MULTIMEDIA LEARNING: PRINCIPLES OF LEARNING AND INSTRUCTIONAL IMPROVEMENT IN MASSIVE, OPEN, ONLINE COURSES (MOOCS)

BY

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DISSERTATION

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Abstract

With good reason, many initial Massive, Open, Online Course (MOOC) studies conducted in the first three years of widespread MOOC hype and adoption have focused on retention rates and completion issues. No longer a new modality, many of the retention questions have now been answered as researchers provided skeptics with myriad examples of success stories and better perspectives on how to examine retention and student success in the massive space [Koller, D., Ng, A., Do, C., & Chen, Z. (2013); Kizilcec, R., Piech, C., & Schneider, E. (2013); Reich, J. (2014); Zheng, S., Rosson, M., Shih, P., & Carroll, J. (2015)]. To fulfill the promise and potential for MOOCs, the enormity of the scale must complement, rather than limit high quality learning outcomes. There has been extensive research (Richard Mayer, et al.) on enhanced learning using multimedia (words and pictures) presentations in clinical settings -- can we see the same success in a MOOC field setting?

Consistent with the cognitive theory of multimedia learning (CTML) and Richard E. Mayer's research with colleagues (Mayer & Bove, 1996; Harp & Mayer, 1998; Moreno & Mayer, 2000; Mayer & Jackson, 2005; Mayer, 2009), I found that learners in the Fall 2015 MOOC offering of "Microeconomic Principles" were able to build more meaningful connections between words and pictures than with words alone as reflected in their performance[1] on practice quizzes across three different course modules.

This finding has a number of implications for instructional design. First, we see that designing assessment feedback to only include verification feedback (acknowledgement of only a correct or incorrect answer) does not produce any positive impact on performance and should not be considered a useful treatment for students other than to simply verify their progress.

[1] Learning performance was measured by recording how many students who missed a particular question then correctly answered a second question on the same topic.

Second, utilizing any type of instant *elaboration* feedback has an immediate impact on student performance. A text narrative providing the student with additional information about the misunderstood subject matter produces better student performance results, up to 3.4 times better, than a student who did not receive any elaboration feedback (text or multimedia).

Third, designing quiz feedback to instantly (dynamically) deploy a multimedia video that covers the topic has the greatest impact on learning performance. Students who had the opportunity to learn the concept visually through the use of pictures, video and audio **performed 5.3 times better than a student who did not receive multimedia feedback. This was true of all learners independent of age, gender, level of education and English-language ability. It was also true across four different types of questions reflecting the first four levels of Bloom's taxonomy.**

There are a number of follow-up studies that will need to be conducted (discussed later in the dissertation), but these are important findings in a quasi-new delivery format that is still finding its bearings. The results are particularly significant in the MOOC space where scale is observed as an advantage despite its nuanced challenges. In a course with tens of thousands of learners, it is not possible for the instructor, or even teaching assistants and community forum managers to provide real-time content feedback. Spending more time on the already detailed design process for MOOCs would only be worthwhile if we had empirical evidence of actual impact on learner performance. As I conclude by discussing where massive, open, online courses may be headed next, multimedia quiz feedback can now be seen as one of a host of emerging design strategies in the massive space that promotes learning while embracing the scale of the course environment.

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CHAPTER I. INTRODUCTION

Background and Statement of the Problem

As the Director of Online Strategy and Development in the Center for Innovation in Teaching & Learning at the University of Illinois, it is my responsibility to manage and oversee the analysis, design, development, implementation, evaluation and support of innovative teaching and learning, which includes a healthy MOOC portfolio. The University of Illinois has been partnered with California-based MOOC provider, Coursera, since the Summer of 2012. Illinois now has nearly 100 MOOCs and is the institution with the third most MOOC offerings of Coursera's 140 strategic partners. The University of Illinois has had over 2.6 million people participate in their Massive, Open, Online Courses and was the first partner to launch a for-credit MOOC-based degree when the iMBA (Master's of Business Administration) was unveiled in January 2016.

Massive, Open, Online Courses are the newest addition to the University of Illinois' cadre of high quality face-to-face, blended and traditional online offerings, yet little pedagogical research has been conducted concerning student performance in this unique delivery modality. It goes without saying that having a better understanding of how we can assist students with their learning in these massive, largely self-directed spaces is worthy of research and discovery. Discerning what design strategies most positively impact student measures has the potential to have meaningful implications for increasing the quality of MOOCs and other offerings for both the University of Illinois and the academy at large. In this dissertation I have worked towards solving the problem of a lack of instructional design information in the massive online space.

Specifically, there are three problems in MOOC design and development that I have attempted to explore:

First of all, I examined the role of different quiz feedback strategies in the massive online space. The quiz feedback strategies involved offering students three different types of feedback after an incorrect answer to a question on the practice quiz. A student could receive (1) no feedback, (2) a simple correct or incorrect response, (3) feedback in text form or (4) feedback in multimedia video form. In understanding more about instructional improvement in this space, we need to solve the problem of *what* educational interventions might help improve learning outcomes. I will particularly look at quiz feedback strategies designed as multimedia interventions here.

Secondly, there has been little research on *where* within a MOOC an intervention can be impactful and *how* it can be best administered. The debate concerning immediate versus delayed feedback is an interesting one and in an attempt to better understand instructional improvement in MOOCs I also examined the idea of moving beyond verification feedback and deployed immediate elaboration feedback as MOOC students learned concepts by taking practice quizzes in a Microeconomics MOOC offered by Illinois through Coursera.

