LEARNING IN MOOCS:
AN EXPLORATORY ANALYSIS OF PARTICIPATION PATTERNS AND THEIR RELATION TO DEMOGRAPHIC VARIABLES AND OTHER INFLUENTIAL FACTORS

BY

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DISSERTATION

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Abstract

One of the recent innovations taking place in higher education is the phenomenon of Massive Open Online Courses, known as MOOCs. MOOCs have grown rapidly over the last several years and have become a popular topic in media and academic research. Much has been said about MOOCs in terms of their impact and reach with a wide range of opinions between supporters and opponents (Daniel, 2012; Liyanagunawardena, Adams, & Williams, 2013; Yuan & Powell, 2013; Chen 2014; Hvam, 2015;). However, there is a lack of research capturing the dynamic of learning and the different ways learners participate in this new massive e-learning ecology. Influenced by theories of constructivism and differentiated learning approaches, this study aimed to explore the different patterns of participation among MOOC learners in the Coursera platform and identify the different demographic variables and influential factors that could relate to these patterns. Data was obtained from the data logs and survey results recorded by the Coursera platform of the session-based “Subsistence Marketplaces” MOOC. This was the first MOOC to be offered by the College of Business at the University of Illinois Urbana-Champaign in Spring of 2014. The study utilized a mixed method approach in the data analysis (Creswell 2014; Greene 2007) combining Educational Data Mining, statistical analysis and content analysis. Findings of this research revealed five different patterns of participation in MOOCs as follows: advanced, balanced, early, limited and delayed. Data analysis have also revealed that there is a relationship between the different patterns of participation and employment status, education level, and age groups, but not gender. Moreover, the content analysis of the open-ended survey questions explored multiple reasons that motivate and limit learners’ level of participation in MOOCs. The findings of this research are significant in helping

to improve future iterations of MOOCs to be more flexible and transparent to the varied levels of participation that learners may need.

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DEDICATION

I dedicate this manuscript to my beloved parents, my family including my husband, my daughters and my siblings. Without their ongoing support and encouragement I couldn’t make it.

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CHAPTER I. RESEARCH OVERVIEW

This chapter provides an overview of the research study of this dissertation. It begins with an introduction to the MOOC phenomena and its surrounding debates. Then, it discusses the research problem and lays down the research questions. Following that, the chapter sheds light on the significance of the research. Finally it ends with a summary of the main points covered in the chapter.

Overview

In a time of globalization and digitization, higher education is undergoing many changes that take advantage of technology innovations to expand learning beyond spatial and temporal boundaries of universities. Among these notable efforts is the evolution of Massive Open Online Courses (MOOCs), which quickly became one of the fastest growing trends in higher education (Daniel, 2012, Pappano, 2012). The MOOC phenomenon aims to deliver courses from prestigious universities, typically free of charge, to any participant who has access to technological devices, technical skills and broadband connections. Potential learners may participate without the need of being officially admitted and regardless of age, location, or previous educational experience (Johnson et al. 2013; Liyanagunawardena et al. 2013; Yuan & Powell, 2013; Nkuyubwatsi 2014; Hvam 2015).

Despite their recent appearance, MOOCs have received a great deal of attention in media and educational research, an attention which has been controversial at levels not seen with previous educational innovations (Yuan & Powell, 2013; Bulfin, Pangrazio, & Selwyn, 2014; Kovanović, Joksimović, Gašević, Siemens, & Hatala, 2015). On the one hand, some people are overly pessimistic about the innovation of MOOCs, seeing them as a threat to negatively disrupt and jeopardize the current model of higher education. For instance, Clayton Christensen (2013), in one of the interviews by *Startup Grind*, warns that "in 15 years from now half of US universities may be in bankruptcy." Christensen was referring to MOOCs as a destructive innovation that is going to put US universities out of business. Similarly, Vardi (2012) wrote, "If I had my wish, I would wave a wand and make MOOCs disappear, but I am afraid that we have let the genie out of the bottle" (p.5). From his point of view, MOOCs will take over the education system, which will eventually displace brick-and-mortar universities.

On the other hand, some scholars hold very ambitious thoughts about MOOCs, seeing them as a savior to problems not only in higher education but also in the globalized world. More specifically, Thomas L. Friedman (2013), in a *New York Times* article "Revolution Hits the Universities" wrote:

> Nothing has more potential to lift more people out of poverty … Nothing has more potential to unlock a billion more brains to solve the world's biggest problems. And nothing has more potential to enable us to reimagine higher education than the massive open online course, or MOOC.

With respect to these two extreme opposing views, MOOCs are not the magic bullet solution to solve all complicated problems facing the globalized world, nor a giant genie that will eventually make public education vanish and replace the traditional institutions. Instead, the MOOC phenomenon acts as an optional e-learning model that continues to proliferate as a part of academic teaching in the complex ecology of higher education. They offer learning opportunities for a wide spectrum of learners to participate in unique ways beyond the restricted rules of universities as we have known them.

Research Problem

Despite the widespread popularity of MOOCs and the learning potential they offer for higher education, there has been little to no progress in developing innovative features in these courses to provide multiple paths of learning. Having multiple paths of learning helps to address learners' diverse needs to achieve their mastery level of learning (Kizilcec & Halawa, 2015; Davis et al., 2017). By design, MOOCs pushed the boundary on the scale of learning by opening up the doors for learners all around the world to join in; however the goal of these courses should not only lie in their great capability of taking content to millions of people, it also needs to be directed towards optimizing their learning in order to provide high quality educational experience to accommodate the different needs of an increasingly diverse student population (Franceschen, 2016). A recent study claims that the pedagogy embedded in MOOC platforms, tends to follow a didactic approach (Ubell, 2017). Although MOOCs provide anytime and anywhere learning, yet the format of these courses are essentially the same regardless of learner differences and course topic. All video lectures, discussion forums assignments and assessments are assembled in a fixed order. This mode of learning is commonly known as the one-size-fits-all educational approach. Previous research studies have shown that following this approach does not allow any flexibility in learning and thus it does not yield good outcomes (Gardner, 2006; Kalantzis & Cope, 2012; Tomlinson, 2014; Kalantzis & Cope 2016a; Cope & Kalantzis 2017; Haniya & Roberts-Lieb 2017; Haniya & Rusch, 2017). Researchers and educators have strongly argued that the one-size-fits-all approach falls short of providing meaningful learning and meeting individuals' needs (Kalantzis & Cope, 2012). They are now calling for a pedagogical reform to move away from this didactic approach to differentiate learning in school settings and beyond in large scale learning environments, such as MOOCs (Kalantzis & Cope, 2016a; Cope

& Kalantzis, 2017). In this sense, learning becomes more transparent to the different needs of learners (Kalantzis & Cope 2016b; Haniya & Roberts-Lieb 2017).

Furthermore, others have begun to problematize the notion of completion rates in MOOCs as it could ignore learners' differences. Some studies argue the relatively low percentages of learners who go on to complete their courses successfully, which typically range between 5 to 15 percent, (Daniel 2012; Liyanagunawardena et al. 2013; Chen 2014; Hew and Cheung, 2014; Ho et al., 2014; Jordan, 2014; Alraimi, Zo, & Ciganek, 2015; Jordan, 2015). Yet, this is because the notion of completion rates by itself is being misinterpreted. It is unjustifiable to compare MOOCs with traditional online classes and not considering the obvious learner differences appear in these two diverse educational settings. According to Clark (2016, April 13),

> Course completion may make sense when you have paid up front for your university course, and have made a huge investment in terms of money, effort, moving to a new location, and so on. In open, free, and online courses there is no such commitment, risk, and investment.

Although it is true that most MOOCs mimic the same design as regular classes taught in universities and may have the same content, same assignments, same structure and sometimes same time to do all the work, MOOC learners are different than those in traditional courses. University courses target officially registered learners who have committed their time, effort and money to take these courses. And, they have the prerequisite knowledge. On the other hand, MOOCs by definition operate with massive number of learners with different employment status, age, educational level, different lifestyles and different motivations to join the course free of charge. Regardless of these differences, the completion rates in MOOCs are currently being measured by the number of learners who successfully complete all the required assignments divided by the number of all learners who signed up for the course; which is how learning in traditional courses is measured (Jordan, 2014; Reich, 2014; Jordan, 2015). However, learning in MOOCs should not be judged this way. Instead, learners should be allowed to have different learning options to complete a course based on their needs. A previous research study has shown that diverse students have different interests and intentions towards their enrollment in MOOCs, and not all MOOC learners care about completing the course (Zheng, Rosson, Shih, & Carroll, 2015).

Unfortunately, dealing with the completion rates this way may overlook the efforts of other learners who participated in the course but could not complete it. In any educational settings, all learners' efforts and trials are valuable regardless whether they are right or wrong, completed or not-completed (Dewey, 1938). Regarding the MOOC context, if only 10% of enrolled learners have completed the course, then what about the other 90% who did not? What did they do in the course? How much did they learn? What do their participation patterns look like? What were the factors that limited their learning? How can we better serve this population? And perhaps most importantly, how can we customize their learning in order to receive the appropriate scaffolding they need to make the most out of their MOOC experience? It is time to move away from an oversimplified view of completion rates since they prevent us from addressing the learning efforts of all learners and focus on the process of knowledge making by exploring the different patterns of participation in MOOCs.

Research Questions

The overarching goal of this research was to explore the different ways learners participate in MOOCs and find the different factors that could relate to these patterns. To do so, the study captured and mined the digital traces of learners' interaction with the primary features of the course including accessing video lectures, participating in the discussion forums and attempting to do the weekly quizzes. The Coursera platform was used in this study as an example of a broadly used platform to deeply investigate the research problem and better understand the way learning operates in MOOCs. The research used a case study of the Subsistence Marketplaces MOOC offered by the University of Illinois Urbana-Champaign, UIUC (further elaboration on this course will follow in chapter 3). This study was guided by the following research questions:

Q1. What kinds of participation patterns exist among MOOC learners in the Coursera platform?

Q2. What is the relationship between the different patterns of participation in Coursera MOOCs and learners' demographic variables including gender, age group, educational level and employment status?

Q3. What are the main factors that motivate and limit learners' level of participation in Coursera MOOCs?

Significance of the Research

The study of this dissertation was designed to fill in the gap of MOOC research concerning the nature of learners' participation. Overall, it is intended to uncover different patterns of participation among MOOC learners and investigate the different factors that may impact these patterns. Understanding learners' participation patterns in MOOCs, as well as knowing the different factors that relate to them, provides significant insights for faculty members, educators, instructional designers and learners about the nature of learning in massive scale learning environments. These findings could better inform faculty members in unique ways to improve teaching practices of MOOCs to be more flexible in future iterations to support learners. Moreover, these findings are useful for educators to rethink the MOOCs' design in Coursera through the lens of differentiated learning and make MOOCs more suitable for the varied levels of participation that students may need. Additionally, the results can help MOOC designers to create different learning options and develop adaptive course features to accommodate the various types of learners' participation. These improvements in teaching practices and the course design of MOOCs can in turn improve the learning experience of learners and increase their participation in MOOCs.

Furthermore, the findings contribute to the research field of online learning in general and to the MOOC space in particular; perhaps by focusing more on what learners are doing in massive learning environments, and how to use technology affordances to help them achieve their learning needs. These findings are also helpful for future researchers who want to replicate the study in different courses, and in similar settings.

Definition of Terms

The following definitions are used in this dissertation.

MOOCs is the acronym for Massive, Open, Online, Courses. They offer free and open online classes from prestigious universities to anyone in the world to take without the need of official registration (Daniel, 2012; Liyanagunawardena et al., 2013; Yuan & Powell, 2013).

Participation patterns are the different ways in which learners participate in the course across the three observed variables (watching the course lectures, participating in the discussion forums and attempting to do the quizzes) over the different weeks of the course in this particular study.

Coursera is one of the most popular MOOC platforms partnered with top universities in the US and the world; it is also the one used by UIUC MOOCs, and it is the focus of this study.

Educational Data Mining can be defined based on the Educational Data Mining Website as follows,

> an emerging discipline, concerned with developing methods for exploring the unique and increasingly large-scale data that come from educational settings and using those methods to better understand students, and the settings which they learn in (http://educationaldatamining.org/)

Clustering is a common data mining techniques that aims to group a set of different objects into different groups (or clusters) that share the same characteristics and features (Witten & Frank, 2005; Baker & Siemens, 2014).

Chapter Summary

In a nutshell, the MOOCs phenomena is one of the recent innovations that is disrupting the nature of higher education in a way that has not seen before in any other innovations in terms of its massive scale and open learning (Daniel, 2012). Despite its popularity, there has been little to no progress in developing innovative features in these courses to provide multiple paths of learning to suit learners' needs (Kizilcec & Halawa, 2015; Davis et al., 2017). Learners' needs and differences are being ignored with the current notion of completion rates, which equates learning in MOOCs with learning in traditional settings. It is unjustifiable to treat MOOCs this way and not considering the obvious learner differences in both settings (Clark, 2016). Hence, the purpose of this dissertation was to explore the different ways learners participate in MOOCs to provide insights in how to improve MOOC learning and redefine the notion of success.

CHAPTER II. LITERATURE REVIEW

This chapter reviews the literature surrounding MOOCs and the influential theoretical frameworks that grounded this research. It is divided into five main sections. The first section explores the evolution of the MOOC phenomenon by tracing its developmental stages to show how it evolved, and where it is now. Then, the second section of the literature review sheds light on the implications of MOOCs to explore how these courses are benefiting higher education. Following that, the third section explores the current literature on learners' participation in MOOCs. Then, the fourth section reviews selected theoretical perspectives that informed my thinking to investigate the research problem. Finally, the fifth section concludes with a summary of the key points discussed.

The Evolution of MOOCs

The innovation of MOOCs began in September 2008. In an organic fashion, George Siemens and Stephen Downs at the University of Manitoba in Canada developed the first MOOC by opening up their course "Connectivism and Connective Knowledge" (CCK08) online to the general public at no cost and for a non-credit option. Surprisingly, about 2,300 students from the general public enrolled in this course. In the meantime, the same course was offered on-campus to 22 officially registered students taking it for credit. In the MOOC format, students had access to the course content and activities via asynchronous discussion forums in Moodle, and some arranged synchronous sessions (Daniel, 2012; Flynn, 2013; Uvalić-Trumbić & Daniel, 2013). This course format was referred to by Siemens (2012) as cMOOCs, in which "c" stands for connectivism. It means that learning occurs by making connections among peers in a network. Following the same path of CCK08, a few additional courses were developed with great success in 2010 and 2011, but overall, the progress of cMOOCs was a bit slow (Rodriguez, 2012).

Despite these early efforts of launching MOOCs, the real revolution did not truly gain momentum until the end of 2011, when Stanford University's educational experiment opened up three graduate level Computer Science courses. These courses, Introduction to Artificial Intelligence (CS 271), Machine Learning (CS 229), and Introduction to Databases (CS 145), were free and open to anyone around the world who had access to technology and the internet. Among these courses, CS 271 is the most famous one to have brought attention to MOOCs. The course was offered in two different formats: face-to-face and the MOOC format. In the face-to-face format, a total of 30 Stanford students registered to take this course for credit. Surprisingly, the MOOC format attracted nearly 160,000 students taking the course online as a non-credit option and about 20,000 of them successfully finished the course and received a "statement of accomplishment" (Rodriguez, 2012; Flynn, 2013; Rodriguez, 2013). The MOOC format of the course mirrored the exact layout of the face-to-face version. Using the current Learning Management System (LMS) of Stanford, the MOOC option contained a set of recorded short video lectures, discussion boards and assessments (Rodriguez, 2012). This type of MOOC is known as xMOOC, in which *x* stands for *extension;* meaning that these courses are extensions of the original course offerings (Nkuyubwatsi, 2014, p.196).

As MOOCs developed, they spread into two different branches, xMOOCs and cMOOCs. In xMOOCs, there is a central content provider, mainly the instructor, who distributes the educational materials to all learners via a well-defined MOOC platform. The content to be delivered are a set of recorded video lectures, computer-based assignments, automated or peer-review assessments and discussion forums to facilitate learning (Gaebel, 2013; Yousef, Chatti, Schroeder, Wosnitza, & Jakobs; 2014). In order to pass the course, learners should follow the provided instructions and do the required assignments.

By contrast, in cMOOCs instructors provide only the big ideas of the subject matter, while the rest of learning is driven by the learners. Learners choose what skills and content to focus on. Specifically, this type of MOOCs intends to hook all learners together to make connections and build mini learning communities of interest to construct and reconstruct their own knowledge (Siemens, 2012; Rodriguez, 2013). However, the practice of cMOOCs seems difficult to operate and assess. Unlike xMOOCs, there are no common and shared platforms for cMOOCs. Instead, cMOOCs rely on a set of multiple platforms including blogs, wikis, and web conferencing software to keep learning going. Also, there are no formal assessments to measure students' performance (Bates, 2014). By and large, knowledge in xMOOCs comes mostly from the professors, but in cMOOCs it comes mostly from the learners. Despite these differences of knowledge delivery, it is important to note that both types of MOOCs share the same characteristics of openness, massiveness and being online courses. Indeed, the xMOOCs model is more popular in MOOC practices and literature than cMOOCs (Kesim & Altınpulluk, 2015). For the purpose of this study, the focus will be in xMOOCs; because they are the more popular ones.

Before moving beyond the two different branches of MOOCs, it is important to highlight their two main providers. After the success of the courses at Stanford, researchers and educators started to develop special kinds of platforms to host future MOOCs. In April 2012, Daphne Koller and Andrew Ng also at Stanford University, developed Coursera as a for-profit organization, which quickly became the most popular platform. Originally, Coursera partnered with four elite universities: Stanford, Princeton, the University of Pennsylvania, and the University of Michigan (Lawton & Katsomitros, 2012; Flynn, 2013). Today, hundreds of universities across the world have joined Coursera.

The second provider of MOOCs is the edX platform. In May 2012, MIT and Harvard University jointly founded this platform. Several other universities later joined the company to deliver their courses. Its function as a non-profit organization distinguishes edX from Coursera (Lawton & Katsomitros, 2012; Flynn, 2013). In addition to these two platforms, Sebastian Thrun founded the Udacity platform as a for-profit organization, however it has recently declared an intention to move away entirely from offering MOOCs as it "seems to have given up on the whole concept of free and is aggressively moving towards monetizing content." (Shah, 2018, January 20) These are not the only platform providers to offer MOOCs, but they are the most popular ones. Several other providers came into existence to serve the same purpose, such as Udemy, FutureLearn, XuetangX and P2P University (Liyanagunawardena et al., 2013; Kesim & Altınpulluk, 2014; Yuan & Powell; 2013). With the development of MOOC platforms, MOOCs started to proliferate rapidly in higher education.

Interestingly, the MOOC phenomenon became the fastest growing trend in higher education. It was the "buzz" word for the year 2012, with the *New York Times* journalist Laura Pappano calling the year of 2012 "the year of MOOCs" (Pappano, 2012). Johnson et al. (2013) expected the MOOCs to continue to grow and become more popular as an e-Learning option in less than a year and so it is certainly the case now. Few years ago MOOCs was just an idea; now they exploded onto the landscape of online education within a relatively short time frame and they still extend each day increasingly. As of January 22, 2018, Dhawal Shah at Class Central, an aggregator that gathers insights on MOOCs, released the latest statistics report on the growth of these courses for the year of 2017. Data have shown a notable increase over the years. According to Shah (2018), more than 800 elite national and international universities are now offering MOOCs as opposed to 700 university partners in the previous year. With the increased number of these partners, MOOC offerings and learners are also growing at an exponential pace. Shah (2018) further reports that there are nearly 78 million unique registered learners enrolling in more than 9,400 MOOC offerings, noting that these enrollments and courses doubled from 2016. These statistical facts about the exponential growth of MOOCs imply a real revolution in the world of higher education that requires an attention to study these massive learning environments.

Implications of MOOCs for Higher Education

Much of the previous literature on MOOCs has primarily focused on the potential of MOOCs in addressing the challenges perceived to be facing higher education, such as values, accessibility and cost. In terms of values, some researchers believe that MOOCs as a new innovation have great potential for providing lifelong learning and, more specifically, professional development for career benefits. According to Johnson et al., (2013) MOOCs offer the possibility of continuing advanced learning for little or no cost, allowing students and lifelong learners to acquire new skills and to improve their intellectual knowledge and credibility in various areas. Steffens (2015) asserts, “I do believe that a MOOC of good quality will help people who are already experienced learners to improve their knowledge and skills in a specific area. Therefore, MOOCs are likely to play a role in lifelong learning” (p. 43).

