8 but had a high ratio of 24.86. Just as with MOOC 1, MOOC 2's optimal cluster 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 .5 and a ratio of sizes of 2.90. Had the results of auto-cluster, 2-cluster solutions been retained, fine-grained information on non-completers would not have been achieved. As stated previously, one of the calls for more research in this domain focused on learning more about non-completers (Khalili & Ebner, 2014; Tamburri, 2012). To support such exploratory clustering methodology, one must consider other distance measures specific to different clustering programs: "The researcher is encouraged to explore alternative cluster solutions obtained when using different distance measures in an effort to best represent the underlying data patterns" (Hair et al., 2015, p. 432).

Quality assessment. Quality was assessed with examination of the silhouette coefficient and ratio of sizes of largest cluster to smallest cluster. Additionally, cluster quality was assessed with five one-way ANOVAs using cluster assignment as the single independent variable and the five continuous clustering variables as the dependent variable. The five continuous clustering variables were: Mandatory Discussion Posts, Optional Discussion Views, Webinar 1 Views, Quiz 1 Attempts, and Quiz 2 Attempts.

Examination of cluster differences. To examine differences of clusters across all variables, descriptive statistics of clusters on days of activity, on RQ1 clustering engagement variables, and on RQ2 survey attributes were calculated.

Reliability and validity of clusters. Since clustering algorithms are known to produce clusters even when no natural groups exist, it was critical to validate cluster solutions for meaningfulness. Prior to validation, reliability must be assessed by examining the stability of cluster solutions by applying multiple algorithms and comparing results or by splitting a sample and comparing cluster solutions (Balijepally, Mangalaraj, & Iyengar, 2011). Reliability was assessed through comparison of the two MOOC classes. Validity was assessed through a check on external validity by comparison of alignment and number and attributes of clusters with what is already established in the literature. Cluster structure verification was conducted by examination of group means across clusters (Antonenko et al., 2012) to confirm significant variation between clusters. Finally, cluster validation was completed by splitting the sample in half to evaluate whether or not solutions were similar in size and characteristics to the final solution obtained with the full sample (Hair et al., 2015). Split files did in fact accurately represent the final three cluster solution, with only minor difference identified.

RQ 2. The second research question, "Based on demographics, days of participation, and course achievement, what are the differences between engagement subgroups?" was explored through ANOVA and Chi-Square analysis. Analysis for RQ2 was conducted to characterize the determined engagement subgroups (clusters) from RQ 1 across the attributes in Table 6.

Table 6

Attributes of Engagement Subgroups (RQ 2)

Attribute	Type	Categories	Source
Age	categorical	13-18, 19-24, 25-34, 35-44, 45-54, 55-64, 65+	Pre-course Survey
Geographic location	categorical	Asia/Pacific, Europe, Latin America, Middle East/North Africa, North America, Sub-Saharan Africa	Pre-course Survey
Education level	categorical	drop-in, passive, active, observer	Pre-course Survey
Employment in aviation industry	categorical	yes or no	Post-course Survey
Intent (to participate)	categorical	drop-in, passive, active, observer	Pre-course Survey
Days of activity	continuous	0 to 14	Canvas LMS
Total quiz score	continuous	0 to 200	Canvas LMS
Record of completion	categorical	yes or no	Canvas LMS

Differences in cluster membership for the categorical variables (age (year bins), geographic area, education, employment, intent, record of completion) were evaluated with five separate Chi-Square tests of independence. Cluster membership served as the independent variable, while age, geographic area, education, employment, intent, and record of completion served as the dependent variables. Differences in cluster membership and the continuous variable days of activity, calculated by taking the difference in days between course start and last date of activity prior to or on the course end date, was examined using ANOVA. Cluster membership served as the independent variable, and days of activity served as the dependent variable. Differences in cluster membership for the continuous variable of final grade were examined with ANOVA preceded by Levene's test or with Kruskal-Wallis test, if assumptions for ANOVA are not met.

Assumptions for ANOVA.

1. Experimental errors are normally distributed – or sample sizes are sufficient $N \geq 25$.
2. Equal variances between treatments – Levene's.
3. Samples are independent.

Assumptions for chi-square independence test (McHugh, 2013).

1. Data is in frequencies, counts, or counts of cases, not percentages or transformed data.
2. Categories or levels of the variable are mutually exclusive. A subject can fit into only one category.
3. Each subject can contribute to data in only one cell in the X^2.
4. Study groups are independent.
5. There are two variables, both measured as categories, usually nominal.
6. Value of cell meets specified expectations / sample size equals at least the number of cells multiplied by 5.

Ethical Considerations

Approval for this study was obtained through Embry-Riddle Aeronautical University's Institutional Review Board (IRB) and from the Canvas Network platform host, Instructure (See Appendix A). This study met the research requirements set forth by the Canvas Network. Canvas Network and Instructure adhere to legal privacy and acceptable use policies (Instructure, 2018a,b) to which all students in the dataset provided consent when they enrolled in the MOOC. Existing data from pre-course surveys also comprised this data set. Pre-course surveys were voluntary in nature, and data were collected with consent within the Canvas Network platform. Data security was handled in accordance with best practices for electronic data (University of California, 2019).

Summary

This study took a quantitative, person-centered approach, through cluster analysis, to better understand behaviors of emergent subpopulations. This approach utilized two-step cluster analysis 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 hierarchical clustering method was selected based on the lack of a theoretical rationale for predicting the number of clusters and based on strong recommendation in other engagement research (Ferguson et al., 2015). This chapter described the population, sample, and data analysis procedures for selecting cluster solutions and assessing quality, reliability, and validity. The next chapter will report the results of these analyses.

CHAPTER IV

RESULTS

As described, variables of engagement in discussions, videos, and assessments were proposed based on literature and theory for use in clustering. For the first research question, clustering was conducted to determine if subpopulations of MOOC students existed. For the second research question, ANOVAs and Chi-Square analyses were conducted to examine cluster differences across key attributes. The two MOOCs were analyzed separately, in order of size, with the smaller one first.

Data Preparation

For the first MOOC analyzed, there were 1,032 cases (students who registered for the course), of which 532 students had course content activity (one day or greater). These 532 cases were initially retained for analysis. For the second MOOC analyzed, there were 4,037 cases (students who registered for the course), of which 1,796 had course content activity (one day or greater). These 1,796 cases were initially retained for analysis. Data to be used in the cluster analysis had no missing values. All variables were simple counts. By design, the LMS assigns nothing to a person that never clicks on a video or makes a discussion post. During data cleaning, zeros were filled in for these data points where the LMS recorded no click or post.

Initial correlation analysis (Pearson's two-tailed) was conducted on the candidate clustering variables (Discussion Posts/Views, Video Views, Quiz Attempts) to determine if the variables were suitable for use in cluster analysis. Cluster analysis can be performed on correlated data, but it is recommended that high correlations, above .8, be considered for removal or retention based on theoretical or empirical necessity of the variable and whether or not another variable, or a composite, can more parsimoniously represent the data (Hair et al., 2015; Sambandam, 2003). In this case, a remedy for highly correlated variables is to simply delete a highly correlated variable and retain one that is most practically useful. Table 7 explains the transformation from initial proposed variables to a more parsimonious set of variables. Some variables were reduced due to multicollinearity issues. Previous literature and slight differences in MOOC content also influenced final variable selection.

Table 7

Variable Reduction Detail

Initial Variable Names / Details	Final Variable Name / Changes
Mandatory Discussion Views / Posts Planning Considerations National Airspace System (NAS)	**Mandatory Discussion Posts** Variables reduced to only posts.
Optional Discussion Views and Posts Introduction Ask the Expert - Miscellaneous Ask the Expert - Operations Ask the Expert - Systems Ask the Expert - Regulations	**Optional Discussion Views** Variables were reduced to only views. This new variable was consistent with other studies (Khalil & Ebner, 2014; Kovanovic, 2017). One additional optional discussion was included for the first (smaller) MOOC (the discussion on the Trusted Operator Program). This discussion was not available for inclusion in the second MOOC. Ask the Expert Operations - Europe version was added for the second, larger MOOC. This was not available for the smaller MOOC.
Video Page Views Webinar 1 AUVSI Trusted Operator Program Webinar 2 Canberra UAVs Webinar 3 Systems Engineering	**Webinar 1 or Webinar Views** Variables were reduced to only Webinar 1 views for first (smaller) MOOC, and to the only webinar variable possible in the second (larger) MOOC, a single page that held links to all webinars. The variable counts included the actual webinar link views and recorded webinar link views.
Quiz Attempts	**Quiz 1 Attempts** **Quiz 2 Attempts**

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

For the final variables, correlations and VIFs were examined for suitability in cluster analysis. For the first MOOC, final correlations were acceptable as all were low to moderate, and VIFs (shown in Table 8) were all acceptable (below 10), ranging from 1.028 to 3.255.

Table 8

Coefficients for Clustering Variables in MOOC 1

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
Constant	72.326	1.271		56.883	0.000		
Mand. Disc. Posts	29.019	2.239	0.304	12.963	0.000	0.307	3.255
Opt. Disc. Views	33.993	1.952	0.384	17.412	0.000	0.348	2.874
Webinar Views	1.487	1.988	0.010	0.748	0.455	0.973	1.028
Quiz 1 Attempts	5.661	2.617	0.032	2.163	0.031	0.780	1.283
Quiz 2 Attempts	36.308	2.555	0.339	14.208	0.000	0.298	3.356

Examination for multivariate outliers with Mahalanobis showed an unacceptably high maximum Mahalanobis distance. The value recommended for outlier removal was 20.52 based on degrees of freedom or five predictors in the model (Hadi, 1992). Outliers were removed by selecting cases with *p* values below .001 (*p* values of the right tail of the Mahalanobis distance variable), which were calculated using accumulative distribution function for Chi-Square. Table 9 shows residuals for the remaining 457 cases. A Mahalanobis distance (25.929) as close to the recommended level as possible was achieved. According to Hair et al., (2015) “outliers may be only an undersampling of divergent groups that, when discarded, introduce bias in the estimation of structure” (p. 437). Further removal of outliers to achieve smaller Mahalanobis distance was not conducted as it was deemed detrimental to the quality of the model in both average silhouette value and ratio of sizes value.

Table 9

Residuals for Clustering Variables in MOOC 1

	Minimum	Maximum	Mean	St. Dev.	*N*
Predicted Value	1.21	304.38	59.17	80.344	457
Std. Predicted Value	-0.721	3.052	0.000	1.000	457
Std. Error of Predicted Value	1.446	5.647	2.423	1.106	457
Adjusted Predicted Value	1.22	309.18	59.26	80.531	457
Residual	-104.380	80.942	0.000	23.111	457
Std. Residual	-4.492	3.483	0.000	0.995	457
Stud. Residual	-4.594	3.495	-0.002	1.006	457
Deleted Residual	-109.184	81.481	-0.089	23.668	457
Stud. Deleted Residual	-4.700	3.539	-0.002	1.014	457
Mahal. Distance	0.767	25.929	4.989	5.773	457
Cook's Distance	0.000	0.162	0.004	0.015	457
Centered Leverage Value	0.002	0.057	0.011	0.013	457

For the second MOOC, a correlation check on the final clustering variables showed variables were acceptable for cluster analysis, as all were low to moderate. Examination for multivariate outliers with Mahalanobis yielded an unacceptably high maximum Mahalanobis distance, and outliers were removed using the same technique as was used in the first data set. After outliers were removed, 1691 cases remained. Maximum VIF was acceptable at 2.324, as shown in Table 10.

Table 10

Coefficients for Clustering Variables in MOOC 2

	Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
Constant	5.478	0.171		31.961	0.000		
Mand. Disc. Posts	1.045	0.117	0.293	8.895	0.000	0.43	2.324
Opt. Disc. Views	0.137	0.026	0.121	5.386	0.000	0.921	1.086
Webinar Views	0.137	0.102	0.035	1.341	0.180	0.674	1.485
Quiz 1 Attempts	0.382	0.093	0.105	4.112	0.000	0.718	1.393
Quiz 2 Attempts	0.333	0.177	0.061	1.877	0.061	0.442	2.261

Maximum Mahalanobis distance, shown in Table 11, was 32.942. While this was above the critical value recommended for outlier removal based on degrees of freedom or five predictors in the model (20.52) (Hadi, 1994), additional iterations to achieve acceptable critical value did not improve, but rather worsened the quality of model in both average silhouette value and ratio of sizes value. To avoid the “bias in estimation of structure” (Hair et al., 2015, p. 437) caused by further removal of outliers, only two iterations of outlier removal were conducted (as opposed to six iterations and a reduced *N* of 1625 it would have required to achieve a Mahalanobis distance of less than or equal to the recommended 20.52).

Table 11

Residuals for Clustering Variables in MOOC 2

	Minimum	Maximum	Mean	St. Dev.	*N*
Predicted Value	5.478	13.919	8.365	1.7988	1691
Std. Predicted Value	-1.605	3.087	0.000	1.000	1691
Std. Error of Predicted Value	0.102	0.488	0.193	0.070	1691
Adjusted Predicted Value	5.459	13.988	8.366	1.8002	1691
Residual	-11.0855	8.3848	0.0000	3.4377	1691
Std. Residual	-3.220	2.435	0.000	0.999	1691
Stud. Residual	-3.228	2.438	0.000	1.000	1691
Deleted Residual	-11.1444	8.4031	-0.0008	3.4496	1691
Stud. Deleted Residual	-3.237	2.442	0.000	1.001	1691
Mahal. Distance	0.494	32.942	4.997	4.932	1691
Cook's Distance	0.000	0.016	0.001	0.001	1691
Centered Leverage Value	0.000	0.019	0.003	0.003	1691

MOOC Demographics

Demographics for age (Table 12), education (Table 13), and geographic location (Table 14) on survey respondents in both MOOCS are shown below.