Finally, an exceptionally large percentage of MOOCs use multimedia to deliver course material, but we know little about how much effect the *quality* of the video has on learning or in what portion of the course video can be most effective. This is a significant problem for institutions of higher education that are engaged in developing MOOCs, because the cost of producing the multimedia can be quite high. In order to keep costs down, which is of utmost importance across the academy today, especially at our public institutions, it would be helpful to know not only when to use video, but also when to use expensive studio quality video and when a well-recorded instructor-created snippet will suffice. While when to spend the extra time and money to produce Hollywood-quality studio video is not directly explored in this dissertation, some preliminary findings here pave the way for additional research in this area.

The purpose of specifically targeting multimedia learning relates to the need to develop more knowledge around the cognitive theory of multimedia learning and cognitive load theory in these massive online settings. Much of what has been published on Mayer's cognitive theory of multimedia learning has been in laboratory settings. This study takes the same principles and applies them in a new modality field trial environment with the hope that the findings can extend beyond MOOCs and impact design in traditional online, blended and face-to-face offerings as well.

We are at a crossroads in higher education. State funding for public institutions continues to decline[2] and many universities are looking towards new, innovative approaches to expand their audience. As part of a host of institutional strategic plans, expansion of online education offerings is at the top of the list (Kelderman, 2016). Given these realities it is paramount that colleges and universities understand more about how to implement these innovative programs with high quality and effectiveness. Not every institution will need to offer MOOCs, but many would be wise to offer them as part of a diversified online portfolio in a rapidly changing marketplace. Those that do must not only have plans to simply offer MOOCs as part of their educational strategy, but also utilize the latest research for high quality MOOC development both administratively and pedagogically.

[2] In fact, at the time this dissertation is being written, the State of Illinois has gone the entire fiscal year 2016 without a budget, only receiving a fraction of the previously allocated amount.

Purpose and Importance of the Study

There has been extensive research (Richard Mayer, et al.) on enhanced learning using multimedia presentations in clinical settings, but did we see the same success in a MOOC field setting? Many of the initial Massive, Open, Online Course (MOOC) studies conducted in the first three years of widespread MOOC adoption have been focused on basic descriptive and demographic frequency data (Perna, L. (2013),…). Any empirical experiments during this time have largely focused on retention rates and completion issues (Koller, D., Ng, A., Do, C., & Chen, Z (2013), Kizilcec, R., Piech, C., & Schneider, E. (2013), Reich, J. (2014), Zheng, S., Rosson, M., Shih, P., & Carroll, J. (2015). There is good reason for retention to have taken the spotlight as the first major MOOC battleground. If this new delivery modality was going to change the world, how would it do so with an average of five percent of the students completing the course? Many of these questions have now been answered as researchers have provided skeptics with myriad examples of success stories and better perspectives on how to examine retention and student success in a massive space where many participants have different needs and intentions. As offering courses to massive audiences becomes more integrated as a core academic strategy in higher education, the next big hurdle that MOOCs must face is pedagogical quality. The need to study impactful instructional design on student performance in these spaces is already growing. Institutions of higher education must move beyond offering MOOCs to stay current and ensure they are offering *high quality* MOOCs that use the latest design practices to improve student performance.

Using assessment feedback to improve student learning outcomes has been a widely used teaching and learning strategy for decades. Although the type and timing of feedback continue to be debated (Skinner, 1968, Kulhavy, 1977, Kulik & Kulik, 1988), the vast majority of educators and educational researchers agree on its utility for enhancing learning. As higher education's work with online learning moves from experimental to mainstream, part of what is needed to ensure that the *quality* of the learning be at the strategic forefront relates to universities continuing to explore what we know about multimedia as a medium and feedback as a pedagogical strategy in this new space. The experiments in this dissertation can play a vital role in the work towards understanding, prioritizing and implementing quality instructional design for instructional improvement in online settings.

Research Hypothesis

Utilizing the cognitive theory of multimedia learning (CTML) as a framework, my hypothesis is as follows:

> (H1) *Designing and implementing a MOOC featuring multimedia quiz feedback options will have a positive impact on measures of (1) learning engagement, (2) learning satisfaction, (3) perceived learning effectiveness and (4) learning performance.*

Additional Research Questions

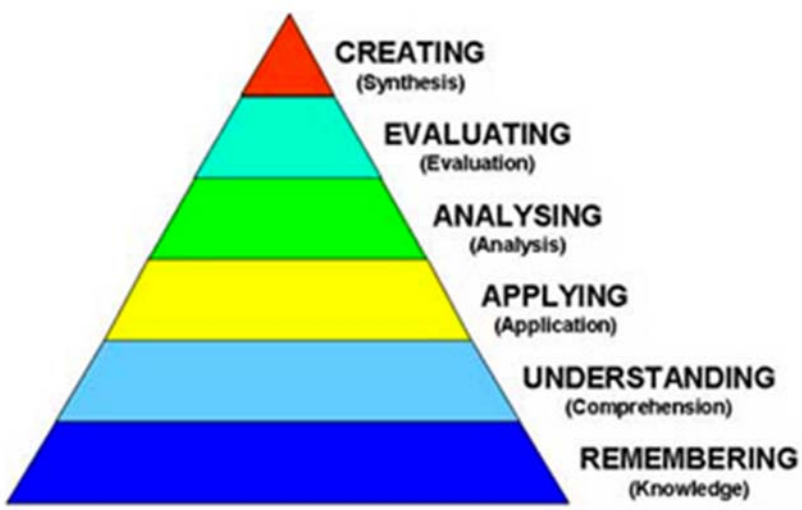
In addition to my hypothesis related to the experiments conducted for this dissertation, I speculate that the data collected for this study will allow me to examine other important questions related to the future role of MOOC in higher education. These questions are listed below.

1.1. *Will different treatment groups learn differentially according to Bloom's taxonomy?*

1.2. *What impact, if any, does the number of times a student attempts the practice quiz have on his/her learning performance?*

1.3. *Do English language ability and/or other key demographic measures interact with any treatment effects?*

Figure 1: Bloom's Taxonomy for Cognitive Behaviors



Theoretical Framework

Theories explored in my research strongly involve two theories in the field of cognitive psychology, one that is relatively newer and one with more of a history.