Furthermore, Liyanagunawardena et al., (2013), in their systematic review of published MOOCs literature from 2008 to 2012, showed that personal enrichment and self-satisfaction, as a lifelong learning element, are considered among the top important motivations for learners to take MOOCs. Similarly, researchers at Duke University discovered that most of the students participate in MOOCs for lifelong learning purposes and to gain a better understanding of the subject matter (Belanger & Thornton, 2013).

In particular, students are taking MOOCs for professional development purposes. Across thirty-two MOOC offerings at the University of Pennsylvania, Christensen and colleagues (2014) revealed that "students' main reasons for taking a MOOC are advancing in their current job" (p.1). Another qualitative study using semi-structured interviews at Northeastern University found that students usually take MOOCs "to gain knowledge that will allow them to better fulfill their current job responsibilities" (Zheng et al., 2015, p. 5). This is in addition to the recent statistical report by Coursera for the year of 2017 indicating some sort of career benefits out of MOOCs for educational purposes and/or sharpening their skills for new career paths (Levin, 2017, April 26). It is stated that, "84 percent of career-focused learners who completed courses reported career benefits; and among education seekers, 93 percent reported educational benefits. These numbers remain consistent with the survey results we reported in 2015."

Other research studies have highlighted the potential of MOOCs to democratize higher education by increasing access to high quality education for minority students. For instance, Carver and Harrison (2013) point out that "because there are no fees, low-income students have the opportunity to participate in courses that might otherwise be unaffordable" (p20). Levin (2017, April 26) in the recent Coursera report further asserts that, "learners seeking career and educational advancement were more likely to report benefits if they came from developing economies, hadn't completed a bachelor's degree, or were of lower socioeconomic status." One of these benefits that has been noted in prior research and specifically with international students is the potential values of MOOCs to improve English language. According to Asiri (2014) international students enroll in MOOCs "to enhance their English proficiency and familiarize themselves to the US educational system before coming to the US" (p.1). Other available research has focused on the value of MOOCs to promote women's human rights in different segregated areas around the world. The journalist Hannah Gais (2014), in her online article "Saudi Arabia gets MOOC'd up", discussed how MOOCs are also benefiting women in the Arab world. Gais pointed out that Saudi Arabia's Ministry of Labor partnered with edX to launch a new MOOC portal, "Edraak", designed specifically for the Arab audience. Its main goal is to empower women's educational experiences and their vocational training. As cited in Gais (2014),

> For women, [offering MOOCs] means improving the quality, not just the quantity, of universities. For example, female law students should have access to the same quality of training that their male peers receive. It also means opening up the workforce to women, providing them with palpable economic incentives and opportunities to put their education and training to use.

However, while this seems to be promising, research shows that the majority of MOOC learners are highly educated males from developed countries (Christensen et al., 2014).

From another perspective, other researchers have argued the potential of MOOCs in reducing the costs of higher education. Indeed, one of the biggest challenges to the traditional model of higher education is the rising cost of school tuition associated with less productivity of learning, in what Bowen (2013) calls "the cost disease". MOOCs, in their early iterations, used to grant only a verified certificate of completion to the students who completed the course and paid the minimum fees, without giving any college credits (Daniel, 2012). However, as MOOCs developed, they took a step forward in providing credits for online specializations and other educational degrees (Lequerica, 2016). According to Haggard and colleagues (2013, p. 5), MOOCs are moving towards being "a standard element of credentialed University education" as they drive down the high tuition costs of traditional higher education. There are several examples of adopting the low-cost MOOCs learning model to be transferable to a traditional college degree. One of these examples is the initiative taken by the State of California. Democratic and Republican state legislators in California mandated a new role for MOOCs by allowing students to transfer MOOC credits to high school and college degrees (California Senate Bill 520, 2013). Likewise, Arizona State University has partnered with edX to offer a full freshman year of MOOCs with a total of 12 courses via the Global Freshman Academy as an initiative to lower the tuition fees (Botelho, 2015). In addition to these examples of transferring MOOC credits to high school and college degrees, University of Illinois at Urbana-Champaign initiated an entire MBA MOOC-based program exclusively online through Coursera in Spring 2015. This program, known as the iMBA, consists of a set of 8 “specializations” relevant to different topics in business administration. Students are required to complete at least 6 paid specializations in order to be eligible to earn the MBA degree. The purpose of iMBA is to lower the tuition fees, as this program costs *one fifth* of what students usually pay in traditional MBA program offered on-campus (Moules, 2015).

Discussing these potential implications of values, accessibility and cost, it is also important to review the current literature on learners’ participation in MOOCs. This is to be highlighted in the following sub-section.

Learners’ Participation in MOOCs

In any educational setting whether in a traditional school system or an eLearning environment, learners’ participation is an important component and a key competency in the learning process. It promotes thinking, develops reasoning and indicates knowledge acquisition (Piaget 1976; Rocca, 2010; Kalantzis & Cope, 2012; Johnson, Johnson, & Smith, 2013; Cope & Kalantzis, 2017). Since learning is a social construct, knowledge acquisition in this context involves doing actions in a communicative relationship with the instructor, among learners and with the course content to produce meaning (Vygotsky, 1962). With this in mind, then how do learners participate in such a complex and a massive e-Learning ecology characterized by MOOCs to produce meaning?

In a review of the literature on learners' participation in MOOCs, different researchers have taken various approaches to study this topic. Some researchers have primarily focused on identifying a set of potential factors that might impact learners' participation and performance in MOOCs. For instance, Cisel (2014) applied correlation techniques and found a significant difference between students' performance in MOOCs and learners' geographic locations, employment status and time constraints. According to Cisel (2014), learners from developed countries and learners who are not employed are more likely to engage in the course. Similarly, Morris, Hotchkiss and Swinnerton (2015) indicated learner performance in MOOCs is related to age, prior online learning experience, employment status and educational level. To illustrate, the authors found that older learners who are unemployed and highly educated with previous knowledge of online learning tend to engage the most in MOOCs. Using survey analysis, Hone and El Said, (2016) reported that MOOC course content and instructors' feedback have a positive impact on learners' engagement in MOOC. According to Hone and El Said, (2016), learners tend to engage in MOOCs if the course content is interesting and when the instructor is more involved in the learning process. Although these researchers have focused on understanding the set of potential factors that might impact learners' participation in MOOCs, they have solely relied on demographic data and survey analyses without considering the actual participation and learners' behaviors in the data log files that MOOCs provide.

Other researchers have taken these data log files into consideration and started to tracing specific activities in a MOOC in an effort of developing predictors to improve participation. For example, Sinha, Jermann, Li, & Dillenbourg (2014) developed a predictive model of student completion derived only from the video lecture clickstream data in order to determine which behavioral action (i.e., fast watching, slow watching, re-watching, skipping) was associated to course dropouts. They found students who like to re-watch the videos are most likely to continue in the course. Others went another step forward to have better predictive understandings of MOOCs' success by combining the clickstream data and natural language processing (Crossley, Paquette, Dascalu, McNamara, & Baker, 2016). Natural language processing includes analyzing learners' posts in the discussions forums. The findings of their study indicated that viewing the lectures and submitting assignments on time are the most predictable variables of MOOCs' completion. Also, there was a notable relationship between the quality of learners' writing and MOOC success. Despite these efforts in predicting factors of leveraging participation in MOOCs, what is needed is an understanding of the distinct ways learners engage and participate in these learning environments.

One of the several studies that has focused on finding the different participation patterns in MOOCs is the study of Milligan, Littlejohn, & Margaryan (2013). To determine the patterns of participation, the researchers conducted semi-structured interviews and identified three distinct patterns: active, lurker and passive learners in a connectivist MOOC. Active pattern represents the most engaged learners in the discussion forums and those who have actively accessed the course content. Lurkers pattern include learners who were active in following the course content but did not engage much in the discussion forums. Passive pattern displays learners who were frustrated with the course and could not engage with their classmates.

However, this study has only relied on twenty-nine participants from a total of 2,300 registered MOOC learners. Because of this very small number of research subjects, the findings cannot be generalized. Furthermore, this study did not take advantage of the multiple types of data available in MOOC data logs.

Another study, however, used data mining techniques to mine the videos' clickstream data and weekly assessment submissions of each student in order to explore the different patterns of engagement (Kizilcec, Piech, & Schneider, 2013). The researchers found four learning patterns of engagement and participation in three computer science MOOCs: completing, auditing, disengaging and sampling. Completing pattern includes learners who completed majority of assessments. Auditing pattern characterizes those learners who watched most of the videos but completed assessments infrequently. Disengaging learners completed assessments early in the course but discounted engagement afterwards. Sampling learners merely explored some course videos. Similarly Anderson, Huttenlocher, Kleinberg, & Leskovec (2014) used clustering analysis techniques to analyze six Coursera MOOCs based on two activities: viewing a lecture video and handing in an assignment for credit. The authors found five patterns of students' engagement: the viewers, solvers, all-rounders, collectors, and bystanders. Viewers pattern describes learners who primarily watched course lectures. Solvers pattern are those learners who primarily solved the assignments for a grade. All-rounders pattern includes those learners who are in the middle of doing both activities of watching lectures and solving assignments. Collectors pattern resembles those learners who downloaded the videos but not necessarily watched them. Bystanders pattern displays those learners with a low activity profile. While these studies mined some of the students' activities in video lectures and weekly assessments, they did not include learners' interaction in weekly discussion forums, an important aspect of learning as it resembles learners-to-learners interaction. This leaves a gap in literature review to conceive an inclusive picture of learners' participation in MOOCs.

Building on the previous literature, the study of this dissertation aimed to fill in the research gap and contribute to the growing scholarly discussion of how better to understand learners' participation in MOOCs. The study adopted the frameworks of Kizilcec et al. (2013) to mine learners' behaviors, but it expands upon this endeavor in two distinct ways. First, the focus here is to highlight the various patterns of participation from a wider perspective in order to better understand how learners participate across multiple activities in the course. Thus, the study is not limited to mining leaners' interaction with video lectures and assessments only as in Kizilcec et al, (2013), but it also adds learning behaviors in the discussion forums. Second, the aim of this dissertation is not only to explore the participation patterns in MOOCs, but also to find the demographic variables and other influential factors that may associate with them. Therefore, the study employed a mixed method approach combining educational data mining, statistical analysis and content analysis. The context of this study is the first iteration of the Coursera MOOC "Subsistence Marketplaces" in UIUC. The term "participation" was identified in this study as longitudinal patterns of interaction with the primary features of the course, including accessing video lectures, attempting to submit weekly quizzes and interacting in discussion forums on a weekly basis.

Theoretical Frameworks

To address the research questions, this study adopts the concepts of constructivist and differentiated learning theories related to knowledge construction and individual engagement.

Constructivism

By the beginning of the twentieth century, educational thinkers and practitioners, from Jean Piaget to John Dewey and Maria Montessori, called for new educational reforms away from the didactic approach to endorse a new mode of learning represented by constructivism. According to Piaget (1976) constructivism is a philosophical theory that is used to explain how learners construct knowledge to make meaningful learning through reflecting on their prior and immediate experiences. The basic idea of this theory is to put learners at the center of the learning process. As learners are engaged in a dynamic learning environment consisting of several interaction processes among other learners, instructors and educational materials, they will then construct their own understanding. Consequently, learning is an active process that entails a change in the learner. Depending on collective understanding and proclivities, each individual interprets learning in a different manner to make meaning. In other words, constructivism is the study of how learning takes place and how learners create knowledge structures based on their interaction with the environment.

Similar to Piaget's points of view of constructivism, John Dewey, called for a pedagogical reform built upon the idea of "experiential learning," with a focus on educating the whole child (Dewey, 1938). Dewey valued the individual experience and learning identity as an important aspect of a meaningful true learning. Furthermore, Maria Montessori (1912) believed that education is a process that develops naturally according to individuals' interests and needs. In this sense, learners construct meaningful learning as they are engaged in free play and/or individual or group activities of their own choice.

With the rapid changes to education and technology and the rise of e-Learning environments in recent days, the necessity to understand learning behavior is higher than ever before. This is because of the increase number of diverse learners in online learning environments and the pressing need to develop a greater understanding of how to work with them (Kalantzis & Cope, 2012; Cope & Kalnatzis 2017). Constructivism may set a solid ground to study learning behaviors in online settings, especially in large scale learning environments (Berland, Baker & Blikstein, 2014; Kevan & Ryan, 2015). At massive scale learning and more specifically in MOOCs, learners do everything online to construct meaning. They visit the course website to learn about the content, read through the texts and assigned readings, view the announcements, watch video, discuss course materials and prompts with classmates and instructors, and submit their quizzes (Daniel, 2012, Liyanagunawardena et al. 2013; Yuan & Powell; 2013) to construct meaning in a monolithic system. Envisioning constructivism in relation to learning analytics and educational data mining can be suited to collect and analyze this rigorous data about learners' behaviors and make sense of how they construct individualized meaningful learning. Guided by this theory of constructivism, this study assumes that individual learners engage in Coursera MOOCs differently to construct a unique learning experience.

Differentiated Learning

Furthermore, this research is guided by the idea of differentiated learning and reflexive/inclusive pedagogy. Differentiated learning can be defined as a philosophy that values learners' prior knowledge and learners' identities and works with them to achieve their mastery level of learning. It is a mind-set to actively engage learners in meaningful learning activities and real-world problems based on their interests and needs. Following this approach aims "to demonstrate better understanding, maximize content knowledge and improve the learning skills of a wide spectrum of learners" (Haniya & Roberts-Lieb 2017, p.185).

Traditionally, educators use a didactic approach of learning characterized with the "one-size-fits-all" pedagogy which assumes sameness and homogeneity. In this didactic approach, all learners learn the same thing (content) in the same way (process) with the same assessments (product), in the same space (learning environment) without paying attention to the varied individuals' needs (Haniya & Roberts-Lieb 2017). Instead of assuming sameness or homogeneity, learners are entitled to an education that values their varied interests and develop their personalities and abilities to a maximum level (Tomlinson & McTighe, 2006, Tomlinson, 2014).

In response to this classical mode of the one-size-fits-all approach, new pedagogy has emerged in line of differentiated learning, such as the "Reflexive/Inclusive approach" (Florian, Rouse, Black-Hawkins, 2016; Kalantzis & Cope 2016b; Cope & Kalantzis, 2017). In contrast with the one-size-fits-all approach, this new pedagogy is a method of teaching that incorporates multiple dynamic practices and learning modes, engaging and diverse content and varied means of assessments. In this sense, learning is reflexive, more flexible, constantly adapted and modified to balance learners' needs and their progress. The overall goal of this pedagogy is to promote productive diversity in learning to meet learners' diverse needs (Florian and Black-Hawkins, 2011; Rouse, Black-Hawkins; 2016).This pedagogy is consistent with the mastery level of learning explained by Benjamin Bloom (1968). According to Bloom (1968), every learner is capable to learn and achieve a mastery level of learning if he/she has the appropriate teaching strategy and the right scaffolding and support to meet their individual needs and educational goals. Likewise, reflexive/inclusive pedagogy offers the possibility to work with learners and see where they are and where they need to be in order to advance in their learning.

Informed by the ideas of differentiated learning and reflexive/inclusive pedagogy, the study seeks to understand how MOOC learners participate differently in massive learning environments and explore the patterns of their learning behaviors. Understanding these patterns would present useful information in how to adjust MOOCs in Coursera to integrate multiple paths of learning in order to meet learners' needs.

Chapter Summary

In reviewing the current literature of MOOCs, these courses have many potential implications for higher education in terms of learning values, accessibilities and reducing cost. Interaction and participation are very important aspects in these courses to keep learning going. Previous studies on learner's participation in MOOCs have mainly focused on identifying and predicting factors that influence engagement. Several other works used data mining techniques to examine the way how learners participate in MOOCs, but they included limited variables (e.g., videos and assessments) and did not include qualitative methods to supplement the analysis. The study of this dissertation however mined learners' behaviors across three different variables (Videos, assessments and discussion forums) to better explore the participations patterns. Also, this study employed a mixed method approach to better analyze the data using educational data mining, statistical analysis and content analysis. The goal is not only to explore the patterns of participation but also to discover the different demographic factors and other influential factors of motivation and barriers that could relate these patterns.

CHAPTER III. RESEARCH DESIGN AND METHODOLOGY

This chapter covers the research design and methodology of this dissertation; divided into five main sections. In the first section I discuss the use of mixed methods containing Educational Data Mining, quantitative (statistical) analysis and qualitative (content) analysis in order to answer the research questions. In the second section, I describe the context of the study which includes a description of the course, the research participants and where the research took place. In the third section, I explain the two different resources used to collect the data including activity logs and surveys. In the fourth section, I review the procedures of data analysis that I used. Finally in the last section I illustrate the process of data curation to prepare for the analysis.

Mixed Methods

To better understand the nature of learners' participation in the "Subsistence Marketplaces" MOOC and how it relates to their demographic and environmental factors, this study employs a mixed methods approach. Creswell and Clark (2006, p. 5) defines mixed methods as follows:

> Mixed methods research is a research design with philosophical assumptions as well as methods of inquiry. As a methodology, it involves philosophical assumptions that guide the direction of the collection and analysis of data and the mixture of qualitative and quantitative approaches in many phases in the research process. As a method, it focuses on collecting, analyzing, and mixing both quantitative and qualitative data in a single study or series of studies.

Mixed methods research is a growing area of methodology among different educators and researchers and across various disciplines (Teddlie & Tashakkori, 2010). This increase in using mixed methods research rather than relying on a single method has many values. For example, using only quantitative methods could provide general information of a large number of participants in a given context. However, this is not adequate to give specific reasons and explanations of why students behaved this way but not the other way. On the other hand, qualitative methods could provide a meaningful understanding of students' answers. Yet, their interpretations are limited for a few participants, which make it hard to generalize outcomes. Both methods have strengths and weaknesses, but when these methods are used together, they can complement each other (Greene and Caracelli, 1997; Greene, 2007). In a previous study, McKim (2017) found that using mixed methods add more values to the outcomes than using a purely quantitative method or qualitative method. He reported "studies that use a mixed methods approach gain a deeper, broader understanding of the phenomenon than studies that do not utilize both a quantitative and qualitative approach" (p. 203).

While the study of this dissertation utilizes a mixed method approach combining quantitative and qualitative methods, it also adds educational data mining as a new and an evolving field in educational research. Using mixed methods in this way helps in taking advantages of the three different methods to better answer the research questions and add values and meaning to the findings. In the following subsections, I will explain the three different methods used in this research, Educational Data Mining, Quantitative research, and Qualitative research.

Method #1: Educational Data Mining

The main method of analysis in this research is Educational Data Mining (EDM). Since EDM is a recent field in education research, I will explore this approach in more details in relation to its emergence, definition, benefits and challenges and the reasons why it is suitable for this study.

The Rise of Big Data

Living in a digital universe, the proliferation of technology advancements, the popularity of digital media applications, the cloud computing revolution and having the ability to connect online at anytime and anywhere, more people are now being digitally connected than ever before. As more people are online, more information and data are being generated, collected and stored in servers in continuous bases. As a consequence, data has become big and varied in terms of its volume and kinds. A white paper released by Forsyth Communication (2012, p. 4) claims that "between now and 2020, the amount of information in the digital universe will grow by 35 trillion gigabytes". The authors indicate that "in 2011 alone, the amount of digital information created and replicated surpassed 1.8 trillion gigabytes" (p.4). Interestingly, they believe that this unprecedented rate of growth would exceed the estimated number of stars in the physical universe. This huge amount of data that are continuously growing at an exponential rate is called "big data". In general, the term "big data" refers to the process of capturing and recording huge datasets from a wide variety of digitally mediated environments, technology applications, online platforms and websites, which are created by every little action an individual can make as he/she is actively online (Cope & Kalantzis; 2016).