Table 12

MOOC Demographics for Age

	MOOC 1 Responders *N* = 296		MOOC 2 Responders *N* = 1015	
	Freq.	%	Freq.	%
13-18	23	7.8%	101	10.0%
19-24	27	9.1%	78	7.7%
25-34	87	29.4%	152	15.0%
35-44	68	23.0%	177	17.4%
45-54	50	16.9%	206	20.3%
55-64	34	11.5%	192	18.9%
65+	7	2.4%	109	10.7%
N	296		1015	

Table 13

MOOC Demographics for Education

	MOOC 1 Responders $N = 297$		MOOC 2 Responders $N = 1083$	
	Freq.	%	Freq.	%
None of these	9	3.0%	22	2.0%
HS or College Prep	28	9.4%	148	13.7%
Some College	51	17.2%	193	17.8%
Completed 2-yr College	41	13.8%	122	11.3%
Completed 4-yr College	61	20.5%	280	25.9%
Some Graduate School	28	9.4%	66	6.1%
Master's Degree	70	23.6%	215	19.9%
Ph.D., J.D., or M.D.	9	3.0%	37	3.4%
N	297		1083	

Table 14

MOOC Demographics for Geographic Location

	MOOC 1 Responders $N = 298$		MOOC 2 Responders $N = 1081$	
	Freq.	%	Freq.	%
Asia / Pacific	38	12.8%	48	4.4%
Europe	25	8.4%	40	3.7%
Latin America	24	8.1%	73	6.8%
Middle East / North Africa	12	4.0%	18	1.7%
North America	169	56.7%	874	80.9%
Sub-Saharan Africa	30	10.1%	28	2.6%
N	298		1081	

RQ 1: Two-Step Cluster to Determine Subgroups

The first RQ was: "Based on engagement in course discussions, videos, and assessments, what distinct subgroups of students exist in an aviation-related MOOC?" Variables were standardized to *Z*-scores prior to the analysis. The hierarchical algorithm used to divide the pre-clusters into subgroups was the distance measure, Log-likelihood, which determines cluster distance or similarity. Although often the Log-likelihood measure is advised for analyzing both continuous or categorical variables or when allowing the number of clusters to be determined automatically, the Euclidian distance, normally employed when specifying fixed number of clusters, did not yield an interpretable solution. Some iterations of cluster analysis returned unclear subgroups or two cluster results that were not interpretable given the aims of this research to learn more about the students who did not complete the course. Thus, cluster solutions using auto-cluster were not retained (e.g., solutions with only two groups: completers and non-completers) and two variables (Mandatory Discussion Views, Optional Discussion Posts) were removed. For both MOOCs, the best cluster solution was obtained using Log-likelihood and a specified fixed 3-cluster setting. The criteria used for best cluster was a solution which was as close as possible to silhouette > 0.6, ratio of sizes < 3, and a solution that was interpretable in that it provided more than just a two-cluster solution of completers and non-completers.

MOOC 1 cluster results. The final three-cluster solution from the 457 cases in the first MOOC yielded a silhouette coefficient, an index of cluster quality, of .6, which was annotated in the good range (Norusis, 2012). The ratio of sizes of largest cluster to smallest cluster was 3 which is considered on the upper edge of acceptable (Larose, 2015). It is noted that having a higher ratio is not unusual in studies where online community participation is a variable (van Osch & Bulgurcu, 2016; Kuk, 2006). The expected unequal distribution in participation from online participants documented in the literature has been used as a rationale for higher than ideal ratio. As shown in Table 17, the suitability of the cluster solution was confirmed with ANOVAs showing the clustering variables varied significantly among clusters.

Cluster 1. This cluster (*N* = 222, labeled "Low Engagers" 48.6% of cases) was below the mean on Mandatory Discussion Posts and Quiz Attempts, well below the mean on Webinar 1 Views, and only slightly below the mean on Optional Discussion Views. This cluster had a mean of 3.23± 3.325 days of activity, and no students finished the course.

Cluster 2. This cluster (*N* = 74, labeled "Moderate Engagers" 16.2% of cases) was below the mean on Mandatory Discussion Posts and Quiz Attempts, well above the mean on Webinar Views, and barely above the mean on Optional Discussion Views. This cluster had a mean of 4.16± 3.811 days of activity, and no students finished the course.

Cluster 3. This cluster (*N* = 161, labeled "High Engagers" 35.2 % of cases) was above the mean on Mandatory Discussion Posts and Quiz Attempts, slightly below the mean on Webinar 1 Views, and above the mean on Optional Discussion Views. This cluster had a mean of 9.21± 4.294 days of activity. In this cluster, 101 (62.7%) finished the course, and 60 (37.4%) did not finish the course.

A graphical presentation of each cluster's size distribution and average *Z*-scores across each clustering variable are shown in Figure 6 and Figure 7. Means of raw values of clustering variables are shown in Table 15. Predictor importance order (for determining cluster assignment) in MOOC 1 was Mandatory Discussions, Quiz 1 Attempts, Quiz 2 Attempt, Webinar 1 Views, Optional Discussion Views.

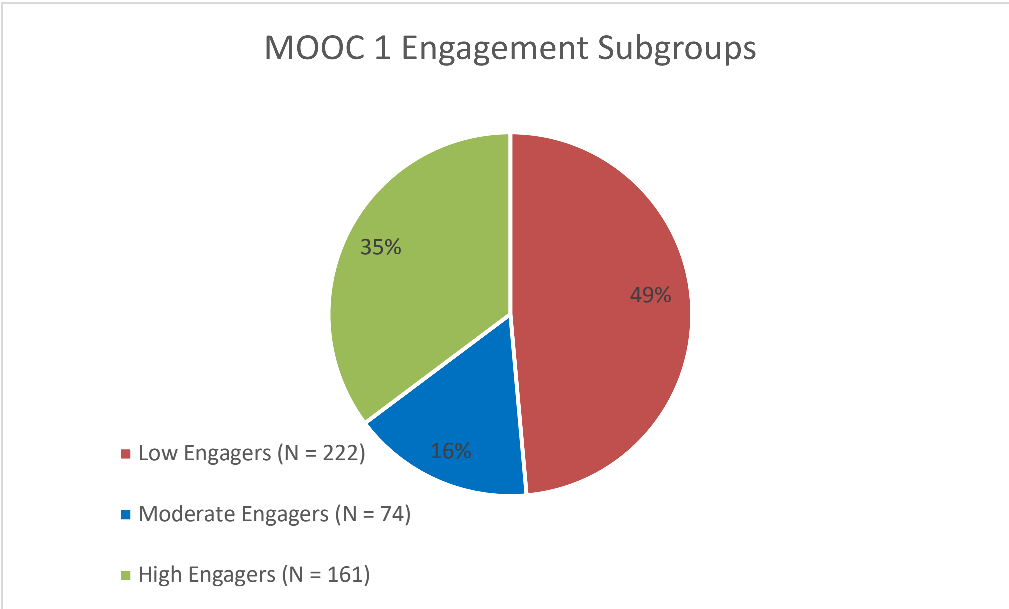


Figure 6. Distribution of MOOC 1 engagement subgroups.

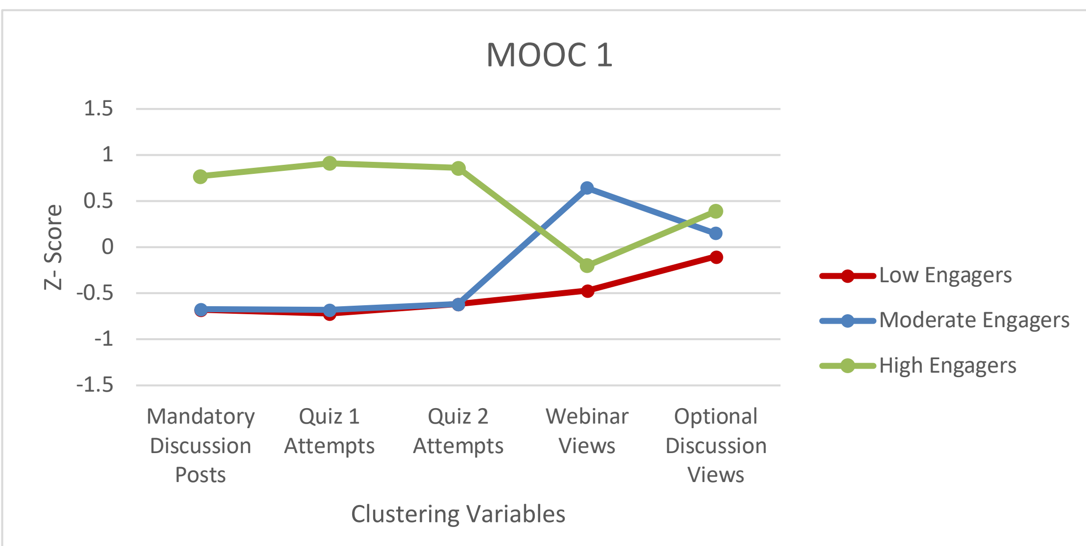


Figure 7. Z-scores of clustering variables for MOOC 1 clusters. Z-score means for each cluster show how far each cluster was (how many standard deviations) above or below the overall sample mean. Zero represents the mean.

Table 15

Descriptive Statistics for MOOC 1 Clusters on Clustering Variables

		N	Mean	Median	*SD*	Min	Max
Mandatory Discussion Posts	Low Engagers	222	0.04	0.00	0.19	0	1
	Moderate Engagers	74	0.05	0.00	0.23	0	1
	High Engagers	161	2.27	2.00	0.88	1	5
Optional Discussion Views	Low Engagers	222	1.94	1.00	1.81	0	8
	Moderate Engagers	74	3.57	2.00	3.78	0	15
	High Engagers	161	5.16	4.00	3.09	1	18
Webinar Views	Low Engagers	222	0.00	0.00	0.00	0	0
	Moderate Engagers	74	1.55	1.00	0.91	0	4
	High Engagers	161	0.37	0.00	0.72	0	3
Quiz 1 Attempts	Low Engagers	222	0.02	0.00	0.13	0	1
	Moderate Engagers	74	0.07	0.00	0.30	0	2
	High Engagers	161	1.84	2.00	0.74	0	4
Quiz 2 Attempts	Low Engagers	222	0.00	0.00	0.00	0	0
	Moderate Engagers	74	0.00	0.00	0.00	0	0
	High Engagers	161	1.20	1.00	0.85	0	3

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

MOOC 2 Cluster Results. The final three-cluster solution from the 1691 cases retained for the second MOOC yielded a silhouette coefficient, an index of cluster quality, of .5, which was annotated at the lower bound of the good range (Norusis, 2012). The ratio of sizes of largest cluster to smallest cluster was 2.90 which is considered acceptable (Larose, 2015). As shown in Table 18, the suitability of the cluster solution was confirmed with ANOVAs showing the clustering variables varied significantly among clusters. The solution is reported as follows.

Cluster 1. This cluster (*N* = 425, labeled “Low Engagers” 25.1% of cases) was well below the mean on Mandatory Discussion Posts, Quiz Attempts, and Webinar Views, and was below the mean on Optional Discussion Views. Low Engagers had a mean of 5.664 ± 3.4964 days of activity. This cluster had 100% students who did not finish the course.

Cluster 2. This cluster (*N* = 325, labeled "Moderate Engagers" 19.2% of cases) was above the mean on Quiz 1 Attempts, well below the mean on Quiz 2 Attempts, below the mean on Mandatory Discussion Posts, very close to the mean on Webinar Views, and below the mean on Optional Discussion Views. Students in Moderate Engagers had a mean of 7.577 ± 3.7977 days of activity. This cluster had 324 (99.7%) students who did not complete the course and 1 (.3%) student who completed the course.

Cluster 3. This cluster (*N* = 941, labeled "High Engagers" 55.6 % of cases) was 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. Students in this cluster had a mean of 9.858± 3.2915 days of activity. In this cluster, 764 (81.2%) students finished the course, and 177(18.8%) students did not finish the course. A graphical presentation of each cluster's size distribution and average *Z*-scores across each clustering variable are shown in Figure 8 and Figure 9.

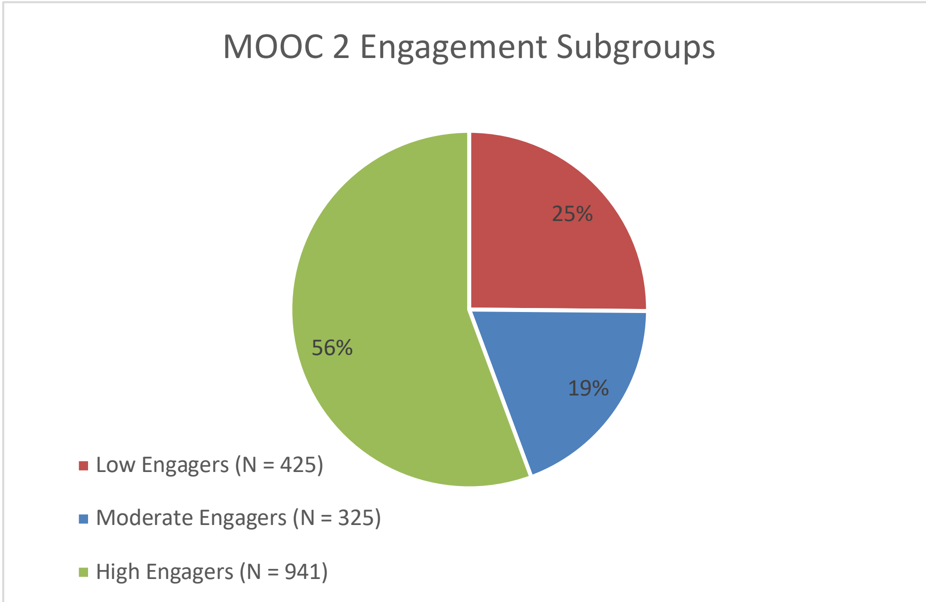


Figure 8. Distribution of MOOC 2 engagement subgroups

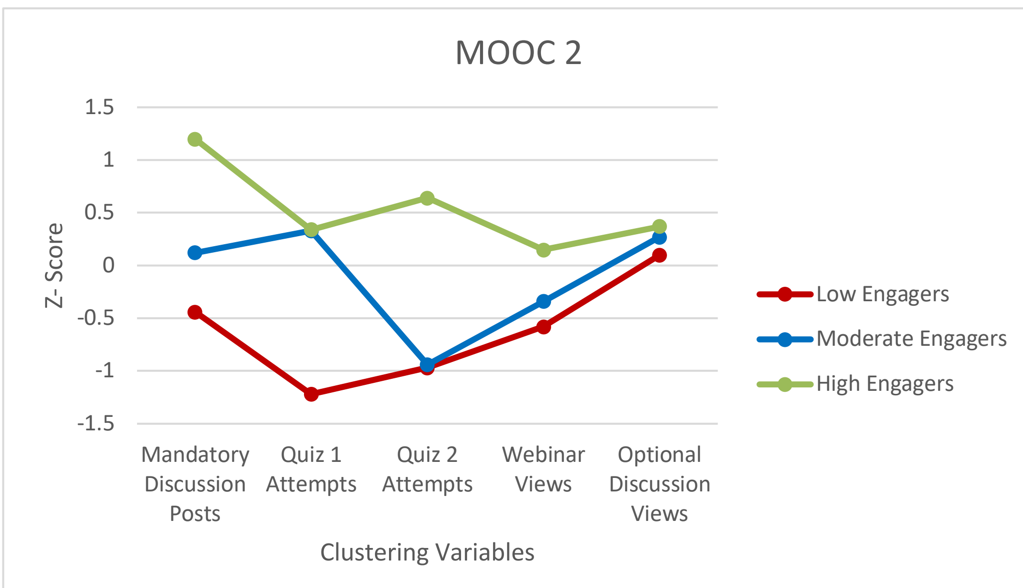


Figure 9. Z-scores of clustering variables for MOOC 2 clusters. Z-score means for each cluster show how far each cluster was (how many standard deviations) above or below the overall sample mean. Zero represents the mean.