As a relatively new and dominant theory without a competing theory in current educational research, the **cognitive theory of multimedia learning (CTML)** centers on the idea that learners attempt to build meaningful connections between words and pictures and that they learn more deeply from multiple media than they could have with words or pictures alone (Mayer & Bove, 1996, Harp & Mayer, 1998, Moreno & Mayer, 2000, Mayer & Jackson, 2005, Mayer, 2009). The cognitive theory of multimedia learning is derived from **cognitive load theory** (Sweller, 2009). Cognitive load theory "suggests that learning happens best under conditions that are aligned with human cognitive architecture and is concerned with techniques for reducing working memory load in order to facilitate the changes in long term memory associated with schema acquisition" (Mayer, 2009, p. 79). There are three kinds of cognitive load: Extraneous, Essential and Generative. "A major challenge of instructional design is that cognitive capacity is limited, so there is only a limited capacity for extraneous, essential and generative processing." (Mayer, 2009, p. 80). These challenges require three solutions: (1) reduce extraneous cognitive processing, (2) manage essential cognitive processing and (3) foster generative cognitive processing (Mayer, 2009). Multimedia learning theory is based on three well-established ideas in cognitive science: dual-channel, limited capacity, and active-learning processing, which can help instructional designers, overcome these challenges (Mayer, 2009). To step back a bit, and in order to understand why CTML is an important framework for this dissertation, I will discuss the essentials related to the science of learning.

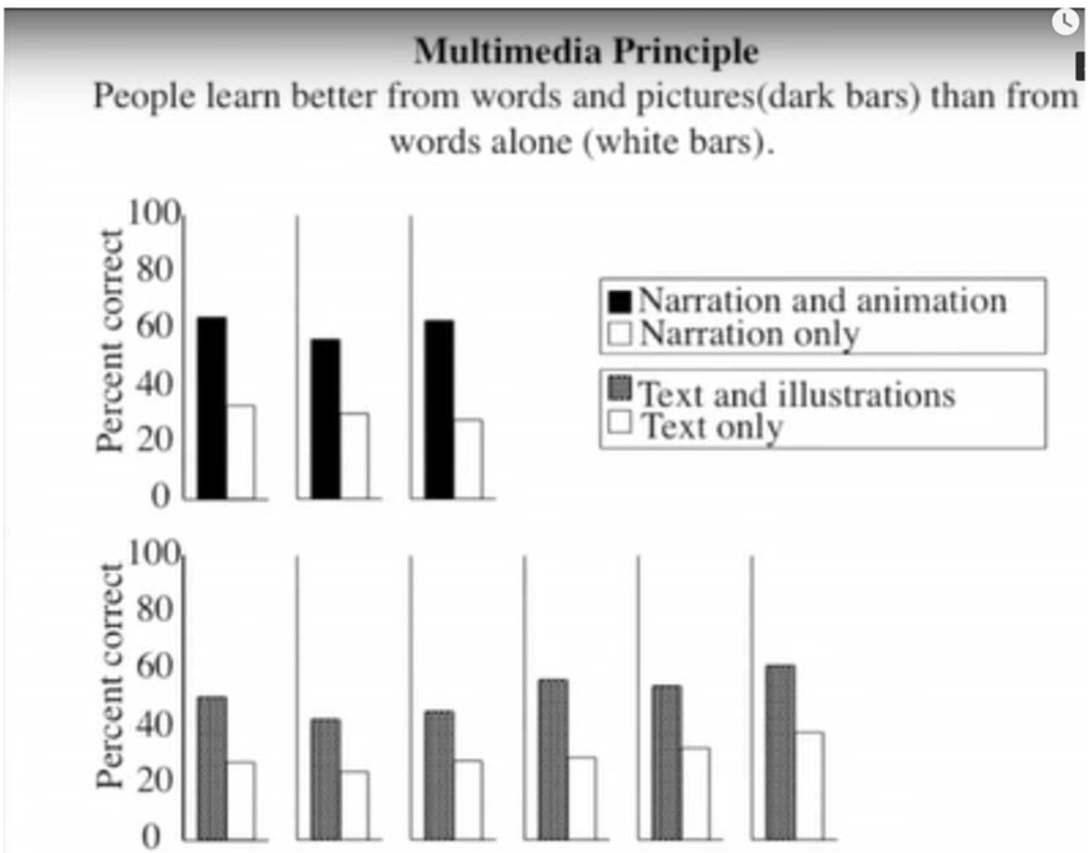
Learning is defined as what happens when there is a change in knowledge that is attributed to experience – that is to say that learning is (1) a change (2) in what the learner knows (3) caused by the learner's experience (Mayer, 2014). In the past century there have been three major conceptualizations that help us understand how people learn: (1) Response strengthening, (2) information acquisition, and (3) knowledge construction, (Mayer, 2014).

Response strengthening commonly uses a reward/punishment system and is at the heart of drill and practice instruction. This pedagogical concept was dominant in the 1920s (from 1900-1950) and centered on recitation. A student who answered incorrectly might be subject to being hit by a ruler or being told to sit in the corner with a "dunce" cap. In this strategy for teaching and learning the student is a passive recipient of the master instructor's knowledge (Mayer, 2014). In the 1950's and 60's as computers were beginning to be developed, learning starting being conceptualized as information acquisition where learning is viewed as a process of adding information to memory. Similar to response strengthening, the student is still a passive recipient in this mode and receives the information in a one-way fashion from the teacher (Mayer, 2014). For better or for worse, humans are not computers and interpret information in personal ways to create knowledge (i.e. knowledge is different than information), so this metaphor for learning is constrained by the fact that the brain functions differently than a hard drive that simply stores and regurgitates data (Mayer, 2014). Towards the latter part of the twentieth century and today, knowledge construction became the dominant conceptualization of learning. This pedagogical concept centers around building natural representations where the learner makes sense out of what is being presented and the teacher is a cognitive guide. Knowledge construction allows learning to be more of a two-way event where the learner can ask questions and the teacher can guide the learner towards appropriate cognitive processing of the presented information (Mayer, 2014).