This tremendous growth of data being generated every second carries a lot of information that may transform how we "live, work and think" (John Walker, 2014). With this data revolution and the information being collected on a massive scale, new methodologies have emerged to find new ways and appropriate techniques to process this data and make sense of it. The goal is to extract the maximum benefits for digital users and inform decision making. Therefore, this big data led to the emergence of the data mining approach. Data mining can be defined as "the process of discovering interesting knowledge, such as patterns, association, changes, anomalies and significant structures, from large amounts of data stored in databases, data warehouses or other information repositories" (Cotofrei & Stoffel, 2005; p.185). The applications of data mining have been widely used in business, commercial fields, health, and finance for many decades to improve the customer experience. More recently it is now being used in the education field.

Defining Educational Data Mining (EDM)

With the development of e-Learning tools and the rise of digitally mediated learning environments that we witness every day, the data mining approach captured the attention of researchers in education and made its way into the field. This approach is being called "Educational Data Mining" (EDM); as it uses educational data that deals with educational issues and problems. Its aim is to improve teaching and learning in a variety of learning contexts in favor of teachers and students (Baker & Siemens, 2014; Papamitsiou & Economides, 2014; Cope & Kalnatzis, 2016). According to Romero and Ventura (2013, p. 12), EDM is the process of "developing, researching, and applying computerized methods to detect patterns in large collections of educational data that would otherwise be hard or impossible to analyze due to the enormous volume of data within which they exist."

It is also important to mention that EDM is not simply the use of machine learning to come up with an outcome; it is an interdisciplinary field which integrates many methods and techniques including artificial intelligence, database systems, statistics, and machine learning, in order to process various amounts of data and then come up with a result. In other words, EDM can develop many new methods of its own (Han, Pei, & Kamber, 2011; Baker & Siemens, 2014).

In addition to the emergence of the educational data mining approach, there is also the field of learning analytics. Although these two methods overlap among research and researchers; they have slight differences in their origins and types of discovery (Baker & Siemens; 2014; Papamitsiou & Economides; 2014, Siemens & Baker; 2012). Both of these approaches attempt to analyze, evaluate and interpret big data files, clickstream data and keystrokes to improve learning. Yet, educational data mining emphasizes on “reducing to components and analyzing individual components and relationships between them”, while learning analytics has a holistic focus to understand “systems as wholes” (Siemens & Baker; 2012, p. 253).

Benefits of EDM

Employing educational data mining and/or learning analytics in any research may bring several benefits and values for education. In general, the goal of EDM is to turn messy and raw educational data into meaningful information to analyze students’ learning in any given environment and develop a better understanding of their behavior (Bienkowski, Feng, & Means, 2012; Cope & Kalanatiz, 2016). Its main goal can be oriented in many different ways. Educational data mining researchers Baker and Yacef (2009) have identified four potential benefits of using EDM. First, this methodology would allow researchers and educators to discover interaction and participation patterns among students. It can also help in developing models to predict students’ future learning. Secondly, beyond this point of discovering and predicting learning behavior, EDM makes it possible to improve educational pedagogies and refine the instructional sequences to accommodate students’ educational needs by identifying what part of educational content or learning activities engaged more learners than others. Third, through EDM it is possible to inform technology developers of possible ways to modify the design and the implementation of the current e-Learning platforms and learning management systems to ensure efficiency and effectiveness in the process of online learning for learners and instructors. Finally, the authors indicate that following this approach may help “to refine and extend educational theories and well-known educational phenomena, towards gaining deeper understanding of the key factors impacting learning” (p.7), especially with the emergence of large scale e-learning ecologies that needs to be explored.

To achieve these goals, the EDM approach utilizes different types of techniques. One of the most popular one is “predictive modeling”. Predictive modeling is typically concerned with performing inferences on data to predict future learning behavior from the current learning performance of the students. It helps in detecting abnormal learning behaviors and problems through the use of classification, regression and/or density estimation techniques (Baker & Siemens, 2014; Baker & Yacef, 2009). Another common type in EDM is called, “Structure Discovery” or “Knowledge inference”. The main focus of this type is to characterize general properties of data in a large-scale database to discover new knowledge without having a previous idea of the outcome. Using techniques of clustering, factor analysis and/or social network analysis, this approach can help in providing useful feedback for teachers to understand students’ learning behaviors (Baker & Siemens, 2014). Indeed, the study of this dissertation utilizes this approach to explore patterns of learners’ participation.

Challenges of EDM

Like any other research method, EDM comes with its own challenges associated with its implementation and interpretation. One of these challenges is the issue of raising ethical concerns by abusing students’ privacy and their digital foot printing. Big data includes very sensitive information about digital users and their online behavior which may put these people at risk (John Walker, 2014). Such information may produce misleading predictions and interpretations that may in turn lead to a negative educational impact on students instead of having a positive one. Another challenge in EDM is the worry of reproducing didactic pedagogies because the use of this method may intensify automated learning and testing while putting teachers on the side and ignoring their accountabilities (Cope & Kalantzis, 2016). In addition to these two challenges, there is the cost concern. As a matter of fact, using EDM is associated with costs in collecting and storing big data logs. There is also an additional cost of hiring algorithm developers to manage and apply EDM applications and techniques (Bienkowski et al., 2012). Regardless of all of these challenges, EDM offers substantial benefits to the field of education that need to be explored especially in massive scale learning.

Rationale of Using EDM in This Study

With the information provided above, EDM generally is the best fit to analyze the tremendous amount of data MOOCs provide. In particular, the enrollments of the Subsistence Marketplace MOOC have reached to a total of 10,063 learners, coming from 165 different countries. These learners interact and participate in the course in various ways and all of their contributions are stored in the system. This interaction with huge number of learners provides a great deal of data to be analyzed.

Therefore, EDM methods will be used in this study to explore the different patterns of participation among learners using clustering techniques. Clustering is defined as the process of grouping a set of objects into different clusters that share the same characteristics and features (Witten & Frank, 2005; Baker & Siemens, 2014). Data to be analyzed include learners' interaction with the video lectures, discussion forums and weekly quizzes.

Method # 2: Quantitative method

Along with the use of EDM, this dissertation also utilizes quantitative methods to supplement and enrich data analysis. Creswell (2014, p. 54) has defined quantitative research as follows:

> Quantitative research is an interrelated set of constructs (or variables) formed into propositions, or hypotheses, that specify the relationship among variables (typically in terms of magnitude or direction). A theory might appear in a research study as an argument, a discussion, a figure, or a rationale, and it helps to explain (or predict) phenomena that occur in the world.

Educators often use quantitative research to test a specific hypothesis and examine a relationship among different variables to find an explanation and answer for the proposed research question(s). In this study, quantitative analysis is used to determine the relationship between the different patterns of participation that emerged from applying EDM techniques and the demographic variables of learners. To examine the relationship between these variables, the study utilizes the Pearson Chi-Square statistical test of independence. This test is used to examine if there is a significant relationship between two categorical variables (Greenwood & Nikulin, 1996; Bagdonavicius & Nikulin, 2011). “The frequency of each category for one variable is compared across the categories of the second variable” (Statistics Solutions, 2018).

Method # 3: Qualitative Method

Qualitative research methods is also used in this study to achieve a more in-depth interpretation of why learners behave in a certain way but not the other way. This is a useful approach to provide a better understating of a specific phenomenon relying on the inner voices and individual experiences of the research subjects. According to Cresswell (2014, p.4),

> Qualitative research is an approach for exploring and understanding the meaning individuals or groups ascribe to a social or human problem. The process of research involves emerging questions and procedures, data typically collected in the participant's setting, data analysis inductively building from particulars to general themes, and the researcher making interpretations of the meaning of the data.

Along these lines, this study used this approach to analyze the open ended questions found in the course survey of the "Subsistence Marketplaces" MOOC. Doing so helps to explore the common themes that could motivate or limit learners' participation across the different patterns found as a result of conducting EDM techniques.

Context of the Study

Prior to describing the research context, it is important to indicate that this study was approved by the Institutional Review Board (IRB) at the University of Illinois Urbana-Champaign (UIUC) (see appendix A). The course to be analyzed is the first iteration of the session-based "Subsistence Marketplaces" MOOC. This is the first MOOC offered by the College of Business at UIUC. The course was launched in 2014 and taught in the Coursera platform. The offering of this course lasted for 8 weeks and it roughly mimicked the same materials as the on-campus course "Subsistence Marketplaces" for graduate and advanced undergraduate students. The decision to choose this course because of its focus on diversity in terms of content and participants. It represents both fields of humanities and science.

The course attracted a total of 10,063 learners from 165 countries and 41% of them are from emerging economies. The purpose of the course is to develop a better understanding of subsistence marketplaces in different areas of the world. It helps learners to think of the global challenges of poverty and thus design solutions for such problems to envision a better world.

This course is woven through with stories of people`s lives--what they go through, how they live, what changes are introduced and how and why--in addition to carrying strong themes of empowerment and showing alternative ways of living. The course activities consisted of a set of short recorded lectures, weekly quizzes, reading materials, online discussion forums and a final project. Reading the course materials, watching video lectures and submitting weekly assessments were required activities. On the other hand, participating in the discussion forums and doing the final project were optional activities. Given this course background, I will next explain the process of data collection.

Data Collection

To adequately answer the proposed research questions, I have collected data from two different resources including, activity logs/clickstream and course surveys. Each one of these resources is explained in the following sub-sections.

Activity Logs/Clickstream

Activity logs/clickstream contain information related to learners' interaction with different aspects of the course. In general, this data includes information on dates of enrollment, page views, learner IP address information, video interaction, forum participation and quiz submission. The study collected information from this data regarding videos, forums and quiz interaction.

Videos Lectures

Video interaction is an important element in any online learning environment and more especially in MOOCs when there is no synchronous sessions to meet in real time (Bishop & Verleger, 2013; Sinha et al., 2014). In the traditional classroom analogy, recorded video lectures in MOOCs substitute face-to-face instruction. In fact, these lectures are the main way that learners will have access to the core content of the course. For this reason the study included the video interaction as one of the variables in mining learners' participation in this MOOC. In general, data of video lectures provides information about learners' interaction with these videos. It tells which videos the learner watched, how many times he/she watched it, and whether the videos were downloaded or streamed and the time when these videos were accessed.

For the purpose of this study, the variable of video lectures participation was calculated to include the number of times the learner clicked on any video lectures from the current week or previous weeks (either by watching or by downloading it) in the identified week. Learners can have access to videos of previous weeks, but it is not be possible for them to watch a video from a future week, since it has not been released yet.

Discussion Forums

Discussion forums play a valuable role in any online educational setting to facilitate teaching and learning and more specifically in MOOCs with the absence of face-to-face interaction and synchronous sessions (Jiang, Williams, Schenke, Warschauer, & O'dowd, 2014). There exists some agreement among social learning research and connectivism regarding the importance of such tools to positively enhance learning (Lave & Wenger 1997; Siemens, 2005; Jenkins, 2006). Forum discussions in online learning are considered one of the most powerful tools to encourage and stimulate learning and add variety of educational benefits. Engaging in these forums helps to develop critical thinking skills and shift the focus from knowledge consumption to knowledge construction by exchanging ideas and conversations which will eventually lead to better educational outcomes (Kalantzis & Cope, 2012; Jiang et al. 2014). For these reasons, the study also gathered information regarding learners' interaction in the discussion forums even though these activities were optional.

Data of the discussion forums usually contains information about the number of forum posts (comments and or threads) a learner has made, the content of these posts and also the time of taking the action to releasing a post. For this study, this variable of measuring discussion forum participation contained the number of times a learner created a post or commented on a forum post during the week.

Quiz Submissions

Formative assessments such as weekly quizzes are very important to include in any online and offline educational setting. These quizzes gauge how much a learner has learned towards the end of a lesson. It also helps to assess knowledge and understanding of the course content (Kalantzis & Cope, 2012). Therefore, it is important to consider quizzes when investigating the learners' behavior and include them in the mining process.

Data files of quizzes provide information about when the quizzes were taken, the number of submissions and scores. For the purpose of this study, the variable of quiz participation was calculated to include the total number of attempts a learner has made to submit a quiz in a week but not the score. In fact, the scores may indirectly matter because learners who receive high scores from the first trial may stop taking the quiz again. There were only three trials for each quiz. Yet, since the aim of this dissertation is studying how learners behave and participate in the course but not how they perform, the study intends to respect all efforts and attempts taken in the quizzes regardless whether the answer is right or wrong.

Survey Data

While activity logs are the main resources of data collection to mine learners' online behaviors and participation in the course, this study also collected data from the course surveys to do further analysis. Mining learners' participation alone is not adequate to understand the reasons behind these behaviors. Therefore, the study collected survey data as to complement the research and understand the different factors that influence learners' different patterns of participation in MOOCs.

Each Coursera MOOC offered at UIUC includes two different types of surveys, pre-course survey and post-course survey. These surveys are generated via Survey Gismo software and developed by the UIUC MOOC team in the Center of Innovation for Teaching and Learning. This team is also responsible for distributing the surveys to all MOOC learners via email invitations with a web link to the survey. The survey questions include simple, straightforward multiple-choice questions, and open-ended questions. The pre-course survey is always sent out at the beginning of the course. It includes demographic information such as gender, age, the level of education, the level of English proficiency, previous online learning experience, employment status as well as open ended questions to understand learners' motivations for taking the course. The post-course survey is always sent out towards the end of the course. This survey is meant to understand learners' experience and satisfaction with the course once it is over.

For the purpose of answering the second and the third research questions, this study analyzed part of the course survey relevant to the demographic variables, motivations and limiting factors.

Data Collection in Relationship to Research Questions

The table below explicitly shows the relationship between each research question and data collection.

1. What kinds of participation patterns exist among MOOC learners in the Coursera platform?	**Activity logs** **Video interaction** • The number of times a learner accessed a video in a week. **Forum interaction** • The number of times a learner has posted in a forum and/or made a comment in a week. **Quiz interaction** • The total number of attempts the learner has made to submit a quiz in a week
Q2. What is the relationship between the different patterns of participation in Coursera MOOCs and learners' demographic variables including gender, age group, educational level and employment status?	**Course Survey Data** Data was collected from the questions that are related to gender, age, education level, and employment status.
Q3. What are the main factors that motivate and limit learners' level of participation in Coursera MOOCs?	**Course Survey Data** **Motivation factors:** Data was collected from the following question: • What are your reasons for taking this course and what do you hope to get out of it? **Limitation factors:** Data was collected from the following question: • What were the factors that limited the extent to which you took advantage of this Coursera opportunity?

Table 1: Data Collection in Relationship to Research Questions.

Data Curation

This section describes several steps of data processing occurred to curate data and prepare the three different variables (videos, quizzes, forums) for the data mining process in weekly bases. The choice of mining learning behavior within a week long is a result of the course structure. Session-based Coursera courses usually present new materials each week. Hence, learners observe a new and different set of resources every week. Therefore, it is more meaningful to study how learners interact and participate in a week.

The initial dataset contained raw data and records of unnecessary data points relevant to the instructor, TAs, community aids and UIUC MOOC staff and Coursera staff. Not only that, but also there were some variables and outliers that were not needed for the purpose of this research, such as IP addresses, scores and content of learners' posts, etc. Thus, the first step of data curation process was to remove this irrelevant data from the dataset and keep things that are relevant to mining learners' behaviors.

Another step in the process of data curation was to transform data into a more workable format and create the variables for the data analysis. For instance, the received raw data included only the timestamp of when the action has been done but it did not capture the action in a week-by-week block. Therefore, I created a new variable by calculating the number of actions happened in each week for video watching data, discussion forums and weekly quizzes. It is also important to mention that although the course was 8 weeks long, I added one extra week (week 9) to trace learners' activities after the course is over.

After rearranging learners' activities in a weekly basis, the third step was to combine all of the data files into a single document and include the three identifiable variables altogether. Learners' participation was measured based on three variables, video watching, forum participation and quiz Submission. The new combined document included 41220 data points coming from the learning behaviors of 4583 learners. While this number of learners is less than the original number of registered learners (10,063) in the course, the number only reflects those who have shown some types of learning behaviors across the three identifiable variables. Hence, the study considers those as active learners.

Lastly, I have noticed a large variation in the data range from one variable to another. Therefore, I had to normalize the data to bring all the values in each variable into the range of 0 and 1. Normalization is a useful technique in EDM in order to guarantee a stable weight among variables and thus it helps to prevent any biases that may affect the clustering model. Also, I used an upper limit for the value of variables to ensure that the normalization process would not be skewed specially for the video interaction. Initially, the video interaction variable has an extremely high readings where there was no other recorded behaviors in other parts of the course. The mean score of this variable was 1.94 ranging from 0 to 3,128. Thus, I selected the upper limit of the video interaction at which learners have shown a learning behavior in at least one of the other variables, which was 185.

Data Analysis

The first aim of this study was to explore the patterns of participation among learners within their interaction with video lectures, quizzes and discussion forums. This happens by grouping learners of similar weekly behaviors together using clustering techniques. As mentioned earlier, clustering analysis is a commonly used technique in EDM to identify and discover different patterns in a large dataset. It is the process of grouping data into similar and dissimilar groups or clusters (Witten & Frank, 2005; Baker & Siemens, 2014). One of the most popular techniques to produce clusters in data mining is the k-means clustering. K-means clustering is a method that aims to group data points of a sample study into a number of *k* clusters based on feature similarity. Each data point in the sample is allocated to the cluster with the nearest mean The mean of a cluster is a collection of characteristics that define the resulting groups (Ahlquist & Breunig, 2012). To better explore the patterns of participation, the study employed the k-means clustering algorithm twice. The first application of the algorithm aimed to cluster learners' behavior in a particular week and provide a general description of how each learner behaves within each week. The second application of the algorithm aimed to group these descriptions according to their similarities and differences and create the prototypical participation patterns for the whole course.

A second aim of this study was to assess the relationship between the different clusters and the demographic factors. The demographic factors are gender, age group, education level, and employment status. The study used Pearson Chi-Square statistical test of independence to examine the relationship between the different clusters and these factors. As previously explained, the goal of this test is to understand the relationship between two categorical variables. In this study, these variables are the demographic factors and the different clusters (Greenwood & Nikulin, 1996; Bagdonavicius & Nikulin, 2011).

A third aim for this study was to understand the different motivations and limiting factors among learners and their relationship to the patterns of participation. To achieve this goal, the study analyzed the following two open-ended survey questions:

1) What are your reasons for taking this course? What do you hope to get out of it?

2) What were the factors that limited the extent to which you took advantage of this Coursera opportunity?

This data was analyzed using a qualitative approach of content analysis to code learners' responses and identify the most common themes (Creswell, 2014).

Chapter Summary

To summarize, this chapter has introduced the methodology and research design of this dissertation. To better answer the research questions, the study employed a mixed methods approach consisting of EDM, quantitative and qualitative research. The context of this study is the "Subsistence Marketplaces" offered by the College of business in UIUC. Data was collected from several resources including activity logs and course surveys. Before working on data analysis, data went through several steps of processing and curation to prepare for the mining process. Data analysis included mining learners' behaviors in videos, quizzes and forums on a weekly basis. This process of data mining was followed by statistical analyses to understand the relationship between the different clusters and the demographic variables. Also, the study analyzed two open ended questions in the survey as to better understand what motive and limit learners' participation in each cluster.

CHAPTER IV. RESEARCH FINDINGS

This chapter presents the findings in response to the research questions described earlier. It is divided into four major sections. The first section reports on the findings of the first research question. In particular, it aims to reveal the different patterns of participation among MOOC Learners as a result of applying the clustering models. Following that, the second section reports on the results of the second research question as to determine the relationship between the different patterns of participation and the demographic variables (gender, education level, employment status and age group) using statistical analysis. The third section answers the third research question by exploring the different themes of motivations and limiting factors in relation to the different patterns of participation utilizing content analysis techniques. Lastly, the fourth section lays out a summary of the chapter.

The First Clustering Model

By applying the first clustering model on the curated dataset, data analysis revealed three different clusters to describe each learner in a particular week. These clusters are as follows: 1) Highly Active, 2) Moderately Active and 3) Less Active. In order to determine the optimal number of clusters, the k-means algorithm was executed multiple times, starting with only 2 clusters and progressively increasing the number of clusters. For each execution of the algorithm, a visual inspection of the resulting clusters was conducted in order to examine whether it contributed to the discovery of new distinctive clusters. Then, the model was evaluated using Silhouette analysis. Silhouette analysis is used to evaluate the quality of the resulting clusters by studying the separation distance between them. It ranges from 0 to 1, where the highest value indicates a strong structure and a lower value indicates a weak structure (Kaufman &

Rousseeuw, 2009). The silhouette score for the resulting set of the clusters was 0.86; which means that the clusters are strong and well-matched.