Means of raw values of clustering variables are shown in Table 16. Predictor importance order (for determining cluster assignment) in MOOC 2 was Quiz 2 Attempts, Mandatory Discussion Posts, Quiz 1 Attempts, Webinar Views, and Optional Discussion Views.

Table 16

Descriptive Statistics for MOOC 2 Clusters on Clustering Variables

		N	Mean	Median	*SD*	Min	Max
Mandatory Discussion Posts	Low Engagers	425	0.07	0.00	0.25	0	1
	Moderate Engagers	325	0.79	1.00	0.65	0	3
	High Engagers	941	2.18	2.00	0.63	1	5
Optional Discussion Views	Low Engagers	425	2.97	2.00	2.03	0	11
	Moderate Engagers	325	4.01	3.00	3.07	0	19
	High Engagers	941	4.64	3.00	3.88	0	22
Webinar Views	Low Engagers	425	0.01	0.00	0.10	0	1
	Moderate Engagers	325	0.45	0.00	0.74	0	4
	High Engagers	941	1.36	1.00	0.99	0	5
Quiz 1 Attempts	Low Engagers	425	0.10	0.00	0.30	0	1
	Moderate Engagers	325	1.82	2.00	0.89	0	4
	High Engagers	941	1.83	2.00	0.84	1	5
Quiz 2 Attempts	Low Engagers	425	0.00	0.00	0.00	0	0
	Moderate Engagers	325	0.02	0.00	0.14	0	1
	High Engagers	941	1.23	1.00	0.48	0	3

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

MOOC 1 cluster differences on engagement variables. As described previously, cluster solution quality was examined by comparing the clusters across the engagement variables used to form the cluster solution. 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.

Since the assumption for homogeneity of variance could not be met, Welch's test was used. Significant differences were found for each variable as shown in Table 17.

Table 17

Characteristics of Three Cluster Subgroups for MOOC 1

	Engagement Subgroups								
	Low Engagers *N* = 222		Moderate Engagers *N* = 74		High Engagers *N* = 161		ANOVA		
Dependent Variables	Mean	SD	Mean	SD	Mean	SD	F	Fw	*p*
Mandatory Discussion Posts	0.04	0.19	0.05	0.23	2.27	0.88	F(2,454) = 869.229 Fw(2,454) = 502.282		<.001 <.001
Optional Discussion Views	1.94	1.81	3.57	3.78	5.16	3.09	F(2,454) = 67.036 Fw(2,454) = 72.106		<.001 <.001
Webinar Views *	0.00	0.00	1.55	0.91	0.37	0.72	F(1,233) = 115.968 Fw(1,233) = 97.968		<.001 <.001
Quiz 1 Attempts	0.02	0.13	0.07	0.30	1.84	0.74	F(2,454) = 786.848 Fw(2,454) = 472.897		<.001 <.001
Quiz 2 Attempts	0.00	0.00	0.00	0.00	1.20	0.85			

Note. * Webinar ANOVA between Moderate and High clusters only.

MOOC 1 cluster differences: Mandatory discussion posts. Significant and not-significant differences were observed between clusters for Mandatory Discussion Posts. Moderate Engagers had on average .018 more Mandatory Discussion Posts than Low Engagers (p = .812) (not significant). High Engagers had on average 2.213 more Mandatory Discussion Posts than Moderate Engagers (p < .001). High Engagers had on average 2.231 more Mandatory Discussion Posts than Low Engagers (p < .001).

MOOC 1 cluster differences: Optional discussion views. Significant differences in Optional Discussion Views were observed between all clusters. Moderate Engagers had on average 1.626 more Optional Discussion Views than Low Engagers

(p = .002). High Engagers had on average 1.594 more Optional Discussion Views than Moderate Engagers (p = .005). High Engagers had on average 3.220 more Optional Discussion Views than Low Engagers (p < .001).

MOOC 1 cluster differences: Webinar views. Due to zero variance in Low Engagers, only the Moderate and High Engager clusters were compared on Webinar views with an ANOVA. Significant differences in Webinar Views were found. Moderate Engagers had on average 1.18 more Webinar Views than High Engagers (p < .001).

MOOC 1 cluster differences: Quiz 1 Attempts. Significant and not-significant differences were observed between clusters for Quiz 1 Attempts. Moderate Engagers had on average .050 more Quiz 1 Attempts than Low Engagers (p = .363) (not significant). High Engagers had on average 1.771 more Quiz 1 Attempts than Moderate Engagers (p < .001). High Engagers had on average 1.820 more Quiz 1 Attempts than Low Engagers (p < .001).

MOOC 1 cluster differences: Quiz 2 Attempts. Since Moderate and Low Engagers did not have any variance in Quiz 2 Attempts, the ANOVA could not be completed. Only mean was compared. High Engagers: had on average 1.2 more Quiz 2 Attempts than both Moderate Engagers and Low Engagers.

MOOC 2 cluster differences on engagement variables. Replicating the procedure used on 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. Since the assumption for homogeneity of variance could not be met, Welch’s test was used. Significant differences were found for each of the variables in MOOC 2, confirming the quality of the cluster solution. These findings are reported in Table 18.

Table 18

Characteristics of Three Cluster Subgroups for MOOC 2

	Engagement Subgroups							
	Low Engagers $N = 425$		Moderate Engagers $N = 325$		High Engagers $N = 941$		ANOVA	
Dependent Variables	Mean	SD	Mean	SD	Mean	SD	F F_w	p
Mandatory Discussion Posts	0.07	0.25	0.79	0.65	2.18	0.63	$F(2,1688) = 2285.210$ $F_w(2,1688) = 3947.042$	<.001 <.001
Optional Discussion Views	2.97	2.03	4.01	3.07	4.64	3.88	$F(2,1688) = 36.595$ $F_w(2,1688) = 56.808$	<.001 <.001
Webinar Views	0.01	0.10	0.45	0.74	1.36	0.99	$F(2,1688) = 459.925$ $F_w(2,1688) = 914.258$	<.001 <.001
Quiz 1 Attempts	0.10	0.30	1.82	0.89	1.83	0.84	$F(2,1688) = 477.778$ $F_w(2,1688) = 1931.774$	<.001 <.001
Quiz 2 Attempts *	0.00	0.00	0.02	0.14	1.23	0.48	$F(1,1264) = 2008.076$ $F_w(2,1264) = 4873.192$	<.001 <.001

Note. * Quiz 2 ANOVA between Moderate and High Engagers only.

MOOC 2 cluster differences: Mandatory discussion posts. Significant differences in Mandatory Discussion Posts were found between all clusters. Moderate Engagers had on average .722 more Mandatory Discussion Posts than Low Engagers ($p < .001$). High Engagers had on average 2.119 more Mandatory Discussion Posts than Low Engagers ($p < .001$). High Engagers had on average 1.397 more Mandatory Discussion Posts than Moderate Engagers ($p < .001$).

MOOC 2 cluster differences: Optional discussion views. Significant differences in Optional Discussion Views were found between all clusters. Moderate Engagers had on average 1.039 more Optional Discussion Views than Low Engagers ($p < .001$). High Engagers had on average 1.672 more Optional Discussion Views than Low Engagers ($p < .001$). High Engagers had on average .633 more Optional Discussion Views than Moderate Engagers ($p < .001$).

MOOC 2 cluster differences: Webinar views. Significant differences in Webinar Views were found between all clusters. Moderate Engagers had on average .433 more Webinar Views than Low Engagers ($p < .001$). High Engagers had on average 1.350 more Webinar Views than Low Engagers ($p < .001$). High Engagers had on average .907 more Webinar Views than Moderate Engagers ($p < .001$).

MOOC 2 cluster differences: Quiz 1 Attempts. Significant and not-significant differences in Quiz 1 Attempts were found between clusters. Moderate Engagers had on average 1.722 more Quiz 1 Attempts than Low Engagers ($p < .001$). High Engagers had on average 1.737 more Quiz 1 Attempts than Low Engagers ($p < .001$). High Engagers had on average .015 more Quiz 1 Attempts than Moderate Engagers ($p = .963$) (not significant).

MOOC 2 cluster differences: Quiz 2 Attempts. Since Low Engagers did not have any variance in Quiz 2 Attempts, only Moderate and High Engagers were analyzed in ANOVA. Significant differences in Quiz 2 Attempts between these clusters were found. High Engagers had on average 1.21 more Quiz 2 Attempts than Moderate Engagers ($p < .001$).

RQ 2: Chi-Square and ANOVA to Characterize Subgroups

In answering the first research question, three distinct subgroups of students were found across engagement variables for two aviation-related MOOCs. The second research question aimed to determine differences among engagement subgroups in demographics, days of activity, and achievement. This analysis was conducted using Chi-Square analysis for categorical data (demographics, record of completion) and ANOVA for continuous data (grades, days of activity).

Missing Data Summary

Complete data for days of activity and achievement were available for each student; however, incomplete data were found for the variables associated with the demographic surveys (Age, Education, Location, Intent, and Employment in Aviation Industry). In the smaller MOOC, for all survey items except Employment in Aviation Industry, the approximate percentages each cluster was missing were consistent for most of the selected post-course survey items ("Low Engagers" were missing 42%, "Moderate Engagers" were missing 42%, "High Engagers" were missing 23%). The survey item Employment in Aviation Industry contained so much missing data it was dropped from Chi-Square analysis; only descriptive statistics were reported. This was due to its inclusion on the end of course survey which had an even lower response rate than the demographic survey offered at the beginning. For the second, larger MOOC, the variables had missing data which varied by cluster and survey item. For variables representing attributes Age, Education, and Location, "Low Engagers" were missing 64%, "Moderate Engagers" were missing 55%, and "High Engagers" were missing 17%. For Intent to Participate, Low Engagers were missing 64%, Moderate Engagers were missing 55% and High Engagers were missing 43%. The survey item Employment in Aviation Industry had considerable missing data. Low and Moderate Engagers had 99% and 96% missing data. High Engagers had only 36% missing data with 37 % of respondents answering “yes” and 63% answering “no.”

MOOC 1 Missing Data Analysis

MOOC 1 non-responders and five clustering variables. To determine if there were any known differences between responders and non-responders for the age (pre-course survey) question, five separate one-way ANOVAs were used to compare group (responder versus non-responder) means for each of the five clustering variables in MOOC 1: Summative Mandatory Discussion Posts, Optional Discussion Views, Webinar 1 Views, Quiz 1 Attempts, and Quiz 2 Attempts. Results were split by cluster. No significant differences were found between the responders and non-responders to the survey question on age for all three clusters. This finding was repeated for the responders and non-responders for the education, location, and intent survey items.

MOOC 1 non-responders and course completion. In an attempt to further examine differences between responders and non-responders, the variable Course Completion was examined. Since 100% of the first two clusters (Low Engagers and Moderate Engagers) were non-completers, there were no comparison tests run on those two clusters. For the third cluster (High Engagers), Chi-Square tests were conducted for responders and non-responders against the Course Completion variable. For each type of missing variable, no associations were found between those with the missing data and

Course Completion. Results are as follows: Missing Age: $X^2(1, N = 161) = .48$, $p = .488$; Missing Education: X^2 $(1, N = 161) = .48$, $p = .488$; Missing Location: X^2 $(1, N =161) = .89$, $p = .345$); Missing Intent: $X^2(1, N = 161) = .31$, $p = .580$). Although a fuller understanding of potential non-response bias caused by students who did not respond would assist in interpreting the results of RQ 2 analysis, no further information beyond LMS data traces from course activity was available to analyze. For the information available in MOOC 1, no significant differences were evident.

MOOC 2 Missing Data Analysis

MOOC 2 non-responders and five clustering variables. To determine if there were any known differences between responders and non-responders for the age (pre-course survey) question in MOOC 2, five separate one-way ANOVAs were used to compare group (responder versus non-responder) means for each of the five clustering variables: Mandatory Discussion Posts, Optional Discussion Views, Webinar Views, Quiz 1 Attempts, and Quiz 2 Attempts). Results were split by cluster.

MOOC 2 Missing Age: Low Engagers. No significant differences in five clustering variables (Mandatory Discussion Posts, Optional Discussion Views, Webinar Views, Quiz 1 Attempts, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Age.