Within knowledge construction, true active learning can occur. Active learning is more than having the learning activities being designed as "hands-on". In order for knowledge construction to occur, cognitive processing must take place. This happens when a learner (1) pays attention to the relevant material, (2) is able to mentally organize the material into a coherent structure and (3) relates the material back to relevant prior knowledge (Mayer, 2014). As mentioned previously, CTML is based on three well-established ideas in cognitive science: dual-channel, limited capacity, and active-learning processing. Dual channels simply refer to the fact that humans have separate channels for processing words (verbal) and pictures (visual) (Mayer, 2014). These channels interact, but they are two separate cognitive systems in different parts of the brain (Mayer, 2014). The idea of limited capacity is essentially referring to cognitive load, i.e. that the human brain can only process a few things (potentially four or five) at any one time in our active consciousness (Mayer, 2014). Too much information will overload working memory. Active processing describes the learners' participation in the three cognitive processes above: paying attention to the relevant material (selecting), mentally organize the material into coherent structures (organizing) and relating the material back to relevant prior knowledge (integrating) (Mayer, 2014).

Utilizing multimedia learning around the framework of CTML, allows for the necessary facets of knowledge construction to occur through true active learning via the three necessary steps for cognitive processing. Since we know that cognitive capacity is limited, multimedia learning can be well utilized to reduce extraneous cognitive processing (less irrelevant material) and manage essential cognitive processing (build representations of the content) while fostering generative cognitive processing (helping the learner to recognize the material in a way that makes more sense) (Mayer, 2009 & 2014). The reason multimedia is well suited for this is simple – we remember about 25% of what we read and transfer of knowledge is quite difficult (Mayer, 2014). When pictures, graphics and/or video is added, knowledge transfer is easier (see Figure 2: Results of nine different research projects comparing multimedia learning to learning with text only).

Figure 2: Results of nine different research projects comparing multimedia learning to text-based learning (Mayer, 2014).



Multimedia learning increases the potential for learners to not only remember what they have learned, but also to be able to apply what they have learned to new situations.

The study in this dissertation is the first of its kind to utilize CTML in the massive, open online course setting, particularly focusing on (1) generative processing which multimedia can achieve by reorganizing concepts in a way that makes more sense to the learner and (2) understanding the dual channel principle that humans have two separate interactive channels for processing words (verbal) and pictures (visual) thus making a multimedia treatment desirable.

Definition of Terms

Cognitive load theory "suggests that learning happens best under conditions that are aligned with human cognitive architecture and is concerned with techniques for reducing working memory load in order to facilitate the changes in long term memory associated with schema acquisition".

Cognitive theory of multimedia learning (CTML) centers on the idea that learners attempt to build meaningful connections between words and pictures and that they learn more deeply from multiple media than they could have with words or pictures alone.

MOOC is an acronym that represents a Massive, Open, Online Course.

Summary

Massive, Open, Online Courses are the newest addition to the Illinois cadre of high quality face-to-face, blended and traditional online offerings, yet little pedagogical research has been conducted concerning student performance in this unique delivery modality. It goes without saying that having a better understanding of how we can assist students with their learning in these largely self-directed spaces is worthy of research and discovery. Having passed the first round of legitimate questioning concerning student retention and, as offering MOOCs to global audiences becomes more integrated as a core academic strategy in higher education, the next big hurdle that MOOCs must face is pedagogical quality. The need to study impactful instructional design on student performance in these spaces is already growing. Discovering what design strategies most positively impact student measures has the potential to have positive implications for increasing the quality of these and other offerings for the University of Illinois and across the academy.

Assessment feedback for student learning has long been a teaching and learning strategy. Although the type and timing of feedback continue to be debated (Skinner, 1968, Kulhavy, 1977, Kulik & Kulik, 1988), the vast majority of educators and educational researchers agree on its utility for enhancing learning. As higher education's work with online learning moves from experimental to mainstream, part of what is needed to ensure the *quality* of the learning be at the forefront relates to continuing to explore what we know about the cognitive theory of multimedia learning (CTML), multimedia as a medium, and feedback as a pedagogical strategy. The experiments in this study can play a vital role in the work towards understanding, prioritizing and implementing quality instructional design in these settings.

CHAPTER II. REVIEW OF THE LITERATURE

A History of MOOCs

The Beginning

In 2011, former University of Michigan president, James Duderstadt, wrote, "The evolution from faculty-centered and -controlled teaching and credentialing institutions to distributed, open learning environments is already happening. The new learning services are increasingly available among many providers, learning agents, and intermediary organizations. Such an open, network-based learning enterprise certainly seems more capable of responding to the staggering demand for advanced education, learning, and knowledge" (Duderstadt, 2011, p. 84). MOOCs, or Massive, Open, Online Courses took the world by storm in 2012, but that is not the true origin of higher education's newest delivery medium. In 2008, George Siemens, a professor at Athabasca University in Alberta (now at the University of Texas at Arlington) and his colleague Stephen Downes, a researcher at the National Research Council of Canada's Institute for Information Technology's e-Learning Research Group, co-taught a massive online course entitled "Connectivism and Connected Knowledge (CCK08)" (Milligan, Littlejohn & Margaryan, 2013). These early MOOCs were later labeled cMOOCs or connectivist MOOCs due to their primary focus on shared, connected learning rather than the more popular MOOCs that emerged in 2012, tagged as xMOOCs, that emphasize a more traditional learning environment with "video presentations that are complemented by short quizzes and other testing" (Zheng, Rosson, Shih & Carroll, 2015, p. 1883). It was in the initial potential of the cMOOCs, where early adopters and education enthusiasts active on social media such as Twitter, began to see the viability of true pedagogical disruption. If nothing more, the sheer size of the early