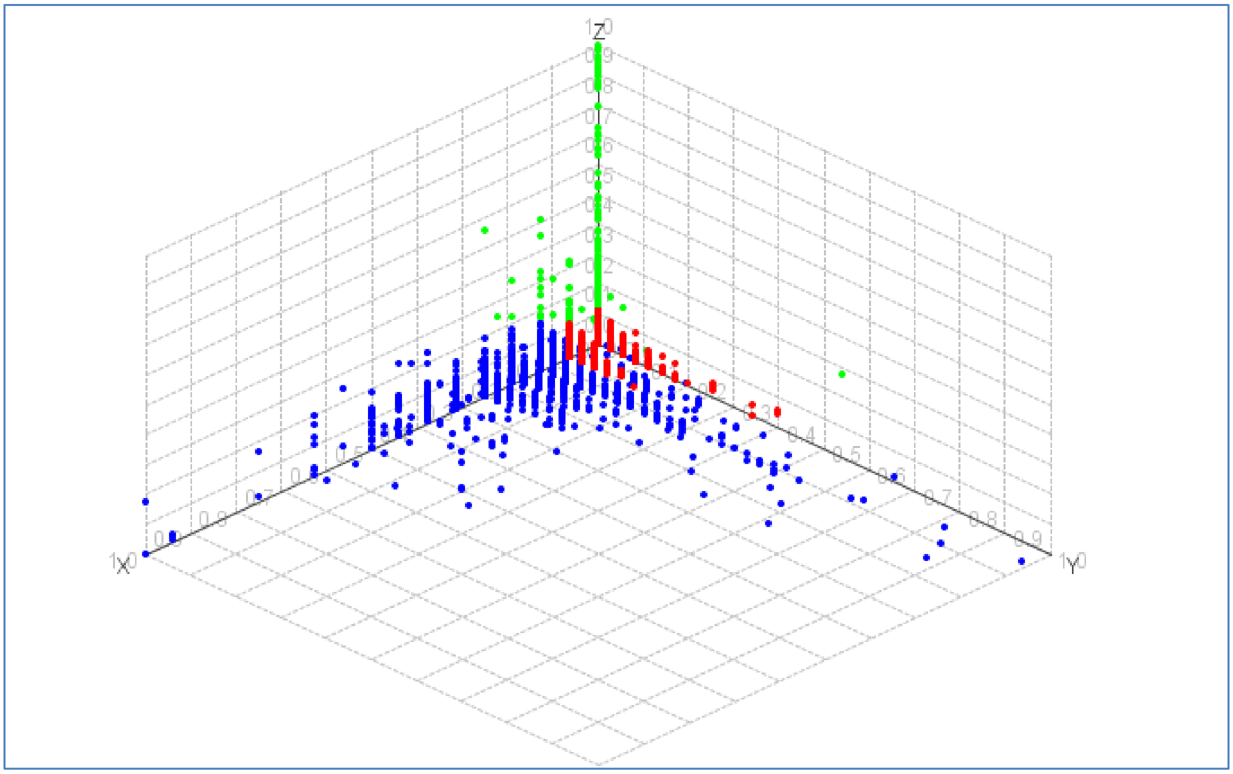

Figure 1: clustering learning behaviors in a week (x = quizzes participation, y = forum participation, and z = video participation). HA =blue plot, MA = green, LA =red

	Highly Active (HA)	Moderately Active (MA)	Less Active (LA)
Video lectures: 4 to 6 lectures a week	5.5	37	0.7
Quizzes: 2 Quizzes a week with 3 attempts	2.6	0.13	0.05
Forums: (Optional) 2 assignments a week	0.9	0.07	0.04

Table 2: Means of learners' participation in a week across videos, forums and quizzes.

The outcomes of this model are shown in figure 1 and table 2. Figure 1 depicts a scatter plot distribution of the generated clusters while table 2 shows the means of the learners' participation in a week across the three identifiable variables of videos, forums and quizzes. The blue plot describes learners who have been characterized as Highly Active (HA) in a particular week. Those learners appear to participate the most in the class compared with other clusters. Unlike the other two clusters, learners in this cluster participated more in the forum activities, submitted more quizzes and watched the expected number of the class lectures (see table 2). The average of their video watching behavior was 5.5 in a week that has 4 to 6 lectures.

On the other hand, the green plot describes learners who have been characterized as Moderately Active (MA) in a particular week. As shown in table 2, those learners have primarily watched lectures more than the other two clusters. Yet, they have submitted a few quizzes and occasionally participated in the forums. Their video watching behavior was exceptionally higher than the other clusters. It reached an average of 37 recorded actions in a week that has 4 to 6 lectures. As a matter of fact, this number does not only reflect the watching behavior, but it also includes re-watching behaviors.

Finally, the red plot in the figure above describes learners who have been characterized as Less Active (LA) in a certain week. As illustrated in table 2, learners in this cluster undertook very few activities across the three identifiable variables compared with the other two clusters. In other words, they watched fewer video lectures, submitted a very limited number of quizzes and rarely participated in the discussion forums.

The Second Clustering Model

The aim of running the clustering algorithm in the second time was to group the resulting values of the first clustering model on a time sequence of the different weeks of the course. This time sequence ran from week1 to week9, which marks any recorded activity after the course was over. Doing so helps to determine the prototypical participation patterns across the whole course. To achieve this goal, I used the output of the first clustering model and assigned a numerical value for each of learner's description: Highly Active, Moderately Active and Less Active in a week. Learners who were described as HA in a certain week were assigned the highest value of number "3". Those who were described as MA were assigned the medium value of number "2". Finally, learners who were described as LA in a given week were assigned the lowest value of number "1". Thus, the second clustering model was generated based on these values. In results, all of these descriptions with similar behaviors were grouped altogether and five different clusters of participation across the whole course were created.

Similar to the previous clusters, the final number of clusters for this analysis was determined using a combination of visual inspection and the silhouette score. The Silhouette score for this model was 0.6 which means that the cluster are in a good structure (Kaufman & Rousseeuw, 2009)

The Participation Patterns

By applying the second clustering model, data analysis yielded illuminating insights and helped to group learners according to their levels of participation. The model revealed five distinct ways in how learners may participate in MOOCs. These clusters are labeled as "Advanced Participation", "Balanced Participation, "Limited Participation", "Early Participation" and "Delayed Participation". I chose these labels to broadly represent the observed level of participation under each cluster. Table 3 shows the numerical values of the participation levels for each cluster across the whole eight weeks of the course and also after the course is over as presented in Week 9. Additionally, figure 2 demonstrates a visualization of the different clusters across the different weeks of the course.

	Advanced	**Balanced**	**Early**	**Limited**	**Delayed**
Week1	2.13	1.27	1.61	1.08	1.03
Week2	2.55	1.71	1.94	1.10	1.03
Week3	2.84	1.31	2.41	1.00	1.01
Week4	2.71	2.08	1.57	1.03	1.03
Week5	2.53	2.68	1.51	1.03	1.01
Week6	2.64	2.28	1.17	1.02	1.03
Week7	2.70	2.64	1.04	1.01	1.02
Week8	2.78	2.48	1.06	1.01	1.02
Week9	1.43	1.89	1.03	1.00	2.08

Table 3: Participation patterns across the 8 weeks of the course and beyond.

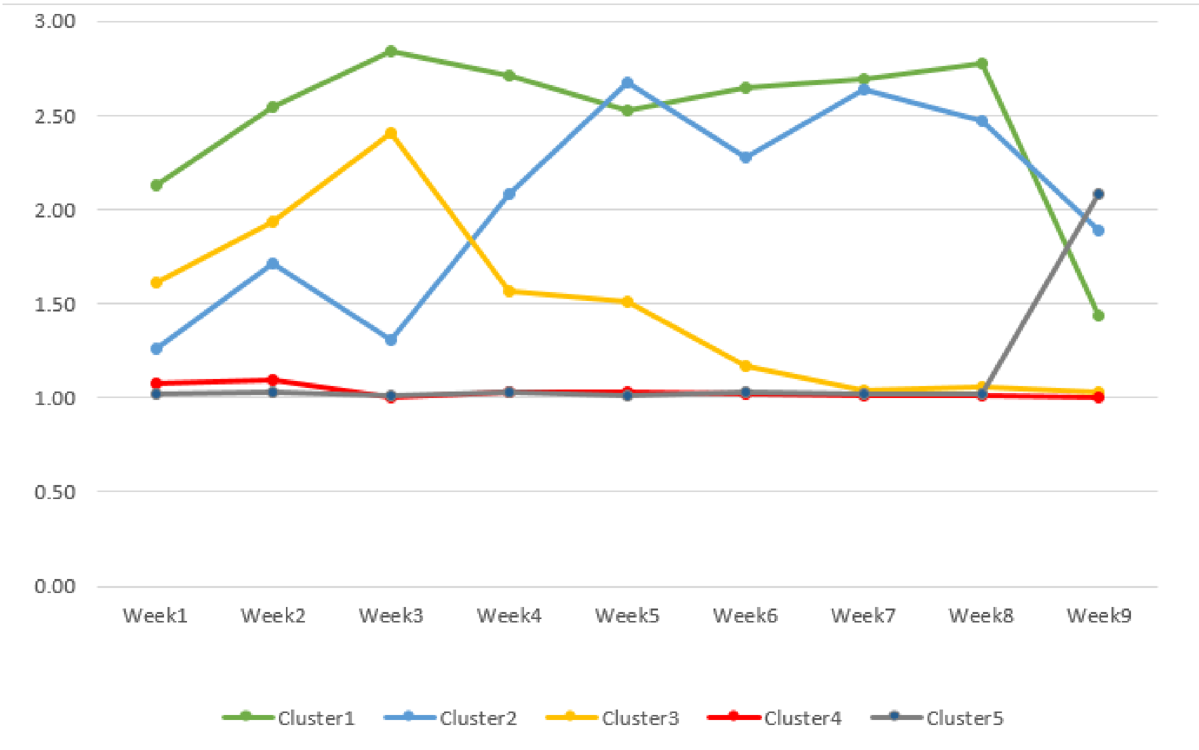

Figure 2: Visulaization of Participation patterns across the weeks.

Cluster 1 "Advanced Participation"

Presented by the green line in figure 2, this cluster characterizes those learners whose overall learning behavior was advanced and highly active across the eight weeks of the course. In other words, learners in this cluster are the most committed ones towards the observed course activities including accessing video lectures, submitting quizzes and participating in the discussion forums throughout the course. Notably, their level of participation is nearly stable across the different weeks of the course with a slight decrease around week 1. This slight decrease in week 1 is expected since this week marks the beginning of the course and usually in any course learners spend a considerable time for the first few days to orient themselves with the syllabus and the course content before committing to the assignments. Also, there is a high drop in week 9, which captures learners' behaviors beyond the 8 weeks of the course. Since learners in this cluster participated throughout the eight weeks of the course; then there is no point for them to participate once the course is over. In general, this architype resembles learners who we would often see in regular university classes as they progressed as directed in the syllabus. This cluster composes 5.4% out of all learners who have shown a learning behavior across the three identifiable variables.

Cluster 2 "Balanced Participation"

Another distinct cluster appears in the findings is cluster 2 (the blue line in figure 2) or what I chose to name it, "Balanced Participation". This was an unexpected cluster, yet it emerged prominently in the data analysis. Interestingly, the overall level of participation in this cluster increases and decreases in a systematic way almost every other week. This is the reason why I chose to name it a "Balanced Participation", as learners in this cluster seem to balance their learning behavior across time.

In particular, learners in this cluster started with a low participation level in week1, then their participation rate increased in week 2. As learners moved to week 3, their participation level dropped again and then it started to rise sharply in week 4 and week 5. Similarly, in week6 the level of participation went down and then it went up again in week 7. Towards the end of the course, there is a slight decrease in week8 and then a larger drop in week 9 after the course is over.

Although the participation level in this cluster increases and decreases almost every week, the range of participation in the first three weeks of the course was significantly lower than the range of participation in the other weeks. Overall, this cluster is the smallest one as it only represents 4.4% of all learners who have shown a learning behavior across the three identifiable variables.

Cluster 3 "Early Participation"

As the yellow line in figure 2 shows, this cluster depicts learners whose overall participation was at a high level early in the course and then it started to go down gradually as the course progressed. This is the reason why I choose to name this cluster as "Early Participation."

As a matter of fact, learners in this cluster were committed to the course activities more than learners in the previous cluster "Balanced Participation" at the beginning of the course. They reached their highest peak of participation around week 3 and then their participation level dropped sharply in week 4. Every week, the participation level gradually decreased until it reached the lowest level in week 7. Then, it stayed on that level on week 8 and week 9. This cluster contains 7.4% of all learners have shown a learning behavior across the three identifiable variables

Cluster 4 "Limited Participation"

Presented by the red color in figure 2, this cluster demonstrates those learners who are less active in the observed course activities, reporting an overall limited level of participation in contrast with the other learners in the other clusters. Despite the slightly increased value for week 1 and week 2, it seems like most learners in this cluster were pretty much stable at level 1. Level 1 marks the lowest level of participation in the course. This indicates that learners in this cluster have done the minimum work in terms of accessing video lectures, submitting quizzes and participating in the forums across the whole eight weeks of the course. As a matter of fact, the majority of learners lie in this cluster containing 76.81% percent of all learners who have shown a learning behavior across the three identifiable variables.

Cluster 5 "Delayed Participation"

One last cluster appeared in the data analysis is the delayed participation cluster with the grey colored line in figure 2. I chose to name it this way because learners in this cluster appear to participate highly in the course after it is finished (defined as week 9). To illustrate, learners in this cluster seem to have similar learning behavior as learners in the previous cluster, i.e., "Limited Participation" cluster. In both clusters, the level of participation is in the low end during the eight weeks of the course. Yet, learners' participation for this cluster sharply goes up beyond these eight weeks (week 9). The type of observed activities found during that time is mainly focused on accessing many video lectures of the course, probably, for later use. Overall, this cluster constitutes 6% of all learners who have shown a learning behavior in the three identifiable variables of the course.

The Relationship between Each Cluster and the Demographic Variables

The next step of the research was to determine if there is any relationship between the clusters and the demographic variables including gender, age, employment status and education level. The questions about demographic information were asked in both surveys. Therefore, data analysis of this part of the research was based on the demographic data collected from the course surveys. In total, there were 531 survey respondents out of 4583 active learners who have shown learning behaviors across the three identifiable variables (as seen in table 4). The survey respondents constitute almost 12% of the entire population. Although this percentage is small, the study is limited by the received data for two reasons. First, in the context of MOOCs it is expected have low response rates in the surveys since there are thousands of learners in the course and there is no obligation for them to take the survey (Crues et al., 2017). Second, this analysis is based on archival data, and in such a situation researchers do not have a control over distributing these surveys which makes it impossible to increase the number of respondents.

After receiving the survey data, the demographic variables were matched with the different patterns of participation using the student identification numbers. The study found adequate responses to perform the statistical analysis across the first four patterns of participation except for the “Delayed Participation” cluster (cluster 5). The sample size of this pattern was limited to five responses only. In any statistical analysis researchers suggest that there should be a minimum of ten observations to perform the test (Gravetter & Wallenau, 2016). Therefore, the study excluded this pattern from the analysis.

Response Group

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Survey1 only	394	8.6	74.2	74.2
	Survey2 only	85	1.8	16	90.2
	Both Survey1 and Survey2	52	1.1	9.8	100.0
	Total	531	11.6	100.0	
Missing	System	4052	88.4		

Table 4: A frequency distribution of survey respondents.

Measures

Before discussing the measures, it is important to first introduce the research hypotheses. To assess the relationship between the different clusters and the demographic variables, the study suggested four substantive hypotheses. Each one of these is to examine the relationship between the participation patterns and one of the four demographic variables: age, gender, education level and employment status. These hypotheses are stated in more details in the following sub-sections.

In order to solve the second research question "what is the relationship between the different patterns of participation in Coursera MOOCs and learners' demographic variables including gender, age group, educational level and employment status?", the study utilized the Pearson Chi-Square measure. This test is used to assess the relationship between two categorial variables that have no meaningful rank or order, such as the participation patterns and the demographic variables. Specifically, this test compares the observed counts with the expected counts within the different categories of the two different variables. Thus, it determines if they are related or not (Greenwood & Nikulin, 1996; Bagdonavicius & Nikulin, 2011). According to Greenwood and Nikulin (1996) if there is an observed relationship, then there is a need to include Cramer's V tests to measure the strength of the relationship. Cramer's V is used when one of the variables or both of them have more than two categories, meaning that there is more than 2 by 2 consistency table in the Pearson Chi-Square test. Indeed, this was the case of all the Pearson Chi-Square models found in this study. Thus, Cramer's V test was included in all models that have an observed relationship.

The Relationship between Gender and the Participation Patterns

To test the relationship between gender and the participation patterns, the study suggested the following hypotheses.

- The null hypothesis: There is no relationship between gender and the participation patterns.
- The alternative hypothesis: There is a relationship between gender and the participation patterns.

These hypotheses were tested by running the Pearson Chi-Square test in the SPSS software. Results of the test are shown in table 5 and 6. Table 5 displays the observed counts and the expected counts in both variables (the participation patterns and gender). Table 6 shows the value of the Chi-Square and the observed *p* value which determines which hypothesis is true. The information in the footnote of this table helps to determine whether the Pearson Chi-Square test is violated or not. The assumption can be violated if more than 20% of the cells have expected counts less than 5.

In this test, the model is not violated since there is not any cell that has an expected count less than 5. As shown in table 6, the observed *p* value of this test equals 0.108. This value is greater than the level of significance ($\alpha = 0.05$). Hence, the results are not significant, and we accept the null hypothesis and conclude that there is no relationship between gender and the participation patterns. This means that males and females are equally likely to participate across the different clusters in this particular MOOC.

Cluster * Gender Crosstabulation

			What is your sex?		
			Male	Female	Total
Cluster	Advanced	Count	30	57	87
		Expected Count	38.7	48.3	87.0
	Balanced	Count	22	17	39
		Expected Count	17.4	21.6	39.0
	Early	Count	34	43	77
		Expected Count	34.3	42.7	77.0
	Limited	Count	121	141	262
		Expected Count	116.6	145.4	262.0
Total		Count	207	258	465
		Expected Count	207.0	258.0	465.0

*Table 5: Cluster * Gender relationship.*

Chi-Square Tests

	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	6.079[a]	3	.108
Likelihood Ratio	6.140	3	.105
N of Valid Cases	465		

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 17.36.

*Table 6: Chi-Square Tests of Cluster * Gender relationship.*

The Relationship between Employment Status and the Participation Patterns

Next, the study examined whether there is any association between the participation patterns and the employment status. To achieve this goal, the study suggested the following hypotheses:

- The null hypothesis: There is no relationship between the employment status and the participation patterns.
- The alternative hypothesis: There is a relationship between the employment status and the participation patterns.

To accept or reject any of these hypotheses, the study performed the Pearson Chi-Square test. Before running the test, the employment status variable was recoded. The original variable contained nine groups and some of them were too small to conduct the analysis. Additionally, having a large number of groups in one variable may complicate the analysis. Thus, this these groups were minimized to three options only based on their similarities. The original nine categories in the employment status were as follows:

1) Employed for salary or wages
2) Self-employed
3) Intern
4) Out of work and looking for a job
5) Not working and not looking for a job
6) A homemaker
7) A student
8) Retired
9) Unable to work

In recoding this variable, option 1, 2 and 3 were combined together with a general name "employed". Option 4, 5, 6, 8 and 9 were also combined together under the name "unemployed". Option 7 stayed the same, which represents the students group.

With this new recoded variable of employment, the study ran the Pearson Chi-Square test as seen in table 7, 8 and 9. Table 7 presents the observed counts and the expected counts between the participation patterns and the employment status, while table 8 reports on the value of the Chi-Square and its observed *p* value. Looking at the footnote of table 8, the results indicate that less than 20% of the cells have an expected count less than 5, therefore the test is not violated. To determine which hypothesis is correct, we should look at the *p* value that corresponds to the Chi-Square value in table 8. Interestingly, the observed *p* value (0.009) is less than the level of significance ($\alpha = 0.05$). Consequently, the results are significant, and we can reject the null hypothesis and conclude that there is a relationship between the employment status and the participation patterns.