MOOC 2 Missing Age: Moderate Engagers**.** There were significant differences in means of Mandatory Discussion Posts between those missing age and not missing age. Those not missing age had more Mandatory Discussion Posts. Because the assumption of homogeneity of variances was not met, Welch’s test was conducted ($F(1,323) = 9.386$, $p = .002$; $Fw(1,323) = 9.283$, $p = .003$.). No significant differences in the remaining four clustering variables (Optional Discussion Views, Webinar Views, Quiz 1 Attempts, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Age.

MOOC 2 Missing Age: High Engagers. There were significant differences in means of Mandatory Discussion Posts between those missing Age and not missing Age. Those not missing Age had more Mandatory Discussion Posts. Because the assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,939) = 10.445$, $p = .001$; $F_w(1,939) = 11.991$, $p = .001$). There were significant differences in means of Optional Discussion Views between those missing Age and not missing Age. Those not missing Age had more Optional Discussion Views ($F(1,939) = 6.469$, $p = .011$). There were significant differences in means of Quiz 1 Attempts between those missing Age and not missing Age. Those missing Age had more Quiz 1 Attempts ($F(1,939) = 3.818$, $p = .020$). No significant differences in the remaining two clustering variables (Webinar Views, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Age.

MOOC 2 Missing Education: Low Engagers. No significant differences in five clustering variables (Mandatory Discussion Posts, Optional Discussion Views, Webinar Views, Quiz 1 Attempts, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Education.

MOOC 2 Missing Education: Moderate Engagers. There were significant differences in means of Mandatory Discussion Posts between those missing Education and not missing Education. Those not missing Education had more Mandatory Discussion Posts. Because the assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,323) = 7.144$, $p = .008$; $F_w(1,323) = 7.076$, $p = .008$). No significant differences in the remaining four clustering variables (Optional Discussion Views, Webinar Views, Quiz 1 Attempts, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Education.

MOOC 2 Missing Education: High Engagers. There were significant differences in means of Mandatory Discussion Posts between those missing Education and not missing Education. Those not missing Education had more Mandatory Discussion Posts. Because the assumption of homogeneity of variances was not met, Welch's test was conducted($F(1,939) = 11.512$, $p = .001$; $F_w(1,939) = 14.439$, $p = .000$). There were significant differences in means of Optional Discussion Views between those missing Education and not missing Education. Those not missing Education had more Optional Discussion Views ($F(1,939) = 13.009$, $p = .000$). There were significant differences in means of Quiz 1 Attempts between those missing Education and not missing Education. Those missing Education had more Quiz 1 attempts. Because of assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,939) = 10.907$, $p = .001$; $F_w(1,939) = 8.165$, $p = .005$). No significant differences in the remaining two clustering variables (Webinar Views, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Education.

MOOC 2 Missing Geographic Location: Low Engagers. No significant differences in five clustering variables (Mandatory Discussion Posts, Optional Discussion Views, Webinar Views, Quiz 1 Attempts, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Geographic Location.

***MOOC 2 Missing Geographic Location: Moderate Engagers*.** There were significant differences in means of Mandatory Discussion Posts between those missing Geographic Location and not missing Geographic Location. Those not missing Location had more Mandatory Discussion Posts. Because the assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,323) = 7.144$, $p = .008$; $F_w(1,323) = 7.076$, $p = .008$). No significant differences in the remaining four clustering variables (Optional Discussion Views, Webinar Views, Quiz 1 Attempts, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Geographic Location.

***MOOC 2 Missing Geographic Location: High Engagers*.** There were significant differences in means of Mandatory Discussion Posts between those missing Geographic Location and not missing Geographic Location. Those not missing Location had more Mandatory Discussion Posts. Because the assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,939) = 11.747$, $p = .000$; $F_w(1,939) = 14.400$, $p = .000$). There were significant differences in means of Optional Discussion Views between those missing Geographic Location and not missing Geographic Location. Those not missing Location had more Optional Discussion Views ($F(1,939) = 12.925$, $p = .000$). There were significant differences in means of Quiz 1 Attempts between those missing Geographic Location and not missing Geographic Location. Those missing Location had more Quiz 1 Attempts. Because the assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,939) = 13.224$, $p = .000$;

$F_w(1,939) = 9.447$, $p = .002$). No significant differences in the remaining two clustering variables (Webinar Views, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Geographic Location.

MOOC 2 Missing Intent to Participate: Low Engagers. No significant differences in five clustering variables (Mandatory Discussion Posts, Optional Discussion Views, Webinar Views, Quiz 1 Attempts, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Intent to Participate.

MOOC 2 Missing Intent to Participate: Moderate Engagers. There were significant differences in means of Mandatory Discussion Posts between those missing Intent to Participate and not missing Intent to Participate. Those not missing Intent had more Mandatory Discussion Posts. Because the assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,323) = 9.386$, $p = .002$; $F_w(1,323) = 9.283$, $p = .003$). No significant differences in the remaining four clustering variables (Optional Discussion Views, Webinar Views, Quiz 1 Attempts, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Intent to Participate.

MOOC 2 Missing Intent to Participate: High Engagers. There were significant differences in means of Mandatory Discussion Posts between those missing Intent to Participate and not missing Intent to Participate. Those not missing Intent had more Mandatory Discussion Posts. Because the assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,939) = 4.508$, $p = .034$; $F_w(1,939) = 4.544$, $p = .033$). There were significant differences in means of Optional Discussion Views between those missing Intent to Participate and not missing Intent to Participate. Those not missing Intent had more Optional Discussion Views. Because the assumption of homogeneity of variances was not met, Welch's test was conducted ($F(1,939) = 15.748$, $p = .000$; $F_w(1,939) = 16.734$, $p = .000$). There were significant differences in means of Quiz 1 Attempts between those missing Intent to Participate and not missing Intent to Participate. Those missing Intent had more Quiz 1 attempts ($F(1,939) = 6.819$, $p = .009$). No significant differences in the remaining two clustering variables (Webinar Views, Quiz 2 Attempts) were found between the responders and non-responders to the survey question on Intent to Participate.

MOOC 2 non-responders and course completion. To further examine differences between responders and non-responders, the variable Course Completion was examined. Since 100% of Low Engagers were non-completers, there were no comparison tests run. In the Moderate Engagers cluster, only one student finished course. This cluster failed the assumption of no more than 20% cells should have expected count of less than five, thus the likelihood ratio was examined, and no significant differences were found.

For the High Engagers cluster, four separate Chi-Square tests were conducted for responders and non-responders against the Course Completion variable. Additionally, expected and observed counts and residuals were examined. For all four survey items, an association was found between responders and non-responders and course completion, as summarized in Table 19. For all four variables, responders (those not missing Age, Education, Geographic Location, or Intent to Participate) were more likely to have completed the course.

Table 19

Non-Response Bias: Differences in Course Completion for MOOC 2

Age	$X^2(1, N = 941) = 57.218, p < .001$
Education	$X^2(1, N = 941) = 95.049, p < .001$
Location	$X^2(1, N = 941) = 92.510, p < .001$
Intent	$X^2(1, \text{N} = 941) = 18.324, p < .001$

Note. High Engager cluster responders on post-course survey items (age, education, location, and intent) were more likely to complete the course. Significance $p < .05$

MOOC 2 non-responders and Days of Activity. To further examine differences between responders and non-responders, the variable Days of Activity was examined. Four separate one-way ANOVA tests were conducted for responders and non-responders against the Days of Activity variable. No significant differences in mean Days of Activity were found between the responders and non-responders to any of the four survey items used in RQ2 (Age, Education, Geographic Location, Intent to Participate).

Missing data analysis conclusions. For MOOC 1, within each cluster, the differences between responders and non-responders were not significant. For MOOC 2, some significant differences were observed in the Moderate and High Engager clusters, as summarized in Table 20. In the Moderate Engagers cluster, the responders tended to have significantly more Mandatory Discussion Posts compared to non-responders. Likewise, in the High Engager cluster, responders had significantly more Mandatory Discussion Posts, but they also had more Optional Discussion views and Course Completions. Finally, High Engager cluster responders were observed to have fewer Quiz 1 Attempts than non-responders.

These findings indicate a non-response bias was present. The results indicating responders were more active in discussions and course completion are logical considering the post-course survey is more likely to be completed by those who stay until the end of the course and see the end-of-course survey prompt. Also, responders may have had fewer Quiz 1 Attempts because if they were serious about completing the course, they were potentially more likely to pass the quiz on their first attempt and not need a second attempt.

Table 20

Non-Response Bias: Summary of Significant Differences for MOOC 2

	Moderate Engagers	High Engagers			
	Mand. Disc. Posts	Mand. Disc. Posts	Opt. Disc. Views	Quiz 1 Attempts	Course Complete
Age Responders (Not Missing Age)	More*	More*	More*	Fewer*	More*
Education Responders (Not Missing Educ.)	More*	More*	More*	Fewer*	More*
Location Responders (Not Missing Loc.)	More*	More*	More*	Fewer*	More*
Intent Responders (Not Missing Intent)	More*	More*	More*	Fewer*	More*

Note. Results from ANOVA and Chi-Square analyses. **p* < .05. Mand. = Mandatory, Disc. = Discussion, Opt. = Optional, Educ. = Education, Loc. = Location.

RQ 2: MOOC 1 Cluster Differences on Age

To find cluster differences across the categorical (age) variable, Chi-Square analysis was conducted after missing data cases were removed. “Low Engagers” (*N* =

222) had 93 cases removed (new $N = 130$). “Moderate Engagers” ($N = 74$) had 31 cases removed (new $N = 43$). “High Engagers” ($N = 161$) had 37 cases removed (new $N = 124$). The first assumption for Chi-Square analysis was that of independence, which the data met. The second assumption was that of expected frequencies have less than 20% of cells with expected count less than 5 in the cross-tabulation on cluster and age. The data as shown in Table 21 could not meet the expected frequencies assumption.

Table 21

Descriptives for MOOC 1 Clusters on Age

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
13-18	9	7.0%	2	4.7%	12	9.7%
19-24	16	12.4%	4	9.3%	7	5.6%
25-34	38	29.5%	14	32.6%	35	28.2%
35-44	27	20.9%	8	18.6%	33	26.6%
45-54	20	15.5%	9	20.9%	21	16.9%
55-64	14	10.9%	5	11.6%	15	12.1%
65+	5	3.9%	1	2.3%	1	0.8%
N	129		43		124	

When this assumption is violated, with data greater than a 2x2 table, data can be collapsed if theoretically sound (Field, 2013). To accomplish this, the two lowest (13-18 and 19-24) and two highest (55-64 and 65+) age brackets were combined in Table 22.

Table 22

Descriptives for MOOC 1 Clusters on Consolidated Age

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
13-24	25	19.4%	6	14.0%	19	15.3%
25-34	38	29.5%	14	32.6%	35	28.2%
35-44	27	20.9%	8	18.6%	33	26.6%
45-54	20	15.5%	9	20.9%	21	16.9%
55+	19	14.7%	6	14.0%	16	12.9%
N	129		43		124	

After consolidation, the Chi-Square test was run. The null hypothesis (H_0) was that there were no significant differences between the cluster groups across the age categories. The *p*-value was greater than the chosen significance level of $\alpha = .05$. No association was found between cluster group and age $X^2(8, N = 296) = 3.1, p = .928$).

RQ 2: MOOC 2 Cluster Differences on Age

To find cluster differences across the categorical (age) variable, Chi-Square analysis was conducted after missing data cases were removed. "Low Engagers" (N = 425) had 270 cases removed (new N = 155). "Moderate Engagers" (N = 325) had 181 cases removed (new N = 144). "High Engagers" (N = 941) had 225 cases removed (new N = 716). The first assumption for Chi-Square analysis was that of independence, which the data met. The second assumption was that of expected frequencies have less than 20% of cells with expected count less than 5 in the cross-tabulation on cluster and age. The data as shown in Table 23 met the expected frequencies assumption.

Table 23

Descriptives for MOOC 2 Clusters on Age

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
13-18	12	7.7%	10	6.9%	79	11.0%
19-24	15	9.7%	3	2.1%	60	8.4%
25-34	28	18.1%	23	16.0%	101	14.1%
35-44	33	21.3%	21	14.6%	123	17.2%
45-54	27	17.4%	33	22.9%	146	20.4%
55-64	29	18.7%	36	25.0%	127	17.7%
65+	11	7.1%	18	12.5%	80	11.2%
N	155		144		716	

The Chi-Square test was run. The null hypothesis (H_0) was that there were no significant differences between the cluster groups across the age categories. The *p*-value was greater than the chosen significance level of $\alpha = .05$. No association was found between cluster group and age $X^2(12, N = 1015) = 20.432$, $p = 0.059$.

RQ 2: MOOC 1 Cluster Differences on Education

To find cluster differences across the categorical (education) variable, Chi-Square analysis was conducted after missing data cases were removed. “Low Engagers” (*N* = 222) had 92 cases removed (new *N* = 130). “Moderate Engagers” (*N* = 74) had 31 cases removed (new *N* = 43). “High Engagers” (*N* = 161) had 37 cases removed (new *N* = 124) as shown in Table 24.

Table 24

Descriptives for MOOC 1 Clusters on Education

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
None of these	3	2.3%	1	2.3%	5	4.0%
HS or College Prep	11	8.5%	2	4.7%	15	12.1%
Some College	26	20.0%	10	23.3%	15	12.1%
Completed 2-yr College	17	13.1%	5	11.6%	19	15.3%
Completed 4-yr College	24	18.5%	9	20.9%	28	22.6%
Some Graduate School	14	10.8%	6	14.0%	8	6.5%
Master's Degree	34	26.2%	8	18.6%	28	22.6%
Ph.D., J.D., or M.D.	1	0.8%	2	4.7%	6	4.8%
N	130		43		124	

Again, assumptions checking for the Chi-Square analysis revealed greater than 20% cells with expected counts less than 5. Thus, education data were collapsed into three suitable categories. The bottom four were combined into a “Less than 4-year degree” category, the next two were combined into a “4-year degree” category, and the final two were combined into a “Graduate degree” category, as shown in Table 25.