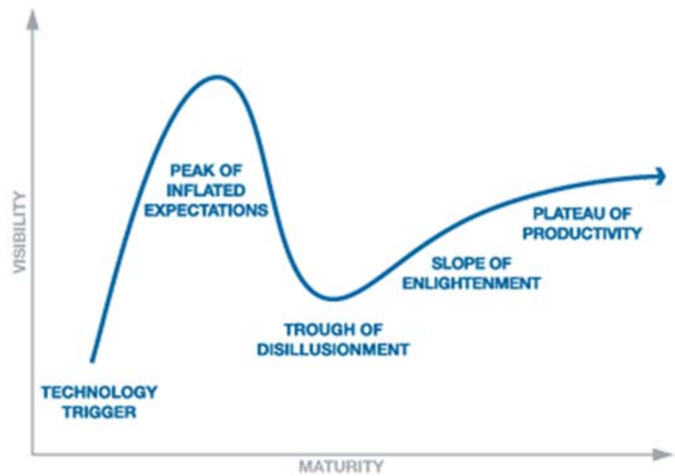
MOOCs, where thousands were learning online rather than dozens in traditional online offerings, brought about curiosity and eventually venture capital. In late 2011 and into 2012, three major companies quickly formed around the idea of commercial partnership with academic institutions specifically focused on massive, open, online courses: Coursera (founded by Stanford professors Daphne Koller and Andrew Ng), Udacity (founded by Stanford professor Sebastian Thrun), and EdX (initially a Harvard-MIT partnership). Lines were drawn and global claims were made about the potential of MOOCs for changing higher education as we know it. Many high quality AAU and research-one universities, beating their collective chests on being responsive to the issue of educating a greater percentage of the uneducated global population, scrambled to align themselves with one or more of the three major providers or, at minimum, discussed a strategy for a unified response and action plan concerning this new twist on an increasingly popular modality. Initial returns from Thrun's first pre-Udacity offering "CS221: Introduction to Artificial Intelligence" were extremely encouraging. In prior years, Thrun's computer science students had averaged 60 percent on the CS221 midterm; in the first MOOC offering they did much better. "Thrun swears the exam was tougher than any other he's given at Stanford. The online (MOOC) classmates averaged 83 percent overall" (Leckart, 2012, para. 29). Thrun, who in 2004 won two million dollars for Stanford in a competition to design and build a self-driving car across the Nevada desert, was now claiming that "Fifty years from now, there would be only 10 institutions in the whole world that deliver higher education" (Leckart, 2012, para. 28).

Hundreds of thousands of students registered for these free or low cost online courses (during the first few months of the initial widespread MOOC push, a professor tweeted that he was receiving one enrollment per minute). Many students flocked to the massive online courses and the "rockstar" professor delivering on a topic formerly forbidden to 99.9% of people who did not sit in (or have the money to sit in) an elite university. Suddenly the world had access to these topics from Earth's brightest minds. Not only were these courses easily accessed, but due to the massive size of the audience, student-to-student interaction was being leveraged in new, innovative ways – this was crowd-sourced education! Assignments were machine-graded or peer-graded and in one study, again due to the massive enrollment of the course, on average, a student was able to get quality assistance from a peer within twenty-two minutes (Kamenetz, 2012). Coursera founder and Stanford Professor Andrew Ng offered his machine learning class that year for free -- 100,000 people enrolled; to put that number in perspective TED blogger Ben Lillie stated, "to get the same number at Stanford, he would have had to teach the class for 250 years" (Lillie, 2012, para. 5). The innovation was not only in the delivery method; like blended/hybrid courses, it was in the flexibility that could potentially lead to more easily allowing cutting-edge learning models. "One of the main advantages is that the professors can move away from constraints imposed by traditional methods. Instead of a 50-minute "hour," the material can be broken up into modular chunks. Students can traverse this in different ways. Different students might need background material, or some might want to supplement it because of their interests" (Lillie, 2012, para. 9).

The blitzkrieg became even more intense when the New York Times tabbed 2012 "The Year of the MOOC" and popular Times columnist Thomas Friedman wrote, "Nothing has more potential to lift more people out of poverty, it's a budding revolution in global online higher education" (2013, para. 1).

The "Gartner Hype Cycle" is an oft-referenced tool for explaining "the maturity, adoption and social application of specific technologies" (Gartner, 2015, para. 1).

Figure 3: Gartner Hype Cycle



In 2012 and into 2013, MOOCs were rapidly escalating the *Peak of Inflated Expectations*. Soon after, as expected, the cycle started descending into the *Trough of Disillusionment*. Early research on the next wave of MOOCs from Udacity, Coursera and EdX were pointing to some troubling trends. The most disturbing development and the one that started to capture the majority of the media attention were the completion rates. There were a "…shockingly low number of students who actually finish the classes, fewer than 10%. Not all of those people received a passing grade, either, meaning that for every 100 pupils who enrolled in a free course, something like five actually learned the topic. If this was an education revolution, it was a disturbingly uneven one" (Chafkin, 2013, para. 9). Even Sebastian Thrun began to have doubts. "We were on the front pages of newspapers and magazines, and at the same time, I was realizing, we don't educate people as others wished, or as I wished. We have a lousy product" (Chafkin, 2013, para. 10). *Inside Higher Ed* and the *Chronicle of Higher*