To assess the strength of this relationship, the model calculated the symmetric measures of Cramer's V as shown in table 9. The results show that the value of this test equals 0.141. Based on Cramer’s V table of interpretation, there is a minimally acceptable relationship between the employment status and the participation patterns (http://groups.chass.utoronto.ca/pol242/Labs/LM-3A/LM-3A_content.htm).

Comparing the observed counts to the expected counts in table 7 shows that unemployed learners are more likely to participate in the “Advanced”, “Balanced” and “Early” participation clusters and they are less likely to participate in the “Limited” participation cluster. Indeed, the observed count between the “Unemployed” category and each one of the “Advanced”, “Balanced” and “Early” clusters is more than the expected count. Meanwhile, the observed count between the “Unemployed” category and the “Limited” participation cluster is less than the expected count. Results also indicate that students and employed learners are more likely to participate in the "Limited" participation cluster since their observed count is higher than what is expected.

Employment status * cluster Crosstabulation

			cluster				
			Limited	Early	Balanced	Advanced	Total
employment	Employed	Count	186	47	17	52	302
		Expected Count	178.4	52.1	20.8	50.7	302.0
	Unemployed	Count	29	18	8	17	72
		Expected Count	42.5	12.4	5.0	12.1	72.0
	Student	Count	42	10	5	4	61
		Expected Count	36.0	10.5	4.2	10.2	61.0
Total		Count	257	75	30	73	435
		Expected Count	257.0	75.0	30.0	73.0	435.0

*Table 7: employment status * cluster relationship.*

Chi-Square Tests

	Value	Df	Asymptotic Significance (2-sided)
Pearson Chi-Square	17.192[a]	6	.009
Likelihood Ratio	18.067	6	.006
Linear-by-Linear Association	.244	1	.622
N of Valid Cases	435		

a. 2 cells (16.7%) have expected count less than 5. The minimum expected count is 4.21.

*Table 8: Chi-Square Tests of employment status * cluster relationship.*

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.199	.009
	Cramer's V	.141	.009
N of Valid Cases		435	

*Table 9: Symmetric Measures of Cramer's V of employment status * cluster relationship.*

The Relationship between Age Groups and the Participation Patterns

Additionally, the study aimed to understand the relationship between the participation patterns and the age groups, and thus it suggested the following hypotheses:

- The null hypothesis: There is no relationship between age groups and the participation patterns.
- The alternative hypothesis: There is a relationship between age groups and the participation patterns.

To determine which of these hypotheses is true, the study ran Pearson Chi-Square test as in the previous two examples. Before performing this test, data have shown that there was only one participant in the age group category "Less than 18 years old". Since the sample size is too small for this particular category, this category was excluded from the analysis (Gravetter & Wallenau, 2016). Then, the study ran the Pearson Chi-Square test. Results of this test are displayed in table 10, 11 and 12. Table 10 displays the observed counts and the expected counts between the participation patterns and age group categories, whereas, table 11 presents the value of the Chi-Square and its corresponding *p* value.

In interpreting the results, the footnote of table 11 shows that 25.0% of the cells have expected count less than 5. This means that the Chi-Square test is violated and thus we should use the "Likelihood Ratio" statistics in this table to determine the status of the relationship (Greenwood & Nikulin, 1996). The corresponding *p* value of the "Likelihood Ratio" statistics equals 0.016, which is less than the level of significance ($\alpha = 0.05$). Hence, the results are significant and we reject the null hypothesis and conclude that there is a relationship between the participation patterns and the age groups.

In measuring the strength of this relationship, the study relied on the symmetric measures of Cramer's V test as seen in table 12. The value of this test equals 0.142. This means that the relationship between the participation patterns and the age groups is minimally acceptable (http://groups.chass.utoronto.ca/pol242/Labs/LM-3A/LM-3A_content.htm).

Data analysis in table 10 reveals that young learners in the age group of 18-29 are more likely to participate in the “Limited” and “Early” participation cluster and they are less likely to participate in the “Advanced” cluster. This is illustrated by the observed counts between this age group and the “Limited” and “Early” participation clusters that are higher than the expected counts, while the observed counts are lower than what is expected for the “Advanced” cluster. Using the same analysis of comparing between the observed values and expected values, the study found that learners in the age group of 40-49 are more likely to participate in the “Advanced” Cluster and they are less likely to participate in the “Limited” cluster.

Age * cluster Crosstabulation

			cluster				
			Limited	Early	Balanced	Advanced	Total
Age	18 – 29	Count	117	37	13	22	189
		Expected Count	109.9	32.0	13.9	33.3	189.0
	30 -39	Count	69	15	11	21	116
		Expected Count	67.4	19.6	8.5	20.4	116.0
	40 – 49	Count	30	9	2	22	63
		Expected Count	36.6	10.7	4.6	11.1	63.0
	50 – 59	Count	33	7	6	11	57
		Expected Count	33.1	9.6	4.2	10.0	57.0
	>= 60	Count	12	8	1	3	24
		Expected Count	14.0	4.1	1.8	4.2	24.0
Total		Count	261	76	33	79	449
		Expected Count	261.0	76.0	33.0	79.0	449.0

*Table 10: Age * cluster relationship.*

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	27.057[a]	12	.008
Likelihood Ratio	24.901	12	.015
Linear-by-Linear Association	3.672	1	.055
N of Valid Cases	449		

a. 5 cells (25.0%) have expected count less than 5. The minimum expected count is 1.76.

*Table 11: Chi-Square Tests of Age * cluster relationship.*

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.245	.008
	Cramer's V	.142	.008
N of Valid Cases		449	

*Table 12: Symmetric Measures of Cramer's V of cluster * age relationship.*

The Relationship between the Participation Patterns and Education Levels

The final step of this part of the analysis was to examine the relationship between the participation patterns and the education levels. Thus, the study created these hypotheses:

- The null hypothesis: There is no relationship between education levels and the participation patterns.
- The alternative hypothesis: There is a relationship between education levels and the participation patterns.

Prior to conducting the Pearson Chi-Square test to examine theses hypotheses, the study had to recode the original variable of education level. This variable originally contained ten categories and having too many categories may negatively influence the results. Therefore, the variable was reduced to four categories by merging some similar ones together. These are the original categories of this variable:

1) No formal schooling completed
2) Some primary or elementary school (nursery school thru 8th grade)
3) Less than secondary or high school graduate
4) Secondary or high school graduate or GED
5) Some post-secondary training or college but no degree
6) 2-year degree, post-secondary certificate, or Associates degree
7) Bachelor degree
8) Masters or professional degree
9) Doctoral degree
10) Post-graduate certificate or diploma program

In recoding the new variable, categories 1, 2 and 3 were combined together in a new category "Less Than High School", whereas, category 4 stayed the same as "High School Level". Additionally, categories 5 and 6 were put together in the category "Less Than Bachelor Degree", and category 7 was kept as is "Bachelor degree". Lastly, categories 8, 9 and 10 were added together in the "Graduate Degree" category.

Furthermore, data have shown that the sample size of the category "less than high school" was only eight participants. Since this is a very small number, it is better to be excluded from the analysis so it will not affect the overall outcomes (Gravetter & Wallenau, 2016).

After preparing the data for the analysis, the study conducted the Pearson Chi-Square test. Results of this test are displayed in table 13, 14 and 15. Table 13 presents the observed counts and the expected counts between the participation patterns and the education level, while table 6 shows the value of the Chi-Square and its observed *p* value.

Results at the footnote of table 14 indicate that the Pearson Chi-Square test is violated because more than 20% of the cells have an expected count less than 5. In this situation, the "Likelihood Ratio" test in the same table is more appropriate to examine the relationship between the participation patterns and the education level (Greenwood & Nikulin, 1996). The observed *p* value of this test equals 0.034, which is less than the level of significance ($\alpha = 0.05$). Hence, the results are significant and we can reject the null hypotheses and conclude that there is a relationship between the education levels and the participation patterns.

To assess the strength of this relationship, the study calculated the symmetric measures of Cramer's V as shown in table 15. Since the value of Cramer's V test = .101, we can conclude that the relationship between the participation patterns and the education level is not generally acceptable (http://groups.chass.utoronto.ca/pol242/Labs/LM-3A/LM-3A_content.htm).

Data in table 13 shows a relationship between the Grad education level category and the different clusters. It appears that learners with a graduate education degree are more likely to participate in the "Advanced" and "Balanced" participation clusters and less likely to participate in the "Limited" participation cluster. Indeed, the observed count between the graduate level group and the "Advanced" and "Balanced" participation clusters are more than the expected count, whereas it is less than what is expected in the "Limited" cluster. On the other hand, learners with a high school education degree are more likely to participate in the "Limited" participation cluster since their observed count is more than the expected count.

Education Level * cluster Crosstabulation

			Cluster: Limited	Early	Balanced	Advanced	Total
Education Level	High School	Count	16	1	0	3	20
		Expected Count	11.9	3.5	1.3	3.4	20.0
	Less than Bachelor Degree	Count	35	10	0	6	51
		Expected Count	30.3	8.8	3.2	8.6	51.0
	Bachelor Degree	Count	95	30	12	23	160
		Expected Count	95.2	27.7	10.1	27.0	160.0
	Graduate Degree	Count	108	33	15	40	196
		Expected Count	116.6	34.0	12.4	33.0	196.0
Total		Count	254	74	27	72	427
		Expected Count	254.0	74.0	27.0	72.0	427.0

*Table 13: Education Level * cluster relationship.*

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	13.150[a]	9	.156
Likelihood Ratio	18.141	9	.034
Linear-by-Linear Association	4.642	1	.031
N of Valid Cases	427		

a. 4 cells (25.0%) have expected count less than 5. The minimum expected count is 1.26.

*Table 14: Chi-Square Tests of Education Level * cluster relationship.*

Symmetric Measures

		Value	Approximate Significance
Nominal by Nominal	Phi	.175	.156
	Cramer's V	.101	.156
N of Valid Cases		427	

*Table 15: Symmetric Measures of Cramer's V of Education Level * cluster relationship.*

Motivations and Limiting Factors to Learners' Participation

The goal of this research was not merely to identify the participation patterns and their relation to the demographic variables. It was also to understand what motivate and limits these patterns of participation from learners' own experiences. Data analysis of this section was based on the two open-ended questions relevant to motivations and barriers found in the course surveys. The first question is, what are your reasons for taking this course and what do you hope to get out of it? In contrast, the second question investigated the limiting factors of learners' participation. It states: What were the factors that limited the extent to which you took advantage of this Coursera opportunity?

To better analyze this data, the study utilized content analysis techniques by Cresswell (2014). First, to prepare for data analysis each response in the survey was matched with the participation pattern of each learner using students' identification numbers. Second, as a researcher of this study, I read through the data to obtain a general sense of the provided information and reflect on its overall meaning. Third, I started the coding process by examining each response carefully and tagging the text with a specific code. In this step of coding, I utilized AtlasTi Software, a qualitative data analysis software that helps to organize codes and themes and quantifies their occurrence across different groups. Then, I presented the findings of the data analysis in numerical and textual forms. The numerical form of the findings presents the different themes that emerged from the data analysis in tables of averages. The textual form of the findings presents the emerging themes along with a selection of excerpts and quotations from the open-ended survey questions.

Motivations:

A total of 358 students responded to the open-ended question: "What are your reasons for taking this course and what do you hope to get out of it?" in the pre-course survey. Out of this number, there were 60 respondents in the "Advanced Participation", 25 in the "Balanced Participation", 64 in the "Early Participation", 206 in the "Limited Participation" and only 3 respondents in the "Delayed Participation" pattern. The number of respondents appears to be small, but this is expected in MOOCs for an open-ended question (Cruess et al, 2017). Table 16 shows the different themes that emerged from the data analysis and what do each theme mean.

No.	Themes	Description
1	**Gaining general knowledge**	This theme describes short responses that have the phrase "general knowledge" in them.
2	**Professional career development:**	This theme describes responses, which report to career and work benefits.
3	**Curiosity and interest**	This theme indicates responses related to learning for curiosity, interest and fun.
4	**Making a difference in subsistence marketplaces**	This theme describes responses where students motivated to use the course content to improve marketplaces in poor areas for the public good.
5	**Fulfilling other needs**	Other needs include, experiencing online education, learning in MOOCs, improving English language, exploring learning in a high-ranking university and certification.

Table 16: Learners' motivations to participate in MOOCs.

The Limiting Factors

The response rate for the limiting factors question in the post-course survey was significantly lower than the response rate in the pre-course question about motivation. A previous research has shown that this is expected in the MOOC post-course survey (Kizilcec &

Halawa, 2015). In addition, this is not in the study's control since it dealt with archival data. There were only 85 respondents for this question. Specifically, 43 of these respondents were in the advanced level of participation, 19 were in the balanced level of participation, 9 were in the early level of participation and 14 were in the overview level of participation. No one in the delayed level of participation answered this question, therefore this cluster was excluded from the data analysis. Even though the response rate is very limited for this particular question, it is worthwhile to analyze and discuss this data as to highlight the experience of these learners. Thus, data analysis cannot be generalized, but it may provide insights of what limit learners to participate in a MOOC. Table 17 shows the different themes that emerged from the data analysis in regard to these limiting factors and a description of each theme.

No.	**Themes**	**Description**
1	**Lack of time**	Not having enough time to contribute to the course activities.
2	**Challenging course project**	The final project of the course was challenging for some learners in terms of not having access to subsistence marketplaces in poor areas to analyze.
3	**None**	No limitation factors were mentioned. Instead, the answers included positive comments
4	**Course technical issues**	Anything related to the technical aspects of accessing the course materials, etc.
5	**Lost interest**	Students lost interest to participate in the course.
6	**Low internet connection**	Having internet connections issues.
7	**Challenging course content**	The course content is dense and complex to understand.
8	**Absence of the instructor**	The instructor is not available.

Table 17: Factors that limited learners' participation in MOOCs.

Motivation and Limiting Factors Across the Different Patterns of Participation

This sub-section describes how the different themes of motivations and limiting factors appear across the different patterns of participation as shown in table 18 and table 19. Specifically, table 18 shows the motivation factors across the different patterns of participation while table 19 presents the limiting factors of these patterns.

Themes	Advanced Participation	Balanced Participation	Early Participation	Limited Participation	Delayed Participation
Gaining General Knowledge	17%	12%	26%	29%	33%
Curiosity and Interest	15%	12%	19%	26%	0
Professional and Career Development	32%	24%	33%	18%	66%
Making a difference in subsistence marketplaces	25%	36%	13%	19%	0
Fulfilling Other Needs	12%	16%	9%	8%	0

Table 18: Percentages of Motivations across the different patterns of participation. Percentages are calculated based on the number of responses received in each theme divided by the total number of responses for all themes within a cluster.

Themes	Advanced Participation	Balanced Participation	Early Participation	Limited Participation
Lack of Time	58%	68%	56%	57%
Challenging Course project	19%	5%	0%	0%
None	16%	5%	0%	7%
Course Technical Issues	5%	16%	0%	7%
Lost Interest	0%	0%	22%	7%
Low Internet Connection	0%	0%	22%	7%
Challenging Course Content	2%	5%	0%	7%
Absence of the Instructor	0%	0%	0%	7%

Table 19: Percentages of Limiting factors across the different patterns of participation . Percentages are calculated based on the number of responses received in each theme divided by the total number of responses for all themes within a cluster.

Motivations of Advanced Participation

The most common motivation in this cluster is the Professional and Career Development theme. About 32% of the survey respondents in this cluster indicated their intention to join the course for that purpose. For some learners, they took this course to advance their current career skills. One of the respondents states the following:

> I am a consultant in food security and rural development. This is an important topic for my work and it wasn't recognized or taught back when I was a student in the 70s. So, I know a bit about it from my experience (mainly in Bangladesh and SE Asia) but would like to expand my knowledge.

Other learners took this course in this cluster to prepare for future career, such as the following person:

> I am living in Spain, with experience in business creation and microfinance sector. At short term, I want to start a business of import /export with Senegal (where my husband comes from), at long term I would love to create social enterprises there, therefore it is important for me to better understand how subsistence marketplaces works, and more specifically the Senegalese one. I hope to get tools to understand the markets as well as to find some interesting ideas that could be implemented.

A second major motivation appeared in this cluster is the theme of making a difference in subsistence marketplaces nationally and globally. One fourth of the survey respondents indicated they were motivated by that reason. A survey respondent said:

> [I took this course] to better understand how to positively affect those living in poverty, to understand microlending and its successes/shortcomings, to find a way into volunteering where my skills could be well-employed for a population and place where I would like to engage.

Another one added:

> I want to understand this subsistence marketplace … [The] majority of people where I live in India are poor and they will qualify for this marketplace, and as a professional in the field of marketing, I would like to understand this market through different

perspective to help them. This course can help me to address the challenges and opportunities available in this market.

Data analyses have also revealed other themes in this cluster such as: gaining general knowledge, curiosity and interest, and fulfilling other needs. However, these themes were not as common as the previous ones.

Limiting Factors of Advanced Participation

One of the major limiting factors that appeared in this cluster is the lack of time. Despite the fact that this is the advanced level of participation, a little more than half of the survey respondents in this cluster surprisingly reported their time concern in participating in the course. However, it is important to mention that their time concern refers to not being able to take full advantage of the course and contribute to the optional activities, not the required ones. More specifically, they meant not being active in the forums and/or completing the final project, as both were optional. This is different than the responses seen in other clusters that will be explained in the following sub-sections.

In this regard, one of the survey respondents stated his experience of missing part of the forum activities because of his busy schedule. He said: “because of my other overlapping work duties and obligations, I couldn't fully take advantage of forum assignments and participate in discussion forums.” Another one added “I work full-time and have many personal obligations, so it was just difficult to devote the time to do all the work. This is why I opted not to participate in the forums.” A third person responded, “since it was optional and only for extra credit, I stopped engaging with the forums.” Others chose to skip the final project because of lack of time, such as the following person, “I couldn't do the project because of travel commitments.” Likewise, another learner added:

> I did not have enough spare time to dedicate to the course. For this reason, I was able to watch all the videos, to read the readings and to take all the quizzes but I did not have time to do the projects for extra-credit.

In addition to the lack of time concern, the course project was challenging for some of the learners in this cluster. As seen in table 17, 19% of the survey respondents reported this limiting factor. To illustrate, the course project required learners to analyze a subsistence marketplace in a poor area. However, some learners do not have access to such things because they simply live in a developed area. One of the survey respondents commented, “I was not in an environment to truly explore the project assignment to attempt to apply the class content in a real-world application.” Another added:

> The assignments seemed best suited for those already working in the field or at least within the subject area, and less suited for interested individuals such as myself. I live in a developed world country (Italy at least!) and although I'm sure subsistence markets exist, they aren't easy for me to access on a practical level.

A third person stated his concern:

> The expectation innate within the assignments that students reside near a subsistence marketplace - many assignments required us to visit and interview participants there. This is overlooking the fact that some students are learning about this topic precisely BECAUSE they have no access to such marketplaces and know nothing about them. It had the effect of distancing me somewhat, and limiting my keen desire to learn more.

As a matter of fact, participating in the final paper was not included in the clustering models in the data analysis because the majority of learners did not do it and it was an optional activity.

It is also significant to mention that many learners in this cluster did not indicate any limiting factors to their participation in the course. Instead, they reported good comments about the course. Here is an example of what one of the survey respondents said:

> This is an excellent course and would recommend that universities worldwide to adopt it. The research skills are gently taught but really Masters level. Even applying the methodology as 'thought experiments' was very useful and I wish I could do more. The course was very well presented (though the layout of sections and links was somewhat tortuous). What I really liked was the course was not terrifying. Students would have no clue that they are really studying at Masters' level and they would just get on and do it. And then have both the skills of a researcher that will stand them in good stead in whatever career they follow and skills of a marketer that are far better practiced than they would learn in an MBA. I salute you.

Motivations of Balanced Participation

As shown in table 18, 36% of the survey respondents indicated that they joined the course to find a better way to make a difference in subsistence marketplaces in poor areas nationally and globally. This reveals that the content of the course plays an important role to engage learners in a MOOC. In this regard, one of the survey respondents said:

> The reason for taking this course is to understand the root cause of poverty as well as try to find out the best possible way to help the poor to cope with it. I am Architect and I always wanted to make a society which sustains in every level. This is just the initial step towards a bigger aspiration.