Table 25

Descriptives for MOOC 1 Clusters on Consolidated Education

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
Less than 4-Year Degree	57	43.8%	18	41.9%	54	43.5%
4-Year Degree	38	29.2%	15	34.9%	36	29.0%
Graduate Degree	35	26.9%	10	23.3%	34	27.4%
N	130		43		124	

After consolidation, the Chi-Square test was run. The null hypothesis (H_0) was that there were no significant differences between the cluster groups across the education categories. The p-value was greater than the chosen significance level of $\alpha = .05$. No association was found between cluster group and education $X^2(4, N = 297) = .65, p = .957$).

RQ 2: MOOC 2 Cluster Differences on Education

To find cluster differences across the categorical (education) variable, Chi-Square analysis was conducted after missing data cases were removed. Cluster 1 (N = 425) "Low Engagers" had 271 cases removed (new N = 154). Cluster 2 (N = 325) "Moderate Engagers" had 177 cases removed (new N = 148). Cluster 3 (N = 941) "High Engagers" had 160 cases removed (new N = 781). Descriptives are shown in Table 26.

Table 26

Descriptives for MOOC 2 Clusters on Education

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
None of these	3	1.9%	4	2.7%	15	1.9%
HS or College Prep	16	10.4%	16	10.8%	116	14.9%
Some College	25	16.2%	21	14.2%	147	18.8%
Completed 2-yr College	18	11.7%	18	12.2%	86	11.0%
Completed 4-yr College	32	20.8%	40	27.0%	208	26.6%
Some Graduate School	20	13.0%	13	8.8%	33	4.2%
Master's Degree	37	24.0%	27	18.2%	151	19.3%
Ph.D., J.D., or M.D.	3	1.9%	9	6.1%	25	3.2%
N	154		148		781	

Assumptions checking for the Chi-Square analysis revealed less than 20% cells (8.3%) had expected counts less than 5. Thus, Chi-Square analysis assumptions were met, and analysis was conducted. The null hypothesis (H_0) was that there were no significant differences between the cluster groups across the Education categories. The *p*-value was less than the chosen significance level of $\alpha = .05$, thus the null hypotheses was rejected. A significant association was found between cluster group and education ($X^2(14, N = 1083) = 31.044$, $p = 0.005$, Cramer's $V = .120$).

To determine the strength of this association, because the table was greater than 2x2, Cramer's *V* (an extension of Phi φ) was evaluated (Hair et al., 2015; Liebetrau, 1983). Effect sizes (Phi φ) for 1 degree of freedom (d*f*) are defined by Cohen (1988) as small (.10), medium (.30), and large (.50). Effect sizes were modified based on d*f* by dividing Phi φ by the square root of d*f*. This resulted in effect size evaluation guidelines for d*f* = 14 of small (.03), medium (.08), and large (.13). Thus, the effect size for the association between cluster group and education was considered medium (.120).

In a post-hoc analysis, cells in a contingency table (Table 27) were examined for adjusted standardized residuals higher than an absolute value of 1.96 which correspond to z-score values with alpha = .05 (Agresti, 2002). Students from the Low and High Engager clusters show statistically significant differences between expected counts and observed counts in the education category of Some Graduate school. Low Engagers showed a statistically significantly higher than expected proportion of students with Some Graduate education, whereas High Engagers showed a statistically significantly lower than expected proportion of students with Some Graduate education.

Table 27

Differences in MOOC 2 Clusters Across Education Levels

	Low Engagers			Moderate Engagers			High Engagers			
	Observed Count	Expected Count	Adj. Std. Res.	Observed Count	Expected Count	Adj. Std. Res.	Observed Count	Expected Count	Adj. Std. Res.	Total
None	3	3.1	-0.1	4	3	0.6	15	16	-0.4	22
HS or Prep	16	21	-1.3	16	20	-1.1	116	107	1.8	148
Some College	25	27	-0.6	21	26	-1.2	147	139	1.4	193
2-year Degree	18	17	0.2	18	17	0.4	86	88	-0	122
4-year Degree	32	40	-1.6	40	38	0.4	208	202	0.9	280
Some Graduate	**20**	**9.4**	**3.9**	13	9	1.5	**33**	**48**	**-4**	66
Master's Degree	37	31	1.4	27	29	-0.5	151	155	-1	215
Doctoral Degree	3	5.3	-1.1	9	5.1	1.9	25	27	-1	37
N	154			148			781			1083

RQ 2: MOOC 1 Cluster Differences on Geographic Location

To find cluster differences across the categorical (geographic location) variable, Chi-Square analysis was conducted after missing data cases were removed. “Low Engagers” ($N = 222$) had 92 cases removed (new $N = 130$). “Moderate Engagers” ($N = 74$) had 31 cases removed (new $N = 43$). “High Engagers” ($N = 161$) had 36 cases removed (new $N = 125$). Again, assumptions checking for the Chi-Square analysis revealed greater than 20% cells with expected counts less than 5, as shown in Table 28. Thus, Geographic Location data were collapsed into four suitable categories. North America and Latin America were combined into “Americas,” and Middle East/North Africa was combined with Sub-Saharan Africa to “Middle East/Africa” in Table 29.

Table 28

Descriptives for MOOC 1 Clusters on Geographic Location

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
Asia / Pacific	14	10.8%	7	16.3%	17	13.6%
Europe	15	11.5%	2	4.6%	8	6.4%
Latin America	11	8.5%	3	7.0%	10	8.0%
Middle East / North Africa	5	3.8%	2	4.6%	5	4.0%
North America	76	58.5%	23	53.5%	70	56.0%
Sub-Saharan Africa	9	6.9%	6	14.0%	15	12.0%
N	130		43		125	

Table 29

Descriptives for MOOC 1 Clusters on Consolidated Geographic Location

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
Americas	87	66.9%	26	60.5%	80	64.0%
Asia / Pacific	14	10.8%	7	16.3%	17	13.6%
Middle East / Africa	14	10.8%	8	18.6%	20	16.0%
Europe	15	11.5%	2	4.6%	8	6.4%
N	130		43		125	

After consolidation, the Chi-Square test was run. The null hypothesis (H_0) was that there were no significant differences between the cluster groups across the geographic location categories. The *p*-value was greater than the chosen significance level of $\alpha = .05$. No association was found between cluster group and geographic location $X^2(6, N = 298) = 5.9, p = .432$.

RQ 2: MOOC 2 Cluster Differences on Geographic Location

To find cluster differences across the categorical (geographic location) variable, Chi-Square analysis was conducted after missing data cases were removed. “Low Engagers” (*N* = 425) had 271 cases removed (new *N* = 154). “Moderate Engagers” (*N* = 325) had 177 cases removed (new *N* = 148). “High Engagers” (*N* = 941) had 162 cases removed (new *N* = 779). Again, assumptions checking for the Chi-Square analysis revealed greater than 20% cells with expected counts less than 5, as shown in Table 30.

Table 30

Descriptives for MOOC 2 Clusters on Geographic Location

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
Asia / Pacific	13	8.4%	4	2.7%	31	4.0%
Europe	10	6.5%	4	2.7%	26	3.3%
Latin America	17	11.0%	6	4.0%	50	6.4%
Middle East / North Africa	0	0.0%	4	2.7%	14	1.8%
North America	109	70.8%	128	86.5%	637	81.8%
Sub-Saharan Africa	5	3.3%	2	1.4%	21	2.7%
N	154		148		779	

Thus, Geographic Location data were collapsed into four suitable categories as shown in Table 31. North America and Latin America were combined into “Americas,” and Middle East/North Africa was combined with Sub-Saharan Africa to make “Middle East/Africa.”

Table 31

Descriptives for MOOC 2 Clusters on Consolidated Geographic Location

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
Americas	126	81.8%	134	90.5%	687	88.2%
Asia / Pacific	13	8.4%	4	2.7%	31	4.0%
Middle East / Africa	5	3.3%	6	4.1%	35	4.5%
Europe	10	6.5%	4	2.7%	26	3.3%
N	154		148		779	

After consolidation, the Chi-Square test was run. The null hypothesis (H_0) was that there were no significant differences between the cluster groups across the geographic location categories. The *p*-value was greater than the chosen significance level of $\alpha = .05$. No association was found between cluster group and geographic location $X^2(6, N = 1081) = 12.104, p = 0.060$).

RQ 2: MOOC 1 Cluster Differences on Intent to Participate

To find cluster differences across the categorical (intent to participate) variable (shown in Table 32), Chi-Square analysis was conducted after missing data cases were removed. “Low Engagers” (*N* = 222) had 92 cases removed (new *N* = 130). “Moderate Engagers” (*N* = 74) had 31 cases removed (new *N* = 43). “High Engagers” (*N* = 161) had 36 cases removed (new *N* = 125).

Table 32

Descriptives for MOOC 1 Clusters on Intent to Participate

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
Drop-In	13	10.0%	3	7.0%	7	5.6%
Passive Participant	54	41.5%	20	46.5%	43	34.4%
Active Participant	48	37.0%	20	46.5%	64	51.2%
Observer	15	11.5%	0	0.0%	11	8.8%
N	130		43		125	

Assumptions were met, and the Chi-Square analysis was run. The null hypothesis (H_0) was that there were no significant differences between the cluster groups across the intent categories. No association was found between cluster group and intent to participate $X^2(6, N = 298) = 11.1, p = .087$).

RQ 2 MOOC 2 Cluster Differences on Intent to Participate

To find cluster differences across the categorical (intent to participate) variable, Chi-Square analysis was conducted after missing data cases were removed. Table 33 shows “Low Engagers” (*N* = 425) had 270 cases removed (new *N* = 155). “Moderate Engagers” (*N* = 325) had 181 cases removed (new *N* = 144). “High Engagers” (*N* = 941) had 402 cases removed (new *N* = 539).

Table 33

Descriptives for MOOC 2 Clusters on Intent to Participate

	Low Engagers		Moderate Engagers		High Engagers	
	Freq.	%	Freq.	%	Freq.	%
Drop-In	8	5.2%	4	2.8%	29	5.4%
Passive Participant	71	45.8%	56	38.9%	210	39.0%
Active Participant	66	42.6%	81	56.3%	281	52.1%
Observer	10	6.5%	3	2.1%	19	3.5%
N	155		144		539	

Assumptions were met, and the Chi-Square analysis was run. The null hypothesis (H_0) was that there were no significant differences between the cluster groups across the intent categories. The *p*-value was greater than the chosen significance level of $\alpha = .05$. No association was found between cluster group and intent to participate $X^2(6, N = 838) = 10.214, p = 0.116$.

RQ 2: Employment in Aviation Industry

The survey item Employment in Aviation Industry had considerable missing data for both MOOCS. As shown in Table 34, within MOOC 1, Low and Moderate Engagers had 100% missing data on employment. High Engagers had 64% missing data on employment. Of those who responded to this question, 48% said “yes” and 52% said “no” to being employed in the aviation industry. As shown in Table 35, within MOOC 2, Low and Moderate Engagers had 99% and 96% missing data. High Engagers had only 36% missing data with 37 % of respondents answering “yes” and 63% answering “no.”

Table 34

Descriptives for MOOC 1 Clusters on Employment in Aviation Industry

		YES		NO	
	N	Freq.	%	Freq.	%
Low Engagers	0	0	0.0%	0	0.0%
Moderate Engagers	0	0	0.0%	0	0.0%
High Engagers	58	28	48.3%	30	51.7%

Table 35

Descriptives for MOOC 2 Clusters on Employment in Aviation Industry

		YES		NO	
	N	Freq.	%	Freq.	%
Low Engagers	2	0	0.0%	2	100.0%
Moderate Engagers	12	4	33.3%	8	66.7%
High Engagers	607	226	37.2%	381	62.8%

RQ 2: Cluster Descriptives on Activity and Quiz Scores

Data were complete for the following RQ2 Variables: Days of Activity, Total Quiz Score, and Course Completion. Table 36 and Table 37 show descriptive statistics for MOOC 1 and MOOC 2 clusters on Days of Activity and Total Quiz Score.

Table 36

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 37

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.

RQ 2: MOOC 1 Cluster Differences on Days of Activity

To find cluster differences across continuous variable of days of activity (1-14), a one-way ANOVA was conducted. Independence assumption was met. Normality assumption was not necessary due to sample size greater than 25. To check for homogeneity of variance assumption, Levene's test was examined. 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 (2,454) = 123.058, $p < .001$ $F_w(2,454) = 110.293$, $p < .001$).

Post-hoc comparisons using the Games Howell test were carried out. There were significant differences between High and Moderate Engagers ($p < .001$) with High Engagers active on average 5.049 days more than Moderate Engagers. There were significant differences between High and Low Engagers ($p < .001$) with High Engagers active on average 5.986 days more than Low Engagers. There were no significant differences between Moderate Engagers and Low Engagers ($p = .147$) with Moderate Engagers active on average .937 days more than Low Engagers.

RQ 2: MOOC 2 Cluster Differences on Days of Activity

To find cluster differences across continuous variable of days of activity (1-14), a one-way ANOVA was conducted. Assumptions for checking normality (if the dependent variable is normally distributed) involved determining the standardized residuals of the continuous variable and then plotting the residuals on a histogram to evaluate the extent to which they displayed a normal shape. Since the sample sizes in this analysis are all $N \geq 25$, the normality assumption check is not needed due to the central limit theorem. To check for homogeneity of variance, the Levene's test was examined. The assumption for homogeneity of variance was not met. Welch's statistic was used. Significant differences were found between clusters and days of activity ($F(2,1688) = 227.472$, $p < .001$ $F_w(2,1688) = 229.335$, $p < .001$).

Post-hoc comparisons using the Games Howell test were carried out. There were significant differences between High and Moderate Engagers ($p < .001$) with High Engagers active on average 2.28 more days than Moderate Engagers. There were significant differences between High and Low Engagers ($p < .001$) with High Engagers active on average 4.19 more days than Low Engagers. There were significant differences between Moderate and Low Engagers ($p < .001$) with Moderate Engagers active on average 1.91 days more than Low Engagers.