Education began publicizing new research highlighting the poor retention rates and the enormous amount of attrition. Inside Higher Ed's Carl Straumsheim summarized a Gates-funded MOOC Research Initiative report from over 200 scholars. "Emerging data ... show that massive open online courses (MOOCs) have relatively few active users, that user 'engagement' falls off dramatically especially after the first 1-2 weeks of a course, and that few users persist to the course end" (2013, para. 4). In May of 2013, a Ph.D. student at Open University UK named Katy Jordan quickly gained notoriety analyzing early MOOCs and released a study where she looked at retention and completion across 29 MOOCs. "The average completion rate for (these) massive open online courses is less than 7 percent" (Parr, 2013, para. 1). Some of the numbers were almost unfathomably low. "*A History of the World since 1300* offered by Princeton University through Coursera, reportedly recruited 83,000 students with just 0.8 percent reaching the end" (Parr, 2013, para. 7). A December 2013 study from The University of Pennsylvania's Graduate School of Education and a group of faculty led by Laura Perna and Alan Ruby "analyzed the movement of a million users through sixteen Coursera courses offered by the University of Pennsylvania from June 2012 to June 2013" (Stein, 2013, para. 2). Their primary finding was cited thusly: "Course completion rates are very low, averaging 4% across all courses and ranging from 2% to 14% depending on the course" (Stein, 2013, para. 3). As recently as the end of 2014 and into early 2015 the issues of attrition, retention and completion had almost completely dismantled the initial excitement for this new course offering modality. In September 2014, TechCrunch released a report entitled "The MOOC Revolution That Wasn't". In the report Dan Friedman shared, "This year, that revolution fizzled. Only half of those who signed up watched even one lecture, and only 4 percent stayed long enough to complete a course" (2014, para. 2).

The *slope of enlightenment* is the stage of the Gartner Hype Cycle where a technology or technological breakthrough becomes more widely understood. In a traditional university setting, only one in every 20 students remaining to the end of a course would be unacceptable. But scholars started questioning whether or not full completion as an isolated measure was the most appropriate basis for comparison when offering opinion on student success in MOOCs (Koller, Ng, Do & Chen, 2013).

<u>The controversy over completion rates and new ways to think about MOOC completion (i.e. why retention was the first big story to arise from the MOOC revolution)</u>

So why the low rates for completion? Much of the second-wave of research available to answer this question started to center on (1) student motivation and intention, (2) how authors are choosing to present the data, and (3) the low-barrier of entry to MOOCs. Important questions that were asked included: "Who is being counted when we're reporting the completion and attrition rates?", "What constitutes completion?", and "What are the actual reasons students choose to enroll?"

In a traditional higher education setting, completion percentages are fairly straightforward and have not changed much since the first universities opened their doors. As Kevin Carey explains in his article entitled "Pay No Attention to Supposedly Low MOOC Completion Rates", it is simply a fraction (2013). The numerator is defined as the number of people who finished the course. The denominator is defined as a person who *tried* to finish the course. It is in discussing the denominator where most of the controversy lies. It is in discussing the denominator where the early research reporting low completion rates fails to fully explain the whole story. As MOOC efforts entered into the slope of enlightenment and researchers began to understand more about the students who are enrolling in MOOCs, they began reporting on the wide variety of student motivations and intentions. New research now separates students into different types of users based on their motivations or their activity level in the early stages of the course. Laura Perna's University of Pennsylvania study classified students as "Users," "Registrants," "Starters," and "Active Users" (Perna, Ruby, Boruch, Wang, Scull, Evans & Ahmad, 2013). Milligan, Littlejohn & Margaryan separated students into the categories of "Passive", "Lurker" and "Active" (2013). Noted educational innovator Phil Hill parsed students into five categories, "No Shows", "Observers", "Drop-ins", Passive", "Active" (Hill, 2013). At Stanford, two separate research studies used the categories "Sampling", "Disengaged", "Auditing", and "Completing" (Kizilcec, Piech, & Schneider, 2013) and "Auditor", "Disengaged", and "Engaged" (Ramesh, Goldwasser, Huang, Daume, & Getoor, 2014). Separating the MOOC student participants into categories has been useful in that it allows researchers to take a closer look at intention. Kevin Carey highlights this importance by taking one of the courses reported as having a low completion rate (1.9%) in Laura Perna et al.'s University of Pennsylvania study. The University of Pennylvania's Mythology course boasted 70,000 registered students, but only ~25,000 attempted to complete the course. "That means that nearly 60 percent of the people the study reported as not finishing the course never tried to finish it in any meaningful way. A quarter of the people in the denominator never even logged on" (Carey, 2013, para. 4). If you remove the "Users", "Registrants" and "Starters", and only count the intended-completers (or "Active Users") the completion percentage rises to 5.4%. While that is still low for traditional completion standards, there were still one thousand, three hundred and fifty students who completed the course. “In other words, the researchers could have taken exactly the same data and issued a report finding that “MOOCs achieve ten-fold increase in course completers for Ivy league class, at zero cost to students” (Carey, 2013, para 11).

Daphne Koller and Andrew Ng, Stanford professors and co-founders of Coursera, took a similar approach in their research across 40 Coursera MOOCs from a variety of institutions. In an attempt to analyze student intent and understand the supposed low completion rates, they categorized participants into “Browsers” and “Committed Learners”. “Browsers often sign up for a class during a burst of interest, but never show up for the first class; others browse for a week or two before disengaging (Koller, Ng, Do & Chen, 2013). Since all it takes to “register” for a MOOC through Coursera is clicking one “Join For Free!” button and entering an email address, “Browsers” may register for a course simply out of passing interest. Some “Browser” types may want to “figure out whether a particular topic might be worth pursuing, or out of curiosity regarding online education in general. Other students sign up for a handful of classes with the idea of shopping around to find a good fit. Yet other students enroll in a MOOC in much the same way that one might "bookmark" an interesting web page for future reference” (Koller, Ng, Do & Chen, 2013). Should these students be counted when calculating completion rates? “Since there is no financial cost or barrier to entry, there is little reason to believe that even a majority of the students who enroll in a MOOC intend to complete the class (Koller, Ng, Do & Chen, 2013).