Similarly, another respondent added:

> I want to learn more about this area of research, as I had seen the situation in my village during my childhood I always want to know what are the bottlenecks of entrepreneurs or companies in this area, the main concept I would like to learn how to serve people who are in bottom of pyramid not through 'NGO' but through 'social business'.

A second major theme that appeared in the data analysis for this specific cluster is the theme of professional and career development. Nearly 24% of the survey respondents in this cluster reported that they were motivated in taking the course for that purpose. For some learners, they were hoping to learn new skills to advance their current professional skills, such as the following person:

> I am currently working with Start-Ups catering to the bottom of the pyramid market. I feel that a better theoretical understanding is essential in order to work in this area. It is for this particular reason that I have joined the course.

Others joined the course to prepare for a future career, such as this respondent:

> Ability to apply my skills to the wider public as the term 'subsistence' implies, thus widening my area of application beyond the routine back office functions I usually perform. [Also] subsistence level solutions could guarantee more jobs and steadier income.

Interestingly, these two major themes of motivations in this cluster are the same ones found in the previous cluster, “Advanced Participation”. Learners in both clusters have high hopes in joining the course for career purposes and making a difference in subsistence marketplaces nationally and globally.

Also, there are other motivations that appeared in the data analysis of this cluster such as: fulfilling other needs, gaining general knowledge, and curiosity and interest. However, these themes were not as common as the previous ones.

Limiting Factors of Balanced Participation

According to the survey respondents, lack of time was also the major limiting factor in this cluster. As shown in table 19, 68% of the survey respondents have reported this specific reason. Here is an example of a survey respondent explaining how his unexpected life situation limited his time to participate in the course. He said:

> Deadlines were a little bit tight for me. I was ill for 2 weeks and couldn't catch up, I was late for some of the quizzes. I wasn't able to participate much in the forums and gain extra credits either because I didn't have enough time.

Others have expressed their time concern in relation to their work and study obligations. One of the survey respondents said: “I am working and studying at the same time. This course was additional activity and I wasn't able to devote high amount of time working on it.” Similarly, another one added:

> While the subject and the class were very interesting and stimulating, I couldn't take advantage fully because I was taking two other Coursera classes that took just as much, if not more, commitment on top of a full-time job … so I felt I couldn't fully participate.

Because of time concern, some learners could not do the optional assignments. One of the survey respondents said: “I truly feel that the only thing holding me back was a lack of time. I work full time and it was difficult to make time for the extra credit forum assignments.”

In addition to this concern of time, data analysis has also shown that some learners experienced some kinds of technical difficulties in the course. For instance, this learner experienced difficulties following up with the forum activities. He commented: “I found the forums and forum assignments a bit difficult to navigate, especially the logistics of posting, having too many posts to read.” Another learner had issues with the quizzes. He said: “I didn’t appreciate the programming of quizzes and assignments. We couldn't make any request to apply for date late. I lost many quizzes because of that.”

Despite these two major themes (lack of time and course technical difficulties), it is also important to mention that the theme of challenging course content and challenging course project appeared in the data analysis only one time. Furthermore, there was one survey respondent who did not report any limiting factor to his participation in the course. Instead, he expressed his appreciation for the course as follows: "this course is hands-on, and that is the beauty of it. I look forward to having the opportunity of applying the concepts in real life.”

Motivations of Early Participation

Similar to the advanced level of participation, the theme of professional and career development was also the most common one in this cluster. Precisely, 32% of the survey respondents were motivated to join the course to acquire knowledge for current and future career purposes. Here is an example of a learner who took the course to advance his current career skills. He stated: “I am a founder of a non-profit organization … I feel that this course will improve my effectiveness in my career field.” Here is another example of a learner who joined the course to prepare for his future career. He said:

> I may have a career change in the future, and I wanted to broaden my horizons to see what interests me. I don't have any specific plans for a future career change; all I know is that it's possible, and I want to get ideas about what I might like studying/working in. I think I might enjoy something related to business and economics.

In addition to advancing career skills, learners in this cluster were motivated to participate in the course to gain general knowledge of the course topic. As shown in table 18, 26% of the survey respondents were motivated by that purpose. For example, one of the learners commented on his intention to join the course: “I would like to expend my knowledge about the topic.” Similarly, another one added: “I joined the course to learn more about the subject and improve my knowledge of the area.” A third person said: “the subject. I want to obtain more information, sources of knowledge and experiences in the field.” Interestingly, here is another learner who joined the course to refresh his old information. He stated: “the subject was in my studies but after I worked in something really different. Now I want to get back to it so I need to refresh my mind.”

Furthermore, some learners of this cluster were motivated to participate in the course out of curiosity and interest. Specifically, 19% of the survey respondents stated that purpose in their answers. For example, one of the survey respondents said: “The title sounds interesting. Maybe, I would like to pursue my carrier in the field.” A second person added, “the scope and topic of this course seemed unique and interesting to me.” Furthermore, 13% of the survey respondents joined the course to make a difference in subsistence marketplaces nationally and globally. Here is an example of what one of the learners said in regard to this motivation:

> I travel a lot and work with needy populations all over the world. I see extreme poverty on fairly common basis. I'm hoping this course will add insight to what I see and help me come up with solutions which might help some of those people.

Although these were the most common themes in this cluster, data analysis has also shown that some learners took the course to fulfill other needs, such as experiencing online education and MOOCs, improving English language and exploring learning in a high-ranking university.

Limiting factors of Early Participation

Same as the previous two clusters (Advanced and Balanced Participation), most of the survey respondents in this cluster indicated issues relevant to time concern. As shown in table 19, 56 % of the survey respondents were limited by that factor. One of the learners said: “lack of time. So many interesting courses on Coursera.” Similarly, another one added:

> I didn't have enough time. I took another Coursera class at the same time and with my job and nonprofit organization involvement I couldn't handle everything. I wish I had because I really enjoyed the way this class was organized.

Another one commented:

> I got too busy in my offline life (family commitments, health, etc), and without the personal camaraderie of humans being next to me, it was hard to keep pushing at the half-way point. I was rather disappointed in myself about this, but there are only so many hours in the day in which to do things.

In addition to time concern, some learners lost their interest to continue in the course. This learner commented:

> I found the course a little slow, I was expecting to learn more. After the simulation on Spent.org I became really really excited about the course, but then all the assignments were not interesting and as I said the lectures a bit slow and I dropped the class.

Others suffered from the slow internet connection, such as the following learner. He stated: “I find myself in Malawi (a genuine 3rd world country). Everyone here is a subsistence farmer … Internet here is much too slow to watch videos. So, I stopped participating in this class."

Motivations of Limited Participation

As seen in table 17, 29% of the survey respondents in this cluster were motivated to join the course to gain general knowledge. This reflects why their participation in the course was limited to the minimal work compared with other clusters. For example, one of the learners said:

> With the dynamic environment around us, it is very important for marketplaces to keep up to the surroundings. I believe this course will enable me to understand better about marketplaces and the strategies to sustain and grow in the changing world.

Another learner added: "[I joined the course] to explore more valuable information and enhance knowledge and experience of the subject." A third person responded: "Some basic understanding. Not much hopes."

Another common motivation appeared in this cluster was the theme of curiosity and interest. Data analysis in table 18 indicates that 26% of the survey respondents in this cluster were motivated to join the course to satisfy their curiosity and interest. In this regard, one of the learners commented: "this is the first time I heard of subsistence marketplace. I chose this course because I know I will learn something very different from my major in Information Technology." Another responded:

> I thought it would be interesting to learn about something new - especially as the topic is based in an environment in which I am completely unfamiliar. It also highlights how many things one takes for granted even after having a basic education.

A third person added: "Not sure, open to possibilities. It has been a long-standing area of interest." Another stated: "I hope it is fun and interesting, or else I won't finish it."

In addition to the themes of gaining general knowledge and curiosity and interest, data analysis shows that19% of the survey respondents in this cluster indicated that they joined the course to make a difference in subsistence marketplaces. One of the survey respondents said:

> The reason for taking this course is to understand the root cause of poverty as well as try to find out the best possible way to help the poor to cope with it. I am Architect and I always wanted to make a society which sustains in every level. This is just the initial step towards a bigger aspiration.

Similarly, another person added: "poverty and the sufferings of the poor in developing countries concerns me deeply. Would like to gain knowledge which could help me in creating micro entrepreneurial networks among needed communities to uplift their social status."

Another emerging motivation theme in this cluster was the theme of professional and career development. As stated in table 16, 18% of the survey respondents indicated that purpose. Here is an example of a survey respondent who took the course to prepare for future career:

I am interested in working in this field in a social enterprise in future, so I hope to gain

- An insight and understanding into subsistence marketplaces.
- A greater appreciation of the needs and desire of people who live in them.
- A greater understanding of how those needs can be met, and some experience of trying to do this.
- A course which will help me decide if and how I would move into working in subsistence marketplaces.

Here is another example of a learner who took the course to advance his current career skills:

> I work for an organization called One Acre Fund in rural Rwanda. I manage our Western Operations, which provides our agricultural services to over 44,000 farmers in 5 Districts.

> Our model provides fertilizer on credit, agricultural trainings and access to markets to farmers in an effort to increase their harvest and double their income. I live subsistence marketplaces every day, but I've never studied it academically. I hope to read different perspectives and better understand the context in which I work.

It is also important to mention that some learners (8%) took the course to fulfill other needs.

Limitation Factors of Limited Participation

Although there were 206 responses in the open-ended motivation question in the pre-course survey, the limiting factor question in the post course survey received only14 responses in this cluster. The most common theme among these responses is the lack of time. Almost more than half of the survey respondents have indicated this concern in limiting their participation in the course. In contrast with other responses in the previous clusters, the limiting factor responses in this cluster were brief. Here is an example of what one of the learners said: “It was my lack of time to devote to the course that limited my ability to take advantage of all that was offered.” Another one added: “because of some personal reasons I couldn't follow the time frame.” A third person commented: “lack of time, taking a large number of other courses.”

Data analysis has also shown other factors that limited learners’ participation in the course. These factors are as follows: challenging course content, course technical issues, low internet connection, losing interest and absence of the instructor. As a matter of fact, all of these limiting factors appeared only one time in the data analysis. Here is the response that appeared in the challenging course content theme: “sometimes, when concepts in the material were claimed to be related it wasn't clear how they were. Especially in the middle of the course.” Here is another response that relates to the course technical issues. A student commented:

> The forums were spammy with too many opinions and forum based approach for students always stymies me. It gets too difficult to traverse. Too many random thoughts from everyone making it difficult to sift through. I lost interest in the forums and then missed out on making projects and assignments.

In terms of the low internet connection, a survey respondent said: “Actually, I had a lot of interest. However, I was limited by resources; access to internet, availability of computers and other commitments.” Additionally, another learner indicated that he lost interest in the course afterward:

> I was very interested in learning more about the topic of subsistence markets and started in week 1 with great enthusiasm. However, after watching and reading the material from week 1 until week3, … the presented information didn't seem much different from what I know. At this point my interest in the course completely waned.

One last respondent was concerned about the absence of the instructor. He said: “there was a profound ignorance and insensitivity in those taking the course. I have to wonder where is the instructor.” On the other hand, another survey respondent did not indicate any limiting factor. Instead, he showed his appreciation and gratitude to the course:

> It was a very noble course and very well presented and many of the students seemed to be people with high moral values. Also, I learned some things that I think will stay with me. I had something of a paradigm shift in the way I see the challenges people face.

Motivations and Limiting Factors of Delayed Participation

Because of the low response rate found in the data collection for this cluster, little is known about learners motivation and limiting factors. Only three responses were reported for the motivation question and none for the limiting factor question. Two of the three motivations appeared under the professional and career development category, while the last one appeared in the gaining general knowledge theme. Even though these responses are too limited, it is worth mentioning them. In regard to the professional and career development theme, the first respondent said: “to develop some new ideas and concepts that I would apply in my actual work in Africa and Latin America.” Similarly, the second respondent added: “it is very useful for my future profession.” As for the gaining knowledge theme, here is the one response that appeared in the data analysis: “Learn more about the subject.”

Chapter Summary

This chapter presented the findings that appeared in the data analysis by clustering learners’ participation in quizzes, forums and video lectures using educational data mining techniques. Results revealed five unique patterns of participation among MOOC learners. These are as follows: advanced, balanced, early, limited and delayed participation. Furthermore, statistical data analysis revealed that there is a relationship between the different patterns of participation and employment status, education level, and age groups, but not gender. Moreover, the content analysis of the open-ended survey questions explored multiple reasons that motivate and limit learner’s level of participation in MOOCs. Overall, data analysis has shown that learners participate in MOOCs in different ways to accommodate their needs.

CHAPTER V. DISCUSSION AND CONCLUSION

This final chapter aims to address the overall discussion and conclusion of carrying out this study in light of the results presented in Chapter 4 and prior related studies. It is divided into five main sections. The first section reflects on and discusses the research findings to better understand what they mean in the current domain of MOOC discourse. The second section is laid out to foreground some of the study's implications for rethinking the MOOC phenomenon to improve its future implementations. The third section aims to address the research challenges and limitations that affected this study. The fourth section provides suggestions and recommendations for future research. Finally, the last section provides the overall concluding remarks for this dissertation.

Discussion

Beyond formal learning: Variations in Learners' participation

The study reported that MOOC learners do not follow only one path of learning, which is how the courses has been designed and structured in a linear model (Ubell, 2017) and how the current literature has been treating MOOCs as traditional university courses (Clark, 2016). Instead, MOOCs operate in a unique and distinguished way of varied levels of participation which is not necessarily similar to the formal learning in conventional and university-accredited online classes. Data analysis found that learning has followed five different patterns of participation associated with learners' educational needs, demographic variables and time availability. Only one of these patterns aligns with traditional educational schemas, which is the "Advanced Participation" cluster. Learners in this cluster progressed in the course according to the course goals set by the instructor in the syllabus. They were the most committed ones towards the observed course activities (forum posts, quiz submissions, and video watching).

Therefore, their learning behavior fits within the archetype of traditional education. The way they participated in this course is also reflected in the statistical analysis of this study. The statistical analysis shows that learners who hold graduate degrees are more likely to participate in the “Advanced” participation cluster. This might explain why these learners value education and take the advanced route.

Beyond that, the learning behavior of other learners was informal and different. These learners have accessed different amounts of the course content at different time spans which is the not case of what we observe in formal school settings. For instance, in the “Balanced Participation” cluster, learners’ participation have increased and decreased in a systematic way almost every other week. Additionally, learners in the “Early Participation” cluster were highly engaged at the beginning of the course and then they started to slow down gradually in the following weeks but they did not stop participating. Furthermore, there is the “Limited Participation” cluster where learners have only shown minimum learning behavior across the course activities (videos, forums, and quizzes) compared with other clusters. Finally, there is this interesting path of learning where learners become more active once the course is over, as seen in the “Delayed Participation” cluster. Learners in this cluster seem to have similar learning behavior as in the previous cluster; however, their level of participation went higher after the last week of the course, specifically in accessing video lectures. They could probably save the materials for a later use.

These findings align with Kizilcec et. al., (2013) study, where the authors utilized educational data mining and survey analysis but not qualitative analysis. They found differences in the way learners engage in MOOCs. Overall, their study reported four different patterns of participation that are similar to the ones found in this dissertation, but not the learning behavior found in the “Balanced Participation” cluster where learners balance their learning according in a 2-week period. This unique way of learning needs to be acknowledged to offer the appropriate learning scaffolding and support.

Learning with Time Limitations and Life Responsibilities

Time is a crucial element for active engagement in any educational setting and most importantly in online settings where there is a limited face-to-face communication. Investigating the relationship between time and learning has been the topic of many educational studies. One of these previous studies reveals that the more times learners stay engaged during instruction, the more they learn (Gettinger & Ball, 2007).

The qualitative data analysis of the Subsistence Marketplaces MOOC found that lack of time is the most influential factor to limit learners’ participation across the different participation patterns. The finding came as no surprise for learners in the “Limited Participation” pattern as they were characterized with a great number of employed learners and students. The surprise was to know that a little more than half of learners in the “Advanced” and “Balanced” participation clusters also complained about time limitations. Although they reported time constraints as frequently as others in different clusters, they differed in their interpretations along those dimensions.

Most of these learners provided explicit answers of how time influenced their participation in the surveys. They spoke about their obligations and responsibilities towards family, work, studies and other priorities in their life that caused their time limitations. They stayed active in the course by choosing to do the required activities and skipping some of the optional ones, such as forum participation and final projects. This issue of time concern might explain why learners in the “Balanced Participation” cluster chose to balance learning in a 2-

week period. However, learners in the "Early Participation" and the "Limited Participation" clusters did not provide enough information on how time affected their participation; their answers were short and more general. Perhaps this is why some learners started very active and then slowed down, why others did not participate as much and why others only participated towards the end. These findings align with the study of Kizilcec and Halawa's (2015). The authors have analyzed twenty MOOCs from different disciplines using the course surveys. Likewise, they found that "the primary obstacle for most learners was finding a time" (p.57) to participate in the course.

Course Topic Matters: MOOC Participation for the Public Good

What was really important to highlight in this study is the fact that most of the survey respondents indicated hopes to learn how to succeed in the workforce and most importantly how to contribute to the production of the public good. Qualitative data analysis from the survey has shown those learners were not necessarily motivated in pursuit of formal credentials or to gain a certificate although there were three of them who had. Instead, the majority of learners participated in this MOOC because they sought experiences and insights that would help them in their professional lives and making a positive change in the subsistence marketplaces nationally and globally. This was mainly observed in the "Advanced" and "Balanced" participation clusters who had the most active learners. Learners who were less active in the course as seen in the "Limited Participation" cluster were mostly motivated to have an overview of the course content and satisfy their curiosity and interest. Despite some learners who also indicated similar purposes of career advancements and improving subsistence marketplaces for the common good. These hopes were in line with the course's focus to improve business practices in underserved areas.

Indeed, the content of this course was one of its kinds as it dealt with strategies and techniques in how to improve the dynamics of subsistence markets in poor areas and cope with related challenging issues. The instructor presented some case studies from India to show successful examples of how subsistence markets work regardless of the complexity of peoples' life. This drew an attention to thousands of learners to seek knowledge of social improvement to apply it in their current career or future plans of starting NGO organizations and small enterprises to reduce poverty. Poverty is one of the big problems of the global world especially in underdeveloped countries and bringing this subject through MOOCs is very well-positioned to encourage motivated learners to enhance the global market. For instance, one of the learners was interested to produce a subsistence market for prison inmates and homeless people who live in the street looking for any opportunity. He said: "I am interested in the subsistence markets of prison inmates, homeless people and street people in the U.S." Another learner from Malaysia had a passion to help poor people in his area to have a better life through business, where people couldn't even afford to have the minimum life needs of electricity, running water and a decent sanitation. He commented:

> While statistically the quality of life in Malaysia is getting better, and extreme poverty has dramatically decline from 1970 to 2002, areas of hard-core rural poverty still exists, especially among the indigenous communities of Sabah and Sarawak. Even in the Peninsular Malaysia, urban poor is still a problem due to lack of job opportunities and low education level. However, many people who are living in poverty, especially those living in the city, are ignorant when it comes to the potential of subsistence marketplaces … It has always been one of my passion to work with people who live in the rural areas of my country, who couldn't even afford to get electricity and running water, or decent

> sanitation. I believe that this course will be able to provide me with the knowledge and insight I could not get from classes or textbooks, and equip me better to serve the people of my country.

Some other learners were already connected with existing organizations in Africa, Asia and other places in the world and aimed to apply the course's information to solve real-world problems and find ways to face the challenges in business operations and reduce poverty.

These findings were also reflected in the course statistics. As a matter of fact, the statistics shows that 41% of learners in this course are coming from emerging economies and developing countries. Additionally, more than half of the survey respondents were employed, seeking for ways to advance their careers and make a positive change in the society. These results reveal the potential of MOOCs to open up channels to some of the motivated people around the world in the name of knowledge dissemination to inspire solving real world problems and advocating for social justice for a better world. Much of research has addressed the usefulness of MOOCs for career development (Liyanagunawardena et al., 2013; Christensen et al., 2014; Zheng et al., 2015; Levin, 2017), but studies around MOOCs and social justice for the public good are still limited. One of the few studies that addressed that issue was Gillani's (2013) study. Through Social Network Analysis of the discussion forums of the Foundations of Business Strategy MOOC offered by the University of Virginia, the author reported that learners were mostly engaged in this course to find ways to solve real world problems and improve people's life for the common good.