RQ 2: MOOC 1 Cluster Differences on Total Quiz Score

To find cluster differences across continuous variable of total quiz score (0 to 200), a one-way ANOVA was conducted. An assumption check for normality was not necessary due to sample sizes greater than 25. For the homogeneity of variance assumption, Levene's test was significant, thus the assumption of equal variances was not met. The data showed unequal variances and unequal sample sizes. Because the data could not meet normality or homogeneity of variances assumptions, a non-parametric test was required. ANOVA was thus interpreted using the Welch statistic and Games-Howell post-hoc test. Significant differences were found between Cluster membership and Total Quiz score ($F(2,454) = 1304.720$, $p < .001$, $F_w(2,454) = 783.920$, $p < .001$).

Post-hoc comparisons using the Games Howell test were carried out. There were significant differences ($p < .001$) between High Engagers and Moderate Engagers, with High Engagers achieving total quiz scores on average 159.07 points higher than

Moderate Engagers. There were significant differences ($p < .001$) between High and Low Engagers with High Engagers achieving total quiz scores on average 162.088 points higher than Low Engagers. There were no significant differences ($p = .421$) between Moderate and Low Engagers, with Moderate Engagers achieving total quiz scores on average 3.01 points higher than Low Engagers.

RQ 2: MOOC 2 Cluster Differences on Total Quiz Score

To find cluster differences across continuous variable of total quiz score (0 to 200), a one-way ANOVA was conducted. Assumptions for independence and normality were met ($N \geq 25$). Assumptions for homogeneity of variance were not met. Welch's statistic was used. Significant differences were found between clusters and Total Quiz Score ($F(2,1688) = 9488.058$, $p < .001$, $F_w(2,1688) = 10931.434$, $p < .001$).

Post-hoc comparisons using the Games Howell test were carried out. There were significant differences between High and Moderate Engagers ($p < .001$) with High Engagers achieving total quiz scores on average 183.976 points higher than Moderate Engagers. There were significant differences between High and Low Engagers ($p < .001$) with High Engagers achieving total quiz scores on average 104.176 points higher than Low Engagers. There were significant differences between Moderate and Low Engagers ($p < .001$) with Moderate Engagers achieving total quiz scores on average 79.801 points higher than Low Engagers.

RQ 2: MOOC 1 Cluster Differences on Course Completion

Frequency of MOOC 1 course completion by cluster is shown in Table 38. To find cluster differences across the categorical variable: Chi-Square analysis was conducted. The null hypothesis (H_0) was that there were no significant differences between the cluster groups and course completion. The *p*-value was less than the chosen significance level of $\alpha = .05$, thus the null hypotheses was rejected. An association was found between cluster group and course completion $X^2(2, N = 457) = 238.371, p < .001$.

Table 38

MOOC 1 Frequency of Course Completion by Cluster

	N	Frequency	%
Low Engagers	222	0	0%
Moderate Engagers	74	0	0%
High Engagers	161	101	62.7%

Note. N = Number of respondents, % = Percentage

To determine the strength of this association, because the table was greater than 2x2 whereby Phi would be used, Cramer's *V* (an extension of Phi φ) was evaluated (Hair et al., 2015; Liebetrau, 1983). Effect sizes were modified based on d*f* by dividing Phi φ by the square root of d*f*. The effect size was large (.722) (Cohen, 1988).

In a post-hoc analysis, cells in contingency table (Table 39) were examined for adjusted standardized residuals higher than an absolute value of 1.96 which correspond to z-score values with alpha = .05 (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.

Table 39

Differences in MOOC 1 Clusters for Course Completion

		Did Not Complete	Complete	Cluster *N*
Low Engagers	Observed Count	222	0	222
	Expected Count	172.9	49.1	222
	Adj. Std. Residual	**11.1**	**-11.1**	
Moderate Engagers	Observed Count	74	0	74
	Expected Count	57.6	16.4	74
	Adj. Std. Residual	**5.0**	**-5.0**	
High Engagers	Observed Count	60	101	161
	Expected Count	125.4	35.6	161
	Adj. Std. Residual	**-15.4**	**15.4**	
	Completion Total	356	101	457

RQ 2: MOOC 2 Cluster Differences on Course Completion

Frequency of MOOC 2 course completion by cluster is shown in Table 40. To find cluster differences across the categorical variable, Chi-Square analysis was conducted. Assumptions were met. The null hypothesis (H_0) was that there were no significant differences between the cluster groups and course completion. The *p*-value was less than the chosen significance level of $\alpha = .05$, thus the null hypothesis was rejected. An association was found between cluster group and course completion ($X^2(2, N = 1691) = 1106.891, p < .001$). To determine the strength of this association, Cramer's V was examined (Hair et al., 2015). The effect size was large (.809).

Table 40

MOOC 2 Frequency of Course Completion by Cluster

	N	Frequency	%
Low Engagers	425	0	0%
Moderate Engagers	325	1	0.3%
High Engagers	941	764	81.2%

Note. N = Number of respondents, % = Percentage

In a post-hoc analysis, cells in contingency table (Table 41) were examined for adjusted standardized residuals higher than an absolute value of 1.96. Low and Moderate Engagers showed a statistically significantly higher than expected proportion of students did not complete the course. The High Engagers cluster showed a statistically significantly higher than expected proportion of students did complete the course.

Table 41

Differences in MOOC 2 Clusters for Course Completion

		Did Not Complete	Complete	Cluster *N*
Low Engagers	Observed Count	425	0	425
	Expected Count	232.7	192.3	425
	Adj. Std. Residual	**21.7**	**-21.7**	
Moderate Engagers	Observed Count	324	1	325
	Expected Count	178.0	147.0	325
	Adj. Std. Residual	**18.1**	**-18.1**	
High Engagers	Observed Count	177	764	941
	Expected Count	515.3	425.7	941
	Adj. Std. Residual	**-33.3**	**33.3**	
	Completion Total	926	765	1691

Summary

The analytical results reported in this chapter include the two-step cluster analysis of engagement variables to determine engagement subpopulation and subsequent analysis of survey data and performance (Chi-Square and ANOVA) to determine attributes of the subpopulations. The cluster analyses revealed three significantly different subgroups for each MOOC. Engagement patterns were similar between MOOCs for the most and least engaged groups, but differences were noted in the middle group; MOOC 1's middle group had a broader interest in optional content (both in discussions and videos), whereas MOOC 2's middle group had a narrower interest in optional discussions. Mandatory items (Mandatory Discussion or Quizzes) were the best predictors in classifying subgroups for both MOOCs. In the subsequent analyses to determine engagement subgroup attributes and differences, significant associations were found between subgroups and education levels, days of activity, total quiz scores, and course completion. The next chapter discusses the engagement subgroups in further detail with attention to existing literature and empirical data and provides theoretical and practical implications. Finally, limitations and recommendations for future research are presented.

CHAPTER V

DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

The purpose of this study was to expand the current understanding of learner engagement in aviation-related Massive Open Online Courses (MOOCs). The method employed was cluster analysis using theory and literature supported variables. There were two research questions that guided this study. The first question asked whether distinct subgroups of students exist in an aviation-related MOOC, based on engagement in course discussions, videos, and assessments. The second question explored the differences among engagement subgroups, based on demographics, days of participation in the course, and achievement. A summary and discussion of the results is presented for each research question. Next, conclusions, including theoretical and practical implications, are discussed. Finally, limitations and recommendations for future research and practice are presented.

Summary and Discussion of RQ 1 Results

RQ 1 asked whether distinct subgroups of students exist in an aviation-related MOOC, based on engagement in course discussions, videos, and assessments. Three distinct subgroups of students with statistically significant differences in engagement variables were found for two aviation-related MOOCs. Although the MOOCs were essentially the same course, there were slight differences in content and arrangement of the content, necessitating separate analysis.

MOOC 1 Clusters

For the smaller MOOC, (N = 457) three subgroups of students were found: Low Engagers (N = 222), Moderate Engagers (N = 74), and High Engagers (N = 161). The most important predictor for determining cluster assignment was Mandatory Discussions, followed by Quiz 1 Attempts, Quiz 2 Attempts, Webinar 1 Views, and finally, Optional Discussion Views.

Low Engagers. This cluster ($N = 222$) represented 48.6% of the cases analyzed for MOOC 1. None of the students in this cluster completed the course. This cluster was designated Low Engagers because it was below the mean on all engagement variables, and its students had the lowest mean days of activity (three days) of all the clusters.

Moderate Engagers. This cluster ($N = 74$) represented 16.2% of the cases analyzed for MOOC 1. Like the Low Engagers, none of the students in this cluster completed the course. Moderate Engagers were below the overall sample mean of Mandatory Discussion Posts and Quiz 1 and 2 Attempts, which is consistent with the finding that the group had no 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 ($N = 161$) represented 35.2% of the cases analyzed for MOOC 1 and had a completion rate of 62%. Students in this cluster were designated High Engagers because they 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 ($N = 101$).

MOOC 2 Clusters

For the larger MOOC (*N* = 1691), three subgroups of students were found: Low Engagers (*N* = 425), Moderate Engagers (*N* = 325), and High Engagers (*N* = 941). 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 (*N* = 425) represented 25.1% of the cases analyzed for MOOC 2. Low Engagers had no course completers. Low Engagers had the lowest means on all engagement variables as well as days of activity (five days).

Moderate Engagers. This cluster (*N* = 325) represented 19.2% of the cases analyzed for MOOC 2 and had 324 (99.7%) students who did not complete the course and 1 (.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 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 (*N* = 941) represented 55.6% of the cases analyzed for MOOC 2 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.

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 in this study consisted of video and optional discussion views, it was notable that for both MOOCs, the moderately engaged cluster was differentiated from the low engaged cluster by an optional content variable. In MOOC 1, the moderate group was above 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 Karpicke and Roediger (2008) and Karpicke and Blunt (2011) also reported similar findings where higher video consumption was correlated with positive learning performance (Tseng et al., 2016). 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 video content in that it was an optional Webinar in this study, where in other studies the variable may have used video content that was mandatory. In the larger sample of MOOC 2, however, the results for video content viewing were similar to findings in the literature. In consideration of the differentiation between low and moderately engaged clusters, as is evident in responses for intent to participate, student motivations seemed to vary from group to group which is a common finding in the literature where intent or motivation is reported to affect attention given to optional content (Kovanović et al., 2015; Wise et al., 2013).

In general, the investigation into what subgroups existed in two aviation-related MOOCs revealed subgroup differences that were less specific than some other reports in the engagement clustering literature. While this study uncovered three distinct subgroups, Kizilcec et al. (2013) found four. In Kizilcec et al.'s (2013) study, a "Completing" group, known for completing most of the assignments and attempting all the assignments, was similar to the High Engager clusters. Likewise, the Low Engager clusters in this study matched Kizilcec et al.'s (2013) "Sampling" group which may have only watched a single video or looked through course material once the class was well under way. Where this study could not differentiate in quite the granularity that Kizilec et al. (2013) could, was in finding any group other than a single middle group occupied by students moderately engaged in optional content. The single moderate groups found in both MOOCs of this study were similar to the "Auditing" group of the Kizilcec et al. (2013) study. The absence of a second distinct middle group similar to Kizilcec et al.'s (2013) "Disengaging group" made of students who started out engaged in assessments then stopped a third of the way into the course, may possibly be due to the short duration of the aviation-related MOOCs, at two weeks, in contrast to Kizilcec et al.'s (2013) approximately nine weeks. Also, if the engagement timeline used for analysis had been expanded to dates beyond the end of course date, simulating a longer course, the subgroup structure may have reflected the presence of another group that was only interested in content on a more relaxed or extended timeline.

Delimited as the study was, the subgroup structures and characteristics of this study most closely resemble that of Kovanović et al.'s (2019) study ($N = 23,648$) which, although focused on technology use, employed similar variables and found three similar subgroups. The majority of students (67%) in Kovanović et al.'s (2019) study were classified as "Disengaged users" and had low course resource engagement with no discussion board activity. This group corresponded to the Low Engagers group in this study (48.6% in MOOC 1 and 25.1% in MOOC 2). Kovanović et al.'s (2019) "Strategic users" accounted for the lowest proportion of students (15%) and had average course resource engagement with almost no discussion activity. This group corresponded to Moderate Engagers in MOOC 1 (16.2%) and Moderate Engagers (19.2%) in MOOC 2. Kovanović et al.'s (2019) "Engaged user" group (18%) had high course resource engagement and used all of the course resources. This group corresponded to the High Engagers in MOOC 1 (35.2%) and in MOOC 2 (55.6%).

While the MOOC 1 subgroups reflected similar results to Kovanović et al.'s (2019) groups with respect to the ordering in size of the three clusters, the proportions were not similar. The Kovanović et al. (2019) study had Disengaged Users at 67%, Strategic Users at 15%, and Engaged Users at 18%, where the present study had Low Engagers at 48.6%, Moderate Engagers at 16.2%, and High Engagers at 35.2%. Instead of finding Kovanović et al.'s (2019) almost-even proportions between Strategic Users and Engaged Users, MOOC 1's Moderate Engager group was a little under half the size of the High Engager group. In MOOC 2, there were even more notable differences found in that the High Engager group was the largest, when based on the literature, the Low Engager group was expected to be the largest. MOOC 2's High Engager (55.6%) group was unusual in that it was more than twice the size of the Low Engager (25.1%) and Moderate Engager (19.2%) groups. This may be due to the marketing efforts targeting a population of students already involved in the host-university. Despite the artificial numbering of the MOOCs in this study ("MOOC 1" and "MOOC 2") ordered in increasing size, the larger MOOC 2 occurred first. While both classes were highly marketed, the first offering potentially attracted many students who were already in the host university's distribution lists. Since the marketing targeted presumably enthusiastic potential students who were already in the marketing audience of the university, it is possible that the MOOC that occurred first (MOOC 2) depleted the population of potential students and at the same time gathered a large portion of highly motivated students in its first offering. Many of these students ended up forming a disproportionately large High Engager group. This disproportionately large group was not found in the MOOC that occurred later in the year (MOOC 1) because this MOOC experienced a relatively smaller registration demand as many prospective students in the marketing distribution potentially had already attended the first offering of the MOOC. Additionally, the time period between these two MOOCs coincided with much business growth in the sUAS industry (FAA, 2019); other training and education providers may have entered the market and depleted some of the population of students.