Within the “Committed Learners” category, where students have some level of engagement throughout the class, the Stanford researchers further parsed students into three sub-groups, “Passive Participants”, “Active Participants”, and “Community Contributors” (Koller, Ng, Do & Chen, 2013). Even in this mostly participatory category, we can observe a variety of motivations that may shed light on the supposed low completion rates.

"Passive participants typically have little need for the external validation provided by earning a Statement of Accomplishment in order to derive value from a MOOC. But even within certain groups, such as the active participants, different subgroups may have different behaviors; for instance, although course completers tend to earn Statements of Accomplishment, we have also observed the existence of "low-intensity" active participants who reduce their own course workload, for example by choosing to attempt quizzes and homework but not longer, in-depth assignments. These individuals are self-motivated learners and rely on quizzes and homework as formative assessments, independent of earning a credential" (Koller, Ng, Do & Chen, 2013, para. 8).

Researchers now argue that in a free, massive, open, online course, measuring retention rates or completion percentages using *all* registered students might be akin to judging the success of a particular book by how many of its readers complete the entire work. Koller et al. offers this useful analogy; "it would be absurd to measure the book's success strictly by the proportion of individuals who read its contents cover-to-cover within the standard loan period. Some people might read a few chapters of a nonfiction book and stop after getting enough information to suit their needs. Others might read more deliberately and renew the book a few times before finishing. In both cases, few would consider the lack of completion or the extra time taken to be a waste or a failure of the book" (Koller, Ng, Do & Chen, 2013, para. 24). In fact, some scholars would posit that one of the benefits of MOOCs are that they offer no or low-risk means to sample particular disciplines. These educators propose that this type of sampling is not possible in the same manner in a traditional higher education setting, even at low-cost community colleges where there may be permanent grade-point-average effects or financial penalties for enrolling in a course and then backing out after a certain timeframe.

5.4% in the University of Pennsylvania Mythology course is quite low for completion, and although that percentage includes intended completers, they are still in the low-barrier to entry group. These participants simply clicked a button to register. In the traditional online setting, it is common to hear the phrase "life happens". For many adult learners, who are often working professionals, it is a juggling act to balance work, school and life. Even tuition paying degree-seeking students have to "stop-out" (temporarily leave with the intention of returning) due to a job change, marriage, divorce, birth, death, etc. Certainly, well-intentioned students enrolled in a free MOOC who will not experience professional, academic or financial consequence for leaving the course, may not be able to complete the entire offering.

Justin Reich, a research fellow at Harvard University, recently explored low completion rates in his article entitled "MOOC Completion and Retention in the Context of Student Intent". He examined nine HarvardX (EdX) courses, which had a total of 290,606 registrants. He organized the participants of his study into "Browsers", "Auditors" and "Completers" (Reich, 2014). As we've observed in other recent studies, he notes that the low-completion percentages can be explained by the fact that "many course registrants never enter the courseware and only a small percentage engage with problems and assignments" (Reich, 2014, para. 11). In addition to these observations about student behavior, Reich surveyed the students and received 79,525 responses. Student respondents self-reported in both the "Browser" category (students who are there to browse the materials, but not planning on completing any course activities) and "Auditor" category (students who plan on completing some course activities, but do not plan on earning a certificate), the intention *not to complete*. In the HarvardX genomics course, for example, 60% of surveyed students admitted they had no intention of completing the course. This data certainly could be construed as an indicator that the reportedly low completion rates have been misleading.

In recent interviews, a Pennsylvania State University faculty research team, Zheng, Rosson, Shih & Carroll utilized the grounded theory methodology (research that begins with a question and, as concepts become apparent, are tagged, organized and logically aggregated with codes) to reveal nine different student motivations for taking a MOOC (2015).

1. To complement other courses they are currently taking.
    a. MOOCs that cover similar subject areas and can provide a high level overview that helps students to grasp their school course content more quickly.
2. To gain knowledge for (current) job performance-related needs.
3. To meet their current research needs.
4. To take a course from a professor who is renowned in the subject matter and employed by a famous institution.
5. To enhance future employability.
6. To shape a college application. Parents enrolled their children in MOOCs as a test run to explore college courses and identify emerging interests.
    a. As support materials in their college applications
7. For personal interest.
8. To access valuable educational resources they were always interested in, but had found difficult to pursue in reality.
9. To find peers with common interests. Self-organized learning groups that included socializing as well as shared study.

(Zheng, Rosson, Shih & Carroll, 2015).

When examining these motivations as they relate to retention rates, the team found that *none* of these reasons for taking a massive, open, online course would necessitate the traditional model of full course completion. Zheng et al. profile a particular student who garnered high value from a MOOC without needing to complete the course or receive an official credential. "Subject P11 just needed to learn linear regression to analyze her data, so she left the lessons on logistic regression unfinished in a statistics course" (Zheng, Rosson, Shih & Carroll, 2015, p. 1888). In this case, "completion" was learning linear regression. It was mastery of a *module* of the course, rather than the whole course itself, as "course" is defined in our (limited) traditional terms. Yet, these scenarios for low completion rates had not been widely reported until recently. In these cases, it is the numerator in our earlier equation that may be inaccurate. Should a student in a *free, non-credit* online course not be counted as completed if they learned the information they intended to learn? Should we be analyzing retention rates and completion percentages without taking these scenarios into account? If a student registers for a free course and never intends to complete, we need to account for that in our data. Researchers now know more about the details and reasoning concerning the supposed low completion percentages in MOOCs and have learned that further analysis has elucidated new information that exposes controversial data reporting and the ignoring of student intention and low-risk barriers to enrollment. These recent discoveries show that the low retention rates are not as troublesome as they were originally reported to be.

A new protocol for evaluating MOOC retention

"Completion rates provide a convenient metric for comparing across a broad range of MOOCs. Despite their simplicity, however, completion rates interpreted at face value sometimes give misleading views of the health of an online course because they fail to capture the diversity of goals and engagement patterns that students may have in a MOOC. Passive lecture watchers, for example, may go through an entire course without ever touching an assessment, yet often derive substantial value from a MOOC without contributing to completion-based notions of retention" (Koller, Ng, Do & Chen, 2013, para. 10). Noting the importance of video watching as a metric for indicating engagement, Koller's team identified that the pattern for video lecture watching is best fit with a two-component mixture model rather than an exponential distribution. Using a two-component mixture model, which is a model where the presence of important subpopulations can be represented *within* the overall population, we can see random drawings from either a population of high-retention students or a population of low-retention students.

"In practice, we have found that exponential distributions fit poorly with the observed data. In contrast, in essentially all Coursera classes, a two-component mixture of exponential distributions — in which students are hypothesized to have been randomly drawn from either a population of high-retention students or a population of low-retention students — appears to model actual lecture watching drop-off very well. When comparing across 40 Coursera classes, the fraction of students inferred to have come from each population varies, and retention rates in the low-retention population also vary to some degree. But among the students in the high-retention group, retention rates are quite consistent across classes, with the median class achieving a retention rate of 92 percent per hour of lecture video" (Koller, Ng, Do & Chen, 2013, para. 14).

Having now used quantitative data to measure the amount of time spent watching videos in order to establish legitimate variation in student intent, the Coursera team then selected one of their courses that used a pre-course survey to ask participants about their intended level of commitment. Koller found that "among students who intended to finish, roughly 24 percent successfully completed the course, compared to fewer than 2 percent in the remaining population of registered students" (Koller, Ng, Do & Chen, 2013, para. 18). When there is more of a commitment, for example, in Coursera's signature track series where students not only declare their intention to finish but actually pay for a verified credential, we see a completion rate more in line with what might be more accurately compared with standard credit-bearing course completion rates.

"The completion rate among paying Signature Track students was 74 percent compared to 9 percent in the non-Signature Track population. Moreover, among students who indicated a strong intent to finish in a survey administered one month into the course, after the Signature Track signup deadline, completion rates were higher in the paying group (96 percent vs. 84 percent, $p = 0.0009$), suggesting that having a financial stake may provide an additional incentive to finish" (Koller, Ng, Do & Chen, 2013, para. 19).

Justin Reich agrees with this manner of evaluating a successful MOOC. "A better approach might be to calculate MOOC completion rates as a percentage of students who enrolled in a course with the intention to complete the course and earn a certificate" (2014, para. 3). Reich's research builds on this idea of examining the engaged students to determine retention. His team created their own pre-course survey in an attempt to probe motivation and retention more deeply. Simply examining the reported descriptive statistics, Reich's data matched that of Koller and the Stanford group's research. "Of those who intended to earn a certificate, between 9.1 and 35.7 percent were successful in doing so. The average across courses was 22.1 percent, quite close to what Koller and colleagues reported for the 'Writing in the Sciences' course (24%)" (Reich, 2014, para. 7). In order to better estimate completion intention, Reich ran a number of logistic regression models that produced an odds ratio (representing the odds that an outcome will occur given a particular exposure) for each model. The regression model corroborated the descriptive statistics in showing a positive association between self-reported intent to complete a course and course completion (Reich, 2014). Reich concludes, "Computing adjusted risk ratios from the odds ratios, I estimate that an intended-completer is 4.5 times more likely to earn a certificate ($p < .001$) than an intended-browser, holding constant demographic characteristics" (Reich, 2014, para. 24). Reich also ran Kaplan-Meier survivor functions test where "higher survivor functions indicate higher levels of persistence on average in the group" (Reich, 2014, para. 29). The test found that the survivor curves show that "intended-completers persist longer than other registrants" (Reich, 2014, para. 34). To further enhance the research, Reich examined the hazard probability for each of his student groups (intended-browsers, intended-auditors, and intended-completers). The results remained consistent. "Intended-completers have a lower hazard rate at any given time than other groups. In the second half of the course, hazard rates for all groups begin to climb again, although they do so more slowly for intended-completers" (Reich, 2014, para. 37).

MOOCs can be evaluated successfully when retention rates are scientifically measured appropriately using student motivation and intention as a quantifiable metric in the equation. Based on the new research data, and to fully understand the brief history of MOOCs, it seems wise to be aware that calculations and reports of completion rates that utilize those students who intend to complete or pre-register for a verifiable credential represent a respectable standard. This is essential as whole-course retention rates are only a portion of what defines success in a massive, open, online course. Students who do not want or need to complete an entire course should not be removed from the completion equation for consuming an accessible, no-risk portion of the course. The ability to evaluate successful MOOCs will be more accurate if this is the case. As discussed, there are reasons why intended completers, who do need and want to learn all of the information in a course, do not finish. Having more accurate data to evaluate retention rates will importantly allow subject matter experts and instructional designers to focus on improving completion percentages, for those who want to complete, by researching best and better pedagogical approaches in these new massive enrollment settings – strategies for enhancing collaboration and utilizing active learning while leveraging the amazing newfound opportunity of having thousands of students from literally hundreds of countries in the *same* course. It goes without saying that there is still much more research that needs to be conducted. While it is important that progress be made in appropriately evaluating, enhancing and improving the quality of MOOCs for intended non-completers, it is of particular interest to examine how we can improve the experience for intended completers.

In current research at the University of Illinois, I am part of a team led by Dr. Jose Cognet-Vazquez, finishing preparation of a paper entitled **“**Motivating the real MOOC