While these are ambitious hopes, the questions to follow is how much did learners benefit from this learning experience, did they change anything and what did they change? This was not explored in this study, but it could be a topic for future investigations.

Implications

The findings of this dissertation have two main implications for rethinking the MOOCs model and provide the best possible educational experience for learners to master their learning and empower them with skills needed for the workplace and beyond. These are pedagogical and socio-cultural implications.

Pedagogical Implications

In light of the variations of learners' participation, the study implies rethinking the pedagogical foundations of MOOCs to allow for differentiation and inclusivity in the way we teach and assess MOOCs. Currently, learning in MOOCs replicates what teachers do in regular university classes. The instructor puts his/her course online and sets unified learning goals for all learners to complete the course at the same pace regardless of their time constraints and educational needs as in the one-size-fits-all approach (Ubell, 2017). This approach does not recognize the changing nature of MOOC learners compared with learners in traditional universities. Thus, the study implies a need for a new approach in MOOCs to tackle learners' differences. Instead of relying on a one-size-fits-all approach, learning needs to be more flexible, adjustable and adaptable. This change entails new innovative approaches to engage massive number of learners with different backgrounds, perspectives and educational needs. This can happen via "reflexive/inclusive" pedagogy.

According to Kalantzis and Cope (2016b), Reflexive/Inclusive pedagogy recognizes learners' differences and cultural productivity. It aims to create different learning options to accommodate learners' needs while making them responsible of their learning. In this approach, learning is assessed differently based on the comparability principle.

> Under the principle of comparability, where assessment rubrics are pitched at a high level of generality, students can be doing different things but of comparable cognitive or practical difficulty. Learners and citizens no longer have to be the same to be equal (Cope & Kalantzis, 2016; p. 324).

In the analogy of MOOCs, learners may not have the same time or educational background, but they might put some practical and cognitive efforts to participate in the course that need to be recognized.

Rethinking Assessment of MOOC Success

A part of rethinking the pedagogical foundations of MOOCs is rethinking the way we assess learning in these environments with respect to learners' variations. Regardless of being right or wrong, and passing all the required activities or not, all efforts need to be acknowledged. The current metric of measuring completion rates and MOOC success ignores these efforts and provides only a superficial view of judging learners' participation. According to Jordan (2015), "completion rates were calculated as the percentage of students (out of the total enrolment for each course) who satisfied the criteria to gain a certificate for the course." For instance, in this course only 4% of the learners are considered completers in this passive view of measuring success. This should not be the way to measure completion rates and judge the success or failure of a MOOC.

In respect to all learners' trials and their varied levels of participation, the study offers a new vision to rethink the notion of assessing MOOC success. Instead of relying on the percentage of learners who complete all course requirements, a more meaningful assessment should equate MOOC success with knowledge gained and efforts taken by each learner to participate in this learning experience as well as understanding the influential factors of motivations and barriers, especially time constraints that might affect their participation.

Following this new vision, the study believes that 45.5% of all registered learners have committed to participate in this MOOC in a way that best suits their interests and needs (see figure 3). This is based on the comparability principles of reflexive/inclusive pedagogy by counting the number of active learners who took cognitive and practical efforts to participate in the course across the three major activities (videos, quizzes and forums). This is not to say that all learners did the same amount of work, but there is a variation in how learners participate in the course that needs to be recognized. The rest of the learners (54.5%) we could call “others.” These learners did not show any learning behavior towards the observed course activities of accessing video lectures, forum interaction, and/or weekly quizzes; however, they might have done other activities, such as page or forum views.

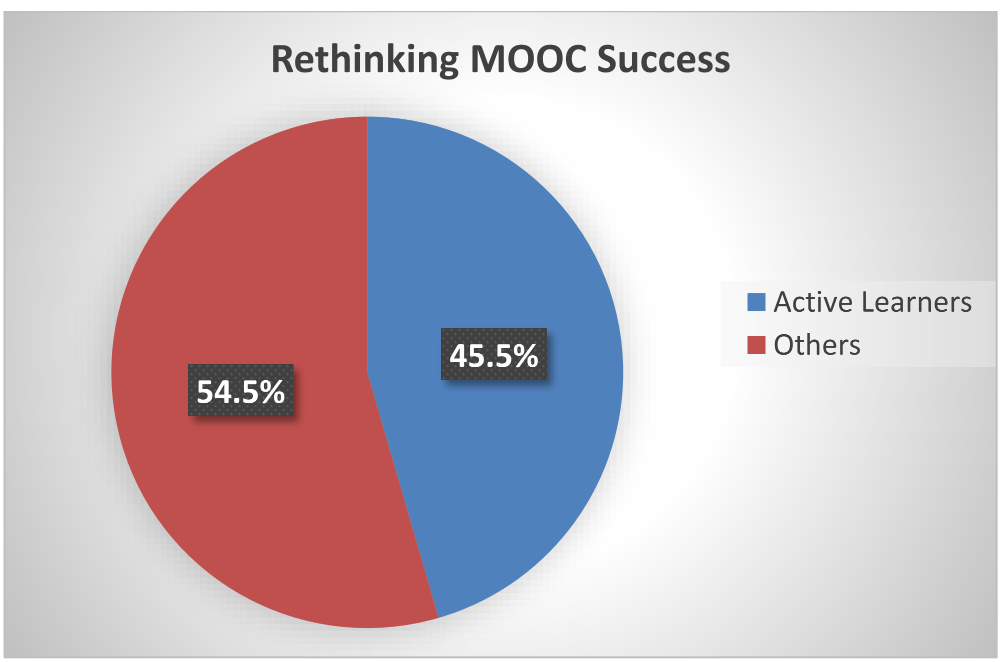

Figure 3: Rethinking MOOC assessments and notion of success.

Rethinking the Curriculum and Course Structure in MOOCs

Another part of rethinking the pedagogy in MOOCs is to restructure the course and differentiate its content to align with the explored patterns of participation. Instead of reproducing the same structure of traditional university courses, the study implies a need for an innovative course structure that honors differentiation. For instance, instructors can rearrange the course content, educational resources, and weekly activities in multiple ways by giving learners different learning options to participate in the course according to their needs. In this case, learners may not feel obligated to do all the requirements in order to complete a MOOC. Providing multiple paths of learning will also serve as a guide to motivate learners to master their intended learning goals. Instead of assuming the negativity of failing a MOOC, we can then push learners to practice, learn and succeed in a MOOC according to the level of participation they choose.

An example of that is the e-learning ecologies MOOC. This was the first MOOC to be offered by the College of Education at Urbana-Champaign in 2014. The course was designed in a unique way to include three levels of participation: “Advanced,” “Intermediate” and “Overview.” As learners sign in for the course and go over the syllabus, they can select one of these options to engage in the course depending on their needs and time availability. Table 20 describes the weekly activities expected for each level of participation for this course.

	Participation Level	Time Estimate	Tasks
O	**e-Learning Ecologies Overview (O)**	1 hour per week	• Watch the videos and view the material marked (O) • Comment on each week's post, made by the course admin
I	**e-Learning Ecologies Intermediate (I)**	3 hours per week	• Watch the videos and view the material marked (O) and (I) • Comment on each week's post, made by the course admin • Make a post of your own
A	**e-Learning Ecologies Advanced (A)**	8–10 hours per week	• Watch the videos and view the material marked (O), (I), and (A) • Comment on each week's post, made by the course admin • Make a post of your own • Create a Case Study; peer review 3 others' Case Studies; revise your Case Study for web publication • If you are working in Scholar, you can choose to make your personal profile page and published Case Study public and permanently visible on the web.

Table 20: Three levels of participation in e-Learning Ecologies MOOC.

Rethinking the Platform Design

Drawing upon the overall findings of how learning varies across different learners, the study implies rethinking the design of the Coursera platform in a way that supports differentiation and personalized learning. While MOOC courses can be differentiated manually, this process consumes time and effort in rearranging content and monitoring progress. To be more efficient and effective, perhaps software developers can use artificial intelligence techniques to calibrate learners' progress instantly and adapt learning according to an individual's educational needs. Learners need to be able to see where they are in the learning process and where they need to be in order to master learning and reach their goals.

One example of how artificial intelligence works in practice is the learning analytics tool embedded in the Common Ground Scholar software (CGScholar). CGScholar is a learning management system that was recently developed by the College of Education at UIUC and founded on multiple affordances that support learning in a digital age. Among these affordances is the notion of differentiated and personalized learning as characterized in the learning analytics tool. This tool provides each learner with a visualization graph of all his/her contributions in a particular course. Based on the philosophical views underpinning this software, this tool would support and motivate learners to stay engaged according to their learning needs (Montebello et al., 2018). Figure 3 shows a screenshot of this tool. The way this tool works is by mining all of a student's activities instantly, up to the moment of the last login. It consists of multiple pedals; each one shows the progress in a particular unit of the course. When a student clicks on any of these pedals, it brings more detailed information about the data used to generate the outcome. The number in the middle of this figure shows the overall scores that a student has gained.

Having a similar tool in the Coursera platform would be a great addition to customize learning and keep learners informed of their progress. Theoretically, as learners watch their progress at any time, they become more responsible for their own learning by pushing themselves to learn according to their intended goals (Cope & Kalantzis, 2017).

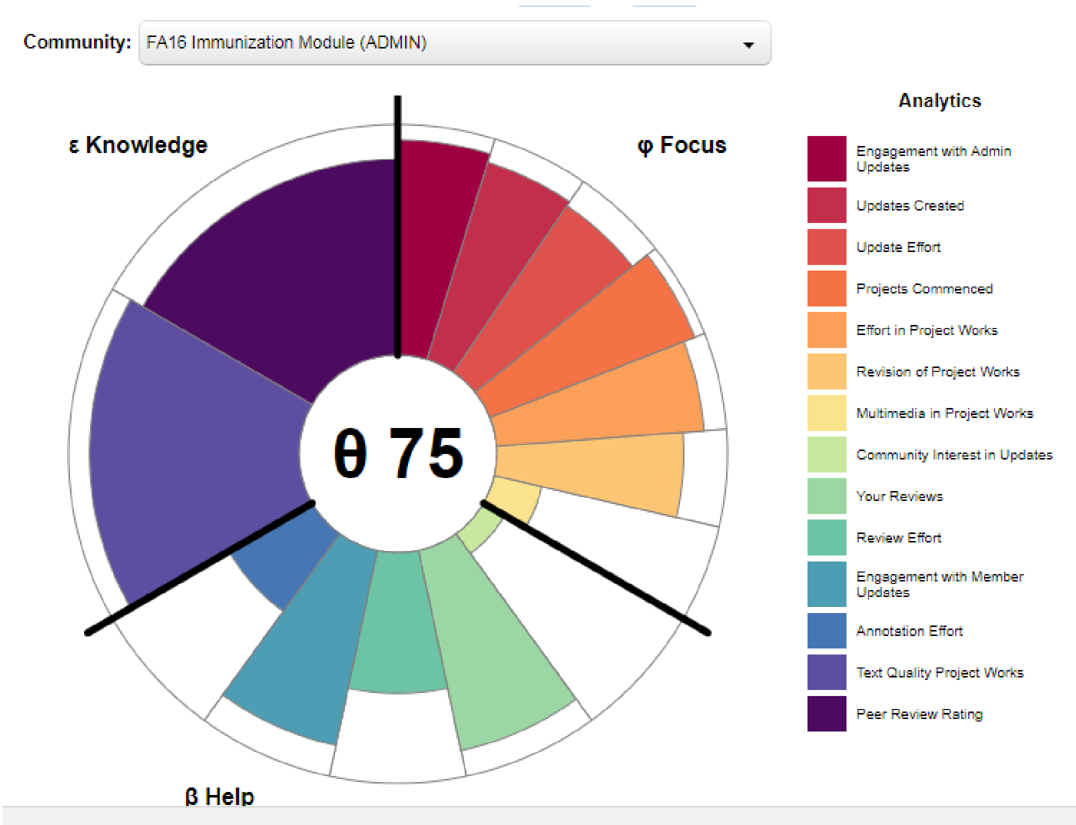

Figure 4: Learning analytics tool in CGScholar.

Socio-cultural Implications

This implication drives from the findings that learners were mostly motivated to participate in the course to gain career skills and contribute to the production of the public good. While many studies have shown that MOOC learners look for technical skills to learn how to code (Funkhouser, 2016) and solve mathematical equations (Lambert, 2015), this study found there are people who are looking for more meaningful purposes and practical ways in how to solve real world problems within the society and beyond. These problems, which include poverty, economy and business are considered the most challenging issues the world suffers from these days. In light of these findings, the study implies that people are in thirst of such knowledge to be engaged in a course. Consequently, there is a need to harness the MOOC experiences to educate learners about different cultures and empower them with knowledge in how to make radical changes in rural and underserved areas. This could happen by enhancing and increasing courses that target such challenging topics while including practical examples in how to transform people’s life to the best.

Limitations

There are several limitations associated with this dissertation. One of these limitations is the dataset. The study addressed only a single MOOC course offered by only one university in a particular domain (social science) in a specific MOOC platform (Coursera). This limitation would lead to several questions. What is going to happen if something has changed? What if the study incorporated more than one course from the same discipline? What if the study added the subsequent iterations of the course? What if the study included courses from a different discipline (e.g., computer science, engineering, arts, etc.) What if the study used a different platform rather than Coursera? If this is to happen, then what are these patterns of participation going to look like? Are they going to be similar or different from those found in this present study?

Another limitation of this study is the survey response rate. As a matter of fact, the survey respondents constitute almost twelve percent (12%) of the whole population. This percentage was even lower in the open-ended questions, reaching only eight percent (8%) of the learners. Although this is expected in such a context (Cruess et al., 2017), future iterations of the course should encourage learners to answer the surveys, perhaps by providing rewards upon completion. It was not possible to offer such a reward in this study since the analyses were limited to these responses retrieved from archival data.

Third, there is the limitation of the new changes happening to the Coursera platform. As I was working on this dissertation, the Coursera platform moved from the session-based version to the on-demand version. The new on-demand version now presents the content in a set of 4 mini short modules instead of 6-to-8 week long in the previous version. Shorter format might help to solve the time issue in the previous version, yet it is still expected that learners would have different goals and learning needs.

Furthermore, Coursera has recently started to split some of their course offerings into standard and premium options. The standard option includes free access to some of the course content while it locks some of the required materials, such as graded assignments, for only paid learners to see. In the premium option, learners have to pay for a certificate or a degree in order to have full access to the course content (Fein, 2017). Monetizing the content in this way might affect the way learners participate in the premium option of MOOCs as there is a price to lose if participation stopped. Yet, it is important to mention that this dissertation is centered around courses that follow the concept of openness as in the standard option since this was the original goal of MOOCs when they started, but not monetization.

Future Research

Although this dissertation presents significant findings to understand learners' participation in MOOCs, there are a number of suggestions and recommendations to strengthen this work in future research. One of these suggestions is to have a wider picture of how the participation patterns would look within various types of MOOCs. Thus, the study recommends expanding the research with additional MOOC courses across different disciplines following the same framework. Doing so will help to determine whether these patterns were unique to the Subsistence Marketplace MOOC, or they can be generalized.

Another suggestion is relevant to the MOOC platform. While this study looked at the Subsistence Marketplace MOOC in the session-based Coursera platform, future research is needed to further investigate the new on-demand format. In addition, this study recommends doing a comparative study between learners' participation in Coursera and other MOOC platforms that support the openness feature, such as EdX. This will help to understand how different platforms support learners' needs.

A third suggestion to improve this work is to add more qualitative data to the study. For instance, the third research question that aimed to understand what motivates and limits learners to participate in MOOCs can be supplemented with follow-up interviews with different learners across the different patterns of participation. This will help us to have a deeper understanding of why learners participated in a certain way but not the other. In particular, I was interested to know the reasons behinds learners' behavior in the "Early Participation" cluster, why their participation has decreased over time. Also, I was interested to hear from the learners in the "Delayed Participation" cluster, why they collected educational resources towards the end of the course? Did they make use of this? Additionally, this study can be supplemented with follow-up interviews with the participants who indicated their willingness to use the course content to do a positive change in the society. It will be interesting to know if the course has really and truly helped them to contribute to the public good. And if so, how and to what extent?

Finally, there is a need for further research surrounding the dynamicity of learning in MOOCs in general and in particular examining their unique features of openness and massiveness. Although MOOCs are going through many changes, they are here to stay. Thus, this phenomenon needs to be explored and well-studied to provide an enjoyable learning experience for all.

Conclusion

In closing, this dissertation has been a great learning experience to explore how learning occurs in a massive scale, incorporating theories and methodologies that I have learned throughout my doctoral study. Interestingly, the study found that learners participate in MOOCs in five different ways. Some learners prefer to take the advanced route, while others prefer to balance their participation across time and thus do the course activities every other week. A third group participated early in the course and then their level of participation went down over time. Compared with other clusters, the fourth group preferred to do the minimum work across the eight weeks of the course, while the last group was interested in accessing content after the course was over. Statistical data analyses revealed that there is an association between the different patterns of participation and employment status, education level, and age groups, but not gender. Data analysis from the open-ended survey questions has shown that there are multiple reasons that motivate and limit learners' levels of participation in MOOCs. Some of these reasons overlap among learners in different groups. What was interesting to discover is that most learners in the "Advanced" and "Balanced" participation clusters were engaged in this MOOC to contribute to the production of the public good.

While these results are significant in understanding the dynamicity of learning in MOOCs, they cannot be generalized because of the limitations of the research depending on a single case study. As stated in the future research section, there is a need for conducting more studies in this area of research to discover learners' participation patterns across a wide variety of MOOC courses in different disciplines and in different MOOC platforms.

REFERENCES

Ahlquist, J. S., & Breunig, C. (2012). Model-based clustering and typologies in the social sciences. *Political Analysis*, *20*(1), 92-112.

Alraimi, K. M., Zo, H., & Ciganek, A. P. (2015). Understanding the MOOCs continuance: The role of openness and reputation. *Computers & Education*, *80*, 28-38.

Anderson, A., Huttenlocher, D., Kleinberg, J., & Leskovec, J. (2014, April). Engaging with massive online courses. In *Proceedings of the 23rd international conference on World wide web* (pp. 687-698). ACM.

Asiri, O. I. (2014). *A Comparison Between International and US Graduate Students' Attitudes and Experiences Using Massive Open Online Courses (MOOCs)*. Rochester Institute of Technology. Retrieved from http://scholarworks.rit.edu/theses/8214/

Bagdonavicius, V. B., & Nikulin, M. S. (2011). Chi-squared goodness-of-fit test for right censored data. *International Journal of Applied Mathematics and Statistics™*, *24*(SI-11A), 30-50.

Baker, R., Yacef, K. (2009) The State of Educational Data Mining in 2009: A Review and Future Visions. *Journal of Educational Data Mining*, 1 (1), 3-17.

Baker, R., Siemens, G. (2014) Educational data mining and learning analytics. In Sawyer, K. (Ed.) *Cambridge Handbook of the Learning Sciences: 2nd Edition*, pp. 253-274

Bates, T. (2014). Comparing xMOOCs and cMOOCs. Philosophy and Practice. *Online Learning and Distance Education Resources*.

Belanger, Y., & Thornton, J. (2013). Bioelectricity: A quantitative approach Duke University's first MOOC. Retrieved from http://dukespace.lib.duke.edu/dspace/handle/10161/6216

Berland, M., Baker, R. S., & Blikstein, P. (2014). Educational data mining and learning analytics: Applications to constructionist research. *Technology, Knowledge and Learning*, *19*(1-2), 205-220.

Bienkowski, M., Feng, M., & Means, B. (2012). Enhancing teaching and learning through educational data mining and learning analytics: An issue brief. *US Department of Education, Office of Educational Technology*, *1*, 1-57.Blake, C. (2011). Text mining. *Annual review of information science and technology*, *45*(1), 121-155.

Bishop, J. L., & Verleger, M. A. (2013). *The flipped classroom: A survey of the research.* Paper presented at the ASEE National Conference Proceedings, Atlanta, GA.