Focus on Middle Groups

As described previously, learning more about the less-engaged middle group of students was an important focus of this study. The middle cluster in the first MOOC stayed active for almost one quarter of the course duration and was significantly distinct from other clusters in all engagement variables except for Mandatory Discussion Posts and Quiz 1 (where it was not significantly different from the Low Engagers, but it was significantly different from the High Engagers). The Moderate Engager group was mostly concerned with optional content (webinars and optional discussions). This group surpassed even the High Engagers on Webinar Views (having on average 1.18 more Webinar Views than the High Engagers ($p < .001$)). Although not as high as the High Engagers, the middle cluster logged significantly more ($p = .002$) activity than the Low Engagers group (1.626 more views) in the Optional Discussion variable, solidifying its characterization as being moderately engaged in optional content. Similarly, MOOC 2's middle cluster stayed active for the same period of time (almost a quarter of the course) and was significantly distinct from other clusters in all engagement variables except Quiz 1 (where it failed to be significantly different from the Low Engagers). Instead of being focused on optional webinars, however, this group was more focused on optional discussions, logging an activity level that was much closer to the level of High Engagers. The gap between the middle and high group was much closer in this variable than it had been in MOOC 1. While in MOOC 1 the High Engager group had on average 1.594 more optional discussion views ($p = .005$) than the Moderate Engager group; in MOOC 2 the High Engager group had only .633 more Optional Discussion Views ($p < .001$).

Potentially due to the absence of the extrinsic reward of a certificate, or the short duration of the MOOCs, this study did not find a unique cluster of the type of strategic engagers which other studies have found. Some descriptions of strategic engagers from other studies carry the negative connotation that such subgroups only engage strategically in just what earns them a certificate. Although even the mere record of completion that this course offered may have been enough to provoke this type of strategic behavior in the High Engager groups, another argument is that behaviors may be attributed to individual goals or to personal preferences for the content offered. Without the extrinsic reward of a certificate, intrinsic motivations may be of greater influence, and the observed activity may provide clearer links to the quality of course content. The moderate clusters in both MOOCs had only one student complete the course, thus course designers may be able to interpret engagement in an activity as more likely associated with the level of stimulation or relevance of content delivered at a given time.

Summary and Discussion of RQ 2 Results

The second RQ explored differences among engagement subgroups based on demographics, days of participation in the course, and achievement. Demographic variables on age, education level, geographic location, and intent to participate were collected in pre-course surveys. One question on employment in the aviation industry was collected in a post-course survey, but due to low response rate, the cluster differences on this question were not tested, only descriptives were reported. In MOOC 1, Low and Moderate Engagers had 100% missing data on employment. High Engagers had 64% missing data on employment. Of the High Engagers who responded to this question (N = 58), 48% said “yes”, and 52% said “no” to being employed in the aviation industry. In MOOC 2, Low and Moderate Engagers had 99% and 96% missing data, respectively.

High Engagers had only 36% missing data, and of these responders (*N* = 607), 37 % of respondents answered “yes”, and 63% answered “no.”

Age. No significant associations were found between cluster membership and age for either MOOC. For all clusters of MOOC 1, the smallest percentage of students were found in the youngest (13-24 years old) and oldest (55+) categories. MOOC 1 clusters all showed the largest percentage of students in the age category 25-34 years old. Similar to MOOC 1, the smallest percentages of students were found in the younger two categories (13-18 and 19-24 years old) or in the oldest category (65+). Unlike MOOC 1, however, the largest concentration of students were not found in the 25-34 age category, but rather in slightly older categories, which were different for each cluster.

Age results from this study are somewhat consistent with other results reported in the literature. Zhenghao et al.’s (2015) study of Coursera MOOC students (*N* ≈ 52,000) reported a median age of 41, and for this study, the median age group bin was 35 to 44 (MOOC 1) and 45 to 55 (MOOC 2). Christiansen et al. (2013) found in their study of MOOCs (*N* = 34,779), 41.1 % of respondents were under 30, and 58.9% were over 30. For this study, exact comparisons could not be made due to age bins, but in MOOC 1, 46.3% of students were under 35 years old, and 53.7% were over 35. In MOOC 2, 32.6% were under 35 years old, and 67.4% were over 35.

Although no significant associations between cluster membership and age were found, the descriptive results have face value in that they are relevant for targeting specific populations for marketers and course designers. For instance, if further study into this data revealed that older students were more engaged in webinars and younger students were more engaged in discussion boards, then content and medium could be tailored to potentially increase engagement for both groups.

Education. One significant association was found between cluster group and education in MOOC 2, with a small effect size (.120). A posthoc analysis showed 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 showed a lower than expected proportion of students reporting some graduate education.

In terms of descriptive results in this study, almost 60% of students reported having a Bachelor's degree or higher. Other MOOC studies in the literature report MOOC students have high levels of educational attainment as well. A large-scale study of Coursera MOOC students (*N* approximately 52,000) showed 79.4% of students have a Bachelor's degree or higher, and EdX reported Harvard and MIT typical course registrants with 66% of registrants at the Bachelor's and above level (Ho et al., 2014).

Since significant findings were reported for MOOC 2 education levels, particularly in the proportions of students with some graduate education, a discussion on descriptives in the upper levels follows. In Low Engagers, 13% of students reported having some graduate education, which was statistically significantly higher than expected, while in High Engagers, only 4% reported that level, which was lower than expected. To compare this higher level of education to Christiansen et al.'s (2013) finding that 44.2% students reported education beyond a Bachelor's degree, it was necessary to combine descriptive results for the Some Graduate School level with the two levels above it (Master's Degree and Ph.D., J.D., or M.D.). MOOC 2, overall, had 29.4%

of students reporting some graduate education or higher. Specific percentages for each cluster were 39% for Low Engagers, 33.1% for Moderate Engagers, and 26.8% for High Engagers. MOOC 2's Low Engagers at 39% had the statistically higher than expected proportion of students reporting some graduate education or higher, and this cluster came the closest to the average Coursera study ($N \approx 52{,}000$) participant education demographic (44.2%). From this comparison, one can see that all three clusters were below the percentage of users reporting higher education in the Coursera study and that the most engaged groups were lower in reported education levels than expected.

Although the significant association of cluster membership and education was small, just as with age, the descriptive findings on education and the comparison to other MOOCs have relevance in that they 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. Thus, designers may consider creating MOOCs which 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) large-scale study of Coursera MOOC students (*N* approximately 52,000) reported that benefits from taking MOOCs are more frequently reported by students with lower socioeconomic status and lower education levels attained. While this study did not focus on socioeconomic status, the finding that group proportions were different than expected for users reporting some graduate education may mean 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.

Geographic Location. No significant associations were found between cluster membership and the variable of geographic location for either MOOC. MOOC 1's Cluster descriptives showed the highest proportion of students were from North America for all clusters (58.5%, 53.5%, 56%). The least reported country for all clusters was Middle East/North Africa (3.8%, 4.7%, 4.0%). For MOOC 2, again, the highest proportion of students were from North America (70.8%, 86.5%, 81.8%). In this MOOC however, the second highest country of origin reported was Latin America for all three clusters (11%, 4.1%, 6.4%).

While geographic region is often discussed in the literature from an achievement perspective, in this study, the perspective that is considered more relevant is the goal perspective. In a study on completers of Coursera MOOCs (N = 51,954), Zhenghao et al. (2015) found that benefits from taking MOOCs are more frequently reported by students from developing countries. Relating to the goal perspective, of the primary desired outcomes Coursera completers were surveyed about, 52% (called "Career Builders") reported their primary goal was to improve their current job or find a new job, whereas only 28% (called "Education seekers") cited an education benefit or an academic goal as their primary reason for enrolling (Zhenghao et al., 2015). While such a goal question was not within the scope of this study, the prominence of career-minded students in the large population of Coursera completers, coupled with the finding that career-benefits are more commonly reported from students of developing countries, makes a case for the relevance of the geographic variable in MOOCs 1 and 2 if the developers assume there exists a similar proportion of students who desire career benefits. If one assumes that the aviation-related MOOCs in this study, as well as others offered in the future, are attracting students who need the aviation knowledge for improving their careers, then content can be better tailored to them based on which countries are showing specific engagement patterns. For instance, developers might analyze the data further to investigate why Latin American students took a solid interest in one MOOC but not the other.

Again, the MOOCs in this study did not offer a traditional certificate of completion but offered only a record of completion. This was done in an attempt to avoid confusing students who might think completing the MOOC would somehow earn them a sUAS certification that is 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 may be much less of an emphasis or not even a possibility, MOOCs may serve as a stop-gap. Although not every MOOC learner has specific goals for professional learning, many learners in professional MOOCs 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. Finer-grained analysis of aviation-related MOOCs on the geographic variable and how MOOC completers are using what they are learning may be a fruitful area of research.

Intent to Participate. No significant associations were found between cluster membership and the variable of Intent to Participate for either MOOC. For this survey item, students could indicate intent in one of four categories: Active: "Bring it on. If it's in the course, I plan on doing it;" Passive: "I plan on completing the course but on my own schedule and without having to engage with other students or assignments;" 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;" or 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."

In MOOC 1, Moderate Engagers had an even split for the most common intent reported. Identical proportions of students reported they intended to be either Passive (46.5%) or Active (46.5%). For Low Engagers, the top categories were Passive (41.5%) followed by Active (36.9%), whereas for High Engagers the distribution was reversed, and the top category was Active (51.2%) followed by Passive (34.4%). In MOOC 1, for all clusters, the least-reported categories were Drop-ins and Observers.

For those who knew they would not complete the course on timeline, results showed the Low Engagers had the largest percentage of students with specific intents other than being passive or active. In other words, this is the group which most utilized the very specific categories designed to capture more information from those not intending to complete the course (Drop-In or Observer). In the Low Engagers cluster, 21.5% chose either the Drop-In or Observer intent category, compared to 7% in Moderate Engagers and 14.3% High Engagers. It is possible that individuals responding in these categories truly registered so little activity consistent with their predetermined limited interest that they ended up in the Low Engager group. It is also possible that had the course been longer than two weeks, or had the study not been delimited to the two week time period, students with these types of intents would have ended up in the Moderate Engager group having had more time to sample bits and pieces of the course. Finally, the wording of the options could have influenced some responses because the Passive category was broad enough to capture all who did not intend to complete the course and many may have selected this if they were unwilling or unsure about how to specify their intent any further.

Similar to MOOC 1, students in MOOC 2 most often chose Passive or Active intent categories. Low Engagers had a higher proportion of students choosing Passive, while Moderate and High Engagers had a higher proportion of students choosing the Active intent category. A closer examination of those who did not intend to complete the course on timeline again revealed the lowest cluster (Low Engagers) had the largest percentage of students with specific intents other than being Passive or Active. Of the Low Engagers, 11.7% chose either the Drop-In or Observer intent category, whereas this number was smaller for the Moderate and High Engagers at 4.9% and 8.9%, respectively.

Results for both MOOC showed the least engaged clusters using these special sampling type categories the most. Although one might hypothesize that those who intend to be drop-ins, with very specific learning goals, might end up in the moderately engaged cluster for both MOOCs; again, just as in MOOC 1, that was not the case. Instead those specific learning goals may have been isolated to one or two content items, or the time period during which engagement was measured did not allow for enough sampling from these students. As such, it is reasonable that some of those ended up in the very bottom, least engaged cluster. Additionally, considering the finding that the predictor importance variables for cluster assignment ended up being mandatory discussions and quizzes, and given the time-bounded nature of those content items in counting toward course engagement, it also makes sense that these Drop-Ins would be more prevalent in the Low Engager clusters.

Days of Activity. For both MOOCs, significant differences ($p < .001$) were found between clusters and days of activity which was limited to between 1 and 14 days during which the course was live. In MOOC 1, there were significant differences between Moderate and High Engagers and between Low Engagers and High Engagers. For MOOC 2, there were significant differences between Low and Moderate Engagers, Moderate and High Engagers, and Low and High Engagers. In all cases, the more highly engaged groups were active more days than the lower engaged groups.

Results of days of activity match what one might expect in that the most and least engaged groups have the most and least days of activity during the course, notably without days of activity as a clustering variable. Previous research found days of activity to be significantly associated with performance for a sample of all students in a particular MOOC, but found that, for those who passed the course, number of days active was not a significant predictor of their end-of-course performance. This finding was explained in part by the rationale that even students working at different speeds (some needing longer than others to work through the material) can finish with the same level of success (Kennedy et al., 2015).

Total Quiz Score. For both MOOCs, significant differences ($p < .001$) were found between Cluster membership and Total Quiz score (calculated by taking the sum of scores from Quiz 1 and Quiz 2). For MOOC 1, there were significant differences between Moderate and High Engagers and Low and High Engagers. For MOOC 2, there were significant differences between Low and Moderate Engagers, Moderate and High Engagers, and Low and High Engagers. Results of quiz score match what is expected based upon variable order of importance in predicting cluster membership. Since the quiz attempts variable was the most important predictor in MOOC 2 and the second most important in MOOC 1, it follows that a noticeable disparity would exist among the groups with the highest engagement cluster having the highest quiz scores and the middle engagement cluster having the next highest, and so on.

Course Completion. For both MOOCs, significant associations were found between cluster group and course completion, with large effect sizes. In both MOOCs, the lower engaged clusters (Low and Moderate Engagers) showed a statistically significantly higher than expected proportion of students did not complete the course. Also, for both MOOCs, the highest engaged group showed a statistically significantly higher than expected proportion of students did complete the course.

Although course completion rate differences between clusters in both MOOCs were significant, they were not unexpected given the cluster descriptions and their order of engagement. Similar to the differences in the total quiz score, these results make sense given the first and second most influential predictor in the clustering solutions were quiz attempts, and quizzes were mandatory for completing the course. What was surprising however, was the difference for the larger MOOC compared to what is reported in the literature. In the literature, MOOC completion rates are reported to average around 7% (Jordan, 2014). MOOC 1's completion rate was only slightly above that with 9.8% (101 out of 1032) of registrants completing the course. Surprisingly however, MOOC 2's rate was well above the average, with 18.9% (765 of the initial 4,037) of registrants completing the course. The disparity between the two MOOCs in this study, again, may be attributed to MOOC 2 occurring first and depleting the pool of likely participants. However, why it had an above average completion rate 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. From that we could hypothesize that a shorter course would have a higher proportion of students complete it compared to the proportion who would complete a longer course. It could also be due in part to the topic, being very vocational or practical. If practical or professional-focused courses are needed immediately for work, it could mean there are more students registered who will persist out of necessity. Thus, it is possible that higher MOOC completion rates may be attributed to course topics that are more practical or vocational (Auyeung, 2015).

Conclusions on Results

Three distinct subpopulations were discovered for both MOOCs in this study. The cluster results for each MOOC showed several similarities, with most and least engaged clusters very similar in nature to what is reported in the literature. In answering the call for more fine-grained research on non-completers, this study discovered a middle cluster in both MOOCs containing mostly non-completers who were different in several ways from the lowest engaged cluster, which was also full of non-completers. For both MOOCs, the moderately engaged cluster was differentiated from the lowest engaged cluster by an optional content variable. In MOOC 1, the moderate group was above 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. The discovery of this middle subgroup allowed for a closer look at the MOOC's less-engaged students, which was an important aim of the study in meeting the broader community's call for research.

Theoretical Implications

Moore's (1997) theory of transactional distance and intrinsic and extrinsic motivation theories proved suitable supports to variable selection for this study. Engagement in discussion boards provided evidence for potential decreased transactional distance and increased feelings of social connectedness which may have related to increased persistence, performance, and positive experience in the course (Falloon, 2011). Consistent with self-determination theory (SDT; Ryan & Deci, 2000), this study also found evidence for social connectedness as relevant to engagement. Assuming students in the more engaged groups were bolstered in feelings of competence and relatedness by positive feedback and interaction from each other or an instructor (Deci et al., 1991) these students may have experienced a resulting increased determination to engage and complete the course. Relative to Moore's (1997) factors of structure and autonomy, this study found engagement variables that represented mandatory content to be the most important predictors in subgroup membership, and the variables reflecting optional content most differentiated the middle subgroups from the others.

Practical Implications

Clow (2012) argues a successful learning analytics cycle has four key steps which include having learners, generating data, producing metrics, analytics, or visualizations, and most importantly, "closing the loop" by delivering interventions back to learners (p. 134). While most archival research may be too late for useful interventions to reach the students who generated the data, it still counts as "closing the loop" if analytics are used to recommend changes to help future students (Clow, 2012).

The way in which clustering variables in this study differentiated the middle clusters (e.g., interest shown in webinars and in optional discussions) offers an immediate starting point for course instructors to discuss why this specific content was relevant to non-completers. Course instructors can consider adding more of this type of content and analyzing future courses to optimize these facets. Additionally, the findings on age demographics and unexpected education levels offer a starting point for more analysis on why MOOC 2 had unexpected proportions of students with some graduate school in the lowest and highest clusters.

This study leveraged learning analytics through analysis of extremely basic data traces, and a resulting methodological implication is that more advanced data traces could be analyzed if the capability were contracted with the host LMS platform. This would allow for analysis of MOOC video watching without the need for proxies. Unlike the static data traces from course content which is read by the student, data traces for video content have the potential to show in-depth dynamic interaction of the student and the content. Based on the capability of the analytics package offered by the LMS, video skips, pauses, fast-forward or backward seeks are potentially information-rich data traces which can be analyzed for information about how a student processed the content.

Studying video-watching patterns can be useful in re-designing videos or providing supplemental content to support students in their learning process. Since frequent or long pauses have been noted as typical of weak students, such fine-grained video data could accurately guide course designers in content improvement.

For MOOC developers who wish to close the loop of the analytics cycle for classes before they are over, interventions such as early warning systems, like Purdue's *Course Signals* system involving predictive analytics might help students to see when they are on track or off track (Pursel et al., 2016). Similar systems could be used for instructors or multiple course facilitators in order to make MOOC discussion boards more engaging when they seem to be lagging. While such interventions are most feasible in smaller traditional online courses where the ratio of instructor to student is optimal, they could be modified for MOOCs based on developer goals. For instance, it would not be practical for a MOOC instructor to elicit more engagement from many students in a MOOC, but learning analytics systems might instead be employed to identify some of Huang et al.'s (2014) "superposters" or "high-volume contributors" (p.1). Although no causal conclusions were drawn, Huang et al.'s (2014) study found that high-volume "superposters" tended to have contributions which added value and correlated positively with not just activity from others, but quality contributions from others. With this in mind, an intervention could be made to encourage more collaborative learning by promoting these computer-identified high-volume individuals to essentially serve as forum-moderators.

Also, course instructors may decide to interpret low engagement in specific discussion forums a result of a student perception that participation in those specific forums do not constitute a valuable learning activity (Kovanović et al., 2019). For MOOC course designers, considering whether or not this perception was in play for certain clusters in both mandatory and optional discussion boards is a starting point. Depending on whether actual content posed for discussion is ineffective or whether a constructivist collaborative learning design is inappropriate, interventions aimed at optimizing the content or approach should be considered.

Limitations

As with any study, there are some specific limitations which must be noted. First, this study was limited in scope by topic, location, and time. Only data from one aviation-related MOOC topic covering small unmanned aerial systems from one location and one year was used, which limited the generalizability of findings. Nevertheless, the discovery of subgroup types and engagement patterns that were similar to those reported in the literature lessens its negative impact on the significance for the aviation education domain. Before making generalizations within aviation education, it will be necessary to ensure the findings are robust across other course topics. Specifically, more analysis including other MOOC 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. Additionally, the representativeness of the study sample should be confirmed by comparing basic student demographics with demographics from other aviation-related MOOCs. Currently this descriptive data is unavailable for comparison.

A limitation related to time was the short duration of the MOOC at only two weeks and the delimitation of the study to only examine activity during the two weeks the course was live instead of after the course, when students still had access to course content. The extent to which this limitation impacted the study is not certain, but the use of such a short time period may have contributed to the finding of only one middle subgroup rather than two groups as some studies have found. If so, this time limitation reduced the granularity of information produced on the moderately engaged non-completers as there may have been an entirely distinct subgroup of students who accessed and benefitted from course content long after the course's live period ended.

Another limitation of this study was related to the exploratory approach and two-step cluster analysis utilized. While exploratory research is common in domains where little research exists, the presence of a solid literature base for MOOC engagement may have sufficiently guided hypothesis testing. Regarding the cluster analysis methodology, Antonenko et al. (2012) warned that "clustering algorithms will sometimes find structure in a dataset, even where none exists" (p. 395), and Ferguson and Clow (2015) noted the relative ease with which "good storytelling" can emerge from data clusters even when cluster quality is not good. While an appropriate algorithm relative to data type was used, and cluster quality was confirmed in group mean and literature comparisons, these limitations were mitigated but not removed entirely.

Finally, this study was limited by the nature of variables selected for analysis of the construct engagement. Measuring engagement with the number of posts written or viewed or by the number of times a student views a page where a video is linked is common and expedient, especially for learning analytics research using large data sets. Even so, the use of these variable types limits the depth of information available for analysis and reveals much less about engagement than what might have been revealed by using more fine-grained data such as length of post, quality of content in posts, or video viewing patterns including pauses, fast-forwards, and re-plays.

Recommendations

Given the lack of research on aviation-related MOOCs, and the growing diverse student body of both aviation professionals and individuals outside the industry who may be considering entry, there are many opportunities for future research. The following recommendations from this study describe future directions that relate to the specific data analyzed and future directions that relate more broadly to the methodology and continuing research problem.

Data recommendations. The primary data-specific recommendations from this study are summarized:

- Future research should prioritize examination of optional content in both MOOCs. Follow-up content analysis should be done to evaluate whether any different subgroups or cluster engagement patterns emerge. One or two survey questions should be embedded in optional content to assess student goals (pre-activity survey) and satisfaction (post-activity survey) with specific optional content.
- Given the unexpected engagement patterns from those reporting some graduate education, future researchers should consider altering course content to be more relevant to those who may already have formal education in the subject or may need a different type of content to increase engagement. In essence, content appropriateness should be considered for more than one education level.
- The sUAS MOOCs analyzed in this study were only two weeks in duration, and the study was delimited to include data from those two

weeks. Future research should include one year beyond the end of the course date, when users still have access to course content, to determine if any additional subgroups of students exist. It is possible that extending the time frame would yield a second middle cluster of students who have an engagement pattern different than the current findings of a single middle cluster.

- Future research may consider adjusting the marketing of the MOOC to specific demographics (e.g., age, country of origin, employment industry). If MOOC designers want to target different students for future MOOCs, a look at archival data in these categories across all MOOCs will be an important first step in that direction.
- Finally, data in this study was not generalizable based on limited knowledge about representativeness of the sample to the population and based on the use of only one of several possible aviation-related MOOC course topics. Demographics for several aviation-related MOOCs will be necessary to better assess the representativeness of the sample. Similar studies on other aviation-related course topics should be conducted to assess the robustness of the subgroups detected.
- Due to low survey response on post-course surveys, the question of employment in the aviation industry should be moved to the pre-course "Welcome Survey."

Methodological recommendations. The broader methodological and research problem recommendations from this study are primarily for instructional designers and are summarized as follows:

- The first methodological recommendation from this study broadly applies to any MOOC researchers. Education providers should ensure more detailed learning analytics packages from the host LMS are available for data collection. Many more valuable research questions can be answered if there is richer data available for video watching (e.g., pauses, skips, fast-forwards, rewinds, and re-visits).
- Future research should be designed in a mixed-method format to include more than just quantitative analysis on simple summed measures. Such research should include more qualitative analysis on content and or length of discussion posts and views.
- As engagement may be influenced by other factors and represented by other variables beyond those which were included in this analysis, future studies should consider exploring engagement through other theories and empirical evidence. Additionally, future research should examine how engagement is influenced by other demographic factors such as language barriers or by contextual factors such as course topic (traditional academic topic versus vocational topic).

Conclusions

Unlike traditional online courses, MOOCs offer students great flexibility in how they can interact in a course with other learners and in how they can consume course content, all of which result in varied engagement patterns among students. Prior to this study, very little was known about students in aviation-related MOOCs (Velázquez, 2017). Outside of the aviation domain, it was known that more research was needed on the large number of students who do not finish MOOCs but who engage, albeit sometimes minimally. While most studies consistently find similar low engager and high engager groups and focus on completion as the primary success metric, those aimed at discovering more about the large number of students who engage in the course without completing it have done so with the goal of "deconstructing disengagement," as Kizilcec et al. (2013, p. 170) describe it. Ultimately this focus on non-completers who legitimately engage but then disengage may help institutions design better courses or offer better tools to support these selective learners.

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 data about the different subpopulations found. Archived datasets of student activity in two sUAS MOOCs were analyzed to answer two research questions. Both MOOCs showed three distinct subgroups of students based on engagement in course discussions, videos, and assessments. Groups 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, offers an immediate starting point for course instructors to discuss why this specific content was relevant and engaging enough to attract students who did not care about completing the course.

Although no professional degrees or FAA certifications were at stake in the two aviation-related MOOCs analyzed for this study, educators and instructional designers in the aviation industry have several important opportunities to consider in the execution and study of such MOOCs. Instructional designers know it is imperative to remain responsive and adaptive to meet emergent needs of students and instructors alike, but revisions informed by research in smaller traditional classes can take a long time due to the limited throughput of students which may cause a lag in feedback (Neal & Hampton, 2016). Results of this study can be used to guide instructional designers who aim to "close the loop" of the learning analytics cycle and make improvements that foster better learning and engagement (Clow, 2012, p. 134). The scale and flexibility of MOOCs offer frequent opportunities 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). The goal of this study was to understand more about how aviation MOOC students engage in their course content. The data-driven recommendations emerging from this study are a first step toward better meeting the needs of the aviation education community now and in the future.

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APPENDIX A

Permission to Conduct Research

Embry-Riddle Aeronautical University
Application for IRB Approval
EXEMPT Determination Form

Principal Investigator: Jennifer Edwards

Other Investigators: Mark Friend

Role: Student **Campus:** Worldwide **College:** Aviation/Aeronautics

Project Title: Understanding Learner Engagement Profiles in Aviation MOOCS

Review Board Use Only

Initial Reviewer: Teri Gabriel **Date:** 08/22/2019 **Approval #:** 20-019

Determination: Exempt

Dr. Michael Wiggins [illegible]el E. Wiggins, Ed.D.
IRB Chair Signature: **Date:** 08/22/2019

Brief Description:

In order to improve and tailor education to the aviation community, additional knowledge must be collected about Massive Open Online Courses (MOOC) participants with respect to engagement in the open online environment. The purpose of this archival study is to expand the current understanding of learner engagement in MOOCs, particularly in aviation-related MOOCs. Additionally, it will fill a gap in research in its person-centered approach that maximizes the rich data available in learning analytics datasets. An increased understanding of the characteristics and engagement patterns of these groups is an important first step for course developers and instructors who aim to meet the diverse needs of the aviation education community. Data will be extracted from the Canvas Learning Management System (LMS) activity log, and de-identified as well as answers to the MOOC's pre-course "Welcome Survey" and post-course "Demographic Survey."

☑ (4) Secondary research for which consent is not required: Secondary research uses of identifiable private information or identifiable biospecimens, if at least one of the following criteria is met: (Applies to Subpart B [Pregnant Women, Human Fetuses and Neonates], does not apply for Subpart C [Prisoners] except for research aimed at involving a broader subject population that only incidentally includes prisoners, Subpart D [Children] involved in research.)

(i) The identifiable private information or identifiable biospecimens are publicly available;

(ii) Information, which may include information about biospecimens, is recorded by the investigator in such a manner that the identity of the human subjects cannot readily be ascertained directly or through identifiers linked to the subjects, the investigator does not contact the subjects, and the investigator will not re-identify subjects;