Bloom, B. S. (1968). Learning for Mastery. Instruction and Curriculum. Regional Education Laboratory for the Carolinas and Virginia, Topical Papers and Reprints, Number

1. *Evaluation comment*, *1*(2).

Botelho, S. (2015). Arizona State and edX offer full freshman year of MOOCs. *University Business, 18*(7), 19-19.

Bowen, W. (2013). higher Education in the Digital. ithaka. *Age, Princeton University Press*.

Bulfin, S., Pangrazio, L., & Selwyn, N. (2014). Making "MOOCs": The construction of a new digital higher education within news media discourse. *The International Review of Research in Open and Distributed Learning*, *15*(5). Retrieved from http://www.irrodl.org/index.php/irrodl/article/view/1856

California Senate Bill 520 (2013). Retrieved November 6, 2015, from http://cms.cerritos.edu/uploads/AcademicAffairsBlog/California_Senate_Bill_520_and_the_Implications_for_the_Community_College_System_.pdf

Carver, L., & Harrison, L. M. (2013). MOOCs and democratic education. *Liberal Education*, *99*(4), 20–25.

Chen, Y. (2014). Investigating MOOCs through blog mining. *The International Review of Research in Open and Distributed Learning*, *15*(2).

Christensen, C. (2013). Clayton Christensen Interview with Mark Suster at Startup Grind 2013. In M. Suster (Ed.), *Startup Grind* https://www.youtube.com/watch?v=KYVdf5xyD8I: Startup Grind

Christensen, G., Steinmetz, A., Alcorn, B., Bennett, A., Woods, D., & Emanuel, E. J. (2013). *The MOOC Phenomenon: Who takes massive open online courses and why?*. Retrieved from: http://ssrn.com/abstract¼2350964

Cisel, M. (2014). Analyzing completion rates in the First French xMOOC. *Proceedings of the European MOOC Stakeholder Summit*, *26*. Retrieved from https://www.openeducationeuropa.eu/sites/default/files/asset/From-field_37_6.pdf

Clark, D. (2016, April 13). MOOCs: Course Completion is the Wrong Measure of Course Success - Class Central. Retrieved May 28, 2018, from https://www.class-central.com/report/moocs-course-completion-wrong-measure/

Cope, B., & Kalantzis, M. (2015). Interpreting Evidence-of-Learning: Educational research in the era of big data. *Open Review of Educational Research*, *2*(1), 218-239.

Cope, B., & Kalantzis, M. (2016). Big Data comes to school: Implications for learning, assessment, and research. *AERA Open*, *2*(2), 2332858416641907.

Cope, B., & Kalantzis, M. (2017). Conceptualizing e-Learning. In B. Cope & M. Kalantzis (Eds.). *e-Learning Ecologies: Principles for New Learning and Assessment* (pp. 1-45). Routledge Publisher.

Cotofrei, P., & Stoffel, K. (2005). First-order logic based formalism for temporal data mining. In *Foundations of Data Mining and Knowledge Discovery* (pp. 185-210). Springer Berlin Heidelberg.

Creswell, J. W., & Clark, V. L. P. (2007). *Designing and conducting mixed methods research*. Thousand Oaks, Calif: SAGE Publications.

Creswell, J. W. (2014). *Research design: Qualitative, quantitative, and mixed methods approaches*. (4th ed.). Thousand Oaks, CA: Sage

Crossley, S., Paquette, L., Dascalu, M., McNamara, D. S., & Baker, R. S. (2016). Combining Click-stream Data with NLP Tools to Better Understand MOOC Completion. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 6–14). New York, NY, USA: ACM.

Crues, R.W., Henricks, G.M., Perry, M., Bhat, S., Anderson, C. J., Shaik, N., & Angrave, L. (2017, accepted). How do gender, learning goals, and forum participation predict persistence in a computer science MOOC? *ACM Transactions on Computing Education, 17*.

Daniel, J. (2012). Making sense of MOOCs: Musings in a maze of myth, paradox and possibility. *Journal of Interactive Media in Education*, *2012*(3). Retrieved from http://jime.open.ac.uk/article/view/2012-18/sirjohn.ca/

Davis, D., Jivet, I., Kizilcec, R. F., Chen, G., Hauff, C., and Houben, G.-J. (2017). Follow the successful crowd: raising mooc completion rates through social comparison at scale. In LAK, pages 454–463.

Dewey, J. (1938). *Experience and education*. New York: Macmillan.

Fein, A. D. (2017). *Multimedia learning: principles of learning and instructional improvement in Massive, Open, Online Courses (MOOCS)* (Doctoral dissertation, University of Illinois at Urbana-Champaign).

Florian, L., & Black-Hawkins, K. (2011). Exploring inclusive pedagogy. *British Educational Research Journal*, *37*(5), 813-828.

Florian, L., Rouse, M., & Black-Hawkins, K. (2016). *Achievement and inclusion in schools*. Routledge.

Flynn, J. (2013). MOOCS: Disruptive innovation and the future of higher education. *Christian Education Journal*, *10*(1), 149-162.

Forsyth Communication (2012.). For Big Data Analytics There's No Such Thing as Too Big. Retrieved from https://www.cisco.com/c/dam/en/us/solutions/data-center-virtualization/big_data_wp.pdf

Franceschen, T. (2016). Completion Rates are the Greatest Challenge for MOOCs. (Retrieved May 28, 2018, from http://edu4.me/en/completion-rates-are-the-greatest-challenge-for-moocs/

Friedman, T. (2013). Revolution hits the universities. *The New York Times*, *26*.

Funkhouser, T. (2016). My favorite MOOCs for learning to code. Retrieved May 28, 2018, from https://www.techrepublic.com/article/my-favorite-moocs-for-learning-to-code/

Gaebel, M. (2013). *MOOCs: Massive open online courses*: EUA.

Gais, H. (2014). Saudi Arabia Gets MOOC'd up. *Al Jazeera America*.

Gardner, H. E. (2006). *Multiple Intelligences: New Horizons in Theory and Practice*. New York: Basic Books.

Gettinger, M., & Ball, C. (2007). Best practices in increasing academic engaged time. In A. Thomas & J. Grimes (Eds.), *Best practices in school psychology* (pp. 1043-1075). Bethesda, MD: National Association of School Psychologists.

Gillani, N. (2013). Learner communications in massively open online courses (OxCHEPS Occasional Paper No. 53). *Récupéré du site de l'Oxford Centre for Higher Education Policy Studies: http://oxcheps. new. ox. ac. uk*.

Gravetter, F. J., & Wallnau, L. B. (2016). *Statistics for the behavioral sciences*. Cengage Learning.

Greene, J. C., & Caracelli, V. J. (1997). *Advances in mixed-method evaluation: The challenges and benefits of integrating diverse paradigms* (No. 658.4032 A244). Jossey-Bass Publishers.

Greene, J. C. (2007). *Mixed methods in social inquiry.* San Francisco, CA: Jossey-Bass.

Greenwood, P. E., & Nikulin, M. S. (1996). *A guide to chi-squared testing* (Vol. 280). John Wiley & Sons.

Haggard, S., Brown, S., Mills, R., Tait, A., Warburton, S., Lawton, W., & Angulo, T. (2013). The Maturing of the MOOC: literature review of massive open online courses and other forms of online distance learning. *Department for Business, Innovation and Skills, UK Government*.

Han, J., Pei, J., & Kamber, M. (2011). *Data mining: concepts and techniques*. Elsevier.

Haniya S., & Roberts-Lieb S. (2017). Differentiated Learning: Diversity Dimensions of e-Learning. In B. Cope & M. Kalantzis (Eds.). *e-Learning Ecologies: Principles for New Learning and Assessment* (pp. 183-206). Routledge Publisher.

Haniya S., & Rusch, A. (2017). Ubiquitous Learning: Spatio-Temporal Dimensions of e-Learning. In B. Cope & M. Kalantzis (Eds.). *e-Learning Ecologies: Principles for New Learning and Assessment* (pp. 46-64). Routledge Publisher.

Ho, A. D., Reich, J., Nesterko, S., Seaton, D. T., Mullaney, T., Waldo, J., et al. (2014). *HarvardX and MITx: The first year of open online courses.* Retrieved from: http://ssrn.com/abstract¼2381263.

Hone, K. S., & El Said, G. R. (2016). Exploring the factors affecting MOOC retention: A survey study. *Computers & Education*, *98*, 157-168.

Hvam, K. (2015). MOOCs--A Challenge or an Opportunity: A Personal View. *Furthering Higher Education Possibilities through Massive Open Online Courses. USA: Information Science Reference, an Imprint of IGI Global. Http://www. Igi-Global. Com/book/furthering-Higher-Education-possibilitiesthrough/121188*, 1–21.

Jenkins, H. (2006). *Confronting the challenges of participatory culture: Media education for the 21st century : an occasional paper on digital media and learning*. Chicago: MacArthur Foundation.

Jiang, S., Williams, A., Schenke, K., Warschauer, M., & O'dowd, D. (2014, July). Predicting MOOC performance with week 1 behavior. In *Educational Data Mining 2014*.

John Walker, S. (2014). Big Data: A Revolution That Will Transform How We Live, Work, and Think. *International Journal of Advertising*, *33*(1), 181–183.

Johnson, L., Adams, S., Cummins, M., Estrada, V., Freeman, A., & Ludgate, H. (2013). The NMC Horizon Report: 2013 Higher Education Edition. Austin, TX: The New Media Consortium. Retrieved October 2, 2013.

Johnson, D. W., Johnson, R. T., & Smith, K. A. (2013). Cooperative learning: Improving university instruction by basing practice on validated theory. *Journal on Excellence in University Teaching*, *25*(4), 1-26.

Jordan, K. (2014) Initial trends in enrolment and completion of massive open online courses. *International Review of Research in Open and Distance Learning,* 15(1). Retrieved from http://www.irrodl.org/index.php/irrodl/article/view/1651

Jordan, K. (2015). Massive Open Online Course Completion Rates Revisited: Assessment, Length and Attrition. *International Review of Research in Open and Distributed Learning*, 16(3), 341-358

Kalantzis, M., & Cope, B. (2005). *Learning by design*. Common Ground.

Kalantzis, M. & Cope, B. (2012). *New learning: Elements of a science of education (2nd ed.)*. New York: Cambridge University Press.

Kalantzis, M, & Cope, B. (2016a). Learner Differences in Theory and Practice. *Open Review of Educational Research, 3*.

Kalantzis, M., & Cope, B. (2016b). New media and productive diversity in learning. In S. Barsch & S. Glutsch (Eds.), *Diversity in der Lehrerinnenbildung* (pp. 310–235). Münster, Germany: Waxmann.

Kaufman, L., & Rousseeuw, P. J. (2009). *Finding groups in data: an introduction to cluster analysis* (Vol. 344). John Wiley & Sons.

Kesim, M., & Altınpulluk, H. (2015). A Theoretical Analysis of Moocs Types from a Perspective of Learning Theories. *Procedia-Social and Behavioral Sciences, 186*, 15-19.

Kevan, J. M., & Ryan, P. R. (2016). Experience API: Flexible, decentralized and activity-centric data collection. *Technology, knowledge and learning*, *21*(1), 143-149.

Kizilcec, R. F., & Halawa, S. A. (2015). Attrition and Achievement Gaps in Online Learning. In *Proceedings of the Second ACM Conference on Learning at Scale, L@S 2015*. Vancouver, Canada.

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing Disengagement: Analyzing Learner Subpopulations in Massive Open Online Courses. In *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 170–179). New York, NY, USA: ACM.

Kovanović, V., Joksimović, S., Gašević, D., Siemens, G., & Hatala, M. (2015). What public media reveals about MOOCs: A systematic analysis of news reports. *British Journal of Educational Technology: Journal of the Council for Educational Technology*, *46*(3), 510–527.

Lambert, S. (2015). Reluctant Mathematician: skills-based MOOC scaffolds wide range of learners. *Journal of Interactive Media in Education*, *2015*(1).

Lave, J., & Wenger, E. (1997). *Situated learning : legitimate peripheral participation*. Cambridge [u.a.: Cambridge Univ. Press.

Lawton, W., & Katsomitros, A. (2012). MOOCs and disruptive innovation: The challenge to HE business models.

Lequerica, A. (2016, March 24). MOOCs for Credit: All the different ways you can get credit from MOOCs - Class Central.. Retrieved May 28, 2018, from https://www.class-central.com/report/moocs-for-credit/

Levin, R. (2017, April 26). Online Learners Report Benefits from Advancing their Careers to Discovering a Field of Study to Gaining Confidence - Coursera Blog. Retrieved May 28, 2018, from https://blog.coursera.org/online-learners-around-world-report-benefits-ranging-advancing-careers-discovering-field-study-gaining-confidence/

Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). MOOCs: A systematic study of the published literature 2008-2012. *The International Review of Research in Open and Distributed Learning*, *14*(3), 202–227.

McKim, C. A. (2017). The value of mixed methods research: A mixed methods study. *Journal of Mixed Methods Research*, *11*(2), 202-222.

Milligan, C., Littlejohn, A., & Margaryan, A. (2013). Patterns of engagement in connectivist MOOCs. *Journal of Online Learning and Teaching / MERLOT*, *9*(2), 149.

Montebello, M., **Haniya, S.,** Pinheiro, P., Cope, W., Kalantzis, M., Searsmith, D., Amina, T., Tzirides, A.O. (2018) Visualizing Learner Performance in an Online Education Platform. In: Proceedings of the *4th* International Symposium on Educational Technology, Osaka, Japan (in review).

Montessori, M. (1912). *The Montessori method: scientific pedagogy as applied to child education in 'the Children's Houses'*. London: Heinemann.

Morris, N. P., Hotchkiss, S., & Swinnerton, B. (2015). Can demographic information predict MOOC learner outcomes? *Proceedings Papers*, 199.

Moules, J. (2015). Illinois College of Business and Coursera launch MBA Mooc. *Business School News.* Retrieved November 6, 2015, from http://www.ft.com/intl/cms/s/2/6c2ffb58-f331-11e4-a979-00144feab7de.html#axzz3nnxobnrZ

Nkuyubwatsi, B. (2014). Cultural Translation in Massive Open Online Courses (MOOCs). eLearning Papers, 37, 1-10.

Pappano, L. (2012). The Year of the MOOC. *The New York Times*, *2*(12), 2012.

Papamitsiou, Z. K., & Economides, A. A. (2014). Learning analytics and educational data mining in practice: A systematic literature review of empirical evidence. *Educational Technology & Society*, *17*(4), 49-64.

Piaget, J. (1976). *Piaget's theory*. Berlin: Springer.

Reich, J. (2014) MOOC completion and retention in the context of student intent. *Educause Review*. Retrieved from http://www.educause.edu/ero/article/mooc-completion-and-retention-context-student-intent

Rocca, K. A. (2010). Student participation in the college classroom: An extended multidisciplinary literature review. *Communication Education*, *59*(2), 185-213

Rodriguez, O. (2012). MOOCs and the AI-Stanford Like Courses: Two Successful and Distinct Course Formats for Massive Open Online Courses. *European Journal of Open, Distance and E-Learning*.

Rodriguez, O. (2013). The concept of openness behind c and x-MOOCs (Massive Open Online Courses). *Open Praxis, 5*(1), 67-73

Romero, C., & Ventura, S. (2013). Data mining in education. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *3*(1), 12-27.

Shah, D. (2018, January 22). A Product at Every Price: A Review of MOOC Stats and Trends in 2017 - Class Central. Retrieved May 28, 2018, from https://www.class-central.com/report/moocs-stats-and-trends-2017/

Shah, D. (2018, January 20). 6 Biggest MOOC Trends of 2017 - Class Central. Retrieved May 28, 2018, from https://www.class-central.com/report/6-biggest-mooc-trends-2017/

Siemens, G. (2005). Connectivism: A learning theory for the digital age. *International journal of instructional technology and distance learning*, *2*(1), 3-10.

Siemens, G. (2012). MOOCs are really a platform. *ELearnspace,[online] Available at: http://www.personal.psu.edu/atb3/blogs/snippets/2012/07/george-siemens---moocs-are-really-a-platform.html*

Sinha, T., Jermann, P., Li, N., & Dillenbourg, P. (2014). Your click decides your fate: Inferring information processing and attrition behavior from mooc video clickstream interactions. *arXiv Preprint arXiv:1407. 7131*. Retrieved from http://arxiv.org/abs/1407.7131

Statistics Solutions. (2018). Chi-Square Test of Independence - Statistics Solutions. Retrieved May 28, 2018, from http://www.statisticssolutions.com/non-parametric-analysis-chi-square/

Steffens, K. (2015). Competences, Learning Theories and MOOCs: Recent Developments in Lifelong Learning. *European Journal of Education*, *50*(1), 41–59.

Teddlie, C., & Tashakkori, A. (2010). Overview of contemporary issues in mixed methods research. *Handbook of mixed methods in social and behavioral research*, 1-41.

Tomlinson, C. A., & McTighe, J. (2006). *Integrating differentiated instruction & understanding by design: Connecting content and kids.* Alexandria, VA: Association for Supervision and Curriculum Development.

Tomlinson, C. A. (2014). *The differentiated classroom: Responding to the needs of all learners* (2nd ed.). ASCD Books.

Ubell, R. (2017). How the Pioneers of the MOOC Got It Wrong. Retrieved March 02, 2017, from http://spectrum.ieee.org/tech-talk/at-work/education/how-the-pioneers-of-the-mooc-got-it-wrong

Uvalić-Trumbić, S., & Daniel, J. (2013). Making sense of MOOCs: The evolution of online learning in higher education *Scaling up Learning for Sustained Impact* (pp. 1-4): Springer.

Vardi, M. Y. (2012). Will MOOCs destroy academia? *Communications of the ACM*, *55*(11), 5.

Witten, I. H., & Frank, E. (2005). *Data mining: Practical machine learning tools and techniques with Java implementations*. Amsterdam: Elsevier.

Yuan, L., Powell, S. (2013). MOOCs and open education: Implications for higher education. Retrieved from http://publications.cetis.org.uk/wp-content/uploads/2013/03/MOOCs-and-Open-Education.pdf

Yousef, A., Chatti, M., Schroeder, U., Wosnitza, M., & Jakobs, H. (2014). *MOOCs-A Review of the State-of-the-Art.* Paper presented at the Proc. CSEDU 2014 conference.

Vygotsky, L (1962). *Thought and language*. Cambridge: M.I.T. Press, Massachusetts Institute of Technology.

Zheng, S., Rosson, M. B., Shih, P. C., & Carroll, J. M. (2015). Understanding Student Motivation, Behaviors and Perceptions in MOOCs. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing* (pp. 1882–1895). New York, NY, USA: ACM.

APPENDIX A: IRB LETTER

UNIVERSITY OF ILLINOIS
AT URBANA-CHAMPAIGN

Office of the Vice Chancellor for Research
Office for the Protection of Research Subjects
805 West Pennsylvania Ave
Urbana, IL 61801

December 8, 2017

William Cope
Educational Policy Studies
326 Education Bldg
1310 South Sixth Street
Champaign, IL 61820

RE: *Learning in MOOCs*
IRB Protocol Number: 17419

Dear Dr. Cope:

This letter authorizes the use of human subjects in your continuing project entitled *Learning in MOOCs*. The University of Illinois at Urbana-Champaign Institutional Review Board (IRB) approved the protocol as described in your IRB application, by expedited continuing review. The expiration date for this protocol, IRB number 17419, is 12/05/2020. The risk designation applied to your project is *no more than minimal risk*.

Under applicable regulations, no changes to procedures involving human subjects may be made without prior IRB review and approval. The regulations also require that you promptly notify the IRB of any problems involving human subjects, including unanticipated side effects, adverse reactions, and any injuries or complications that arise during the project.

You were granted a three-year approval. If there are any changes to the protocol that result in your study becoming ineligible for the extended approval period, the RPI is responsible for immediately notifying the IRB via an amendment. The protocol will be issued a modified expiration date accordingly.

If you have any questions about the IRB process, or if you need assistance at any time, please feel free to contact me at the OPRS office, or visit our website at https://www.oprs.research.illinois.edu.

Sincerely,

Michelle Lore

Michelle Lore, MS
Human Subjects Research Specialist, Office for the Protection of Research Subjects

c: Samaa Haniya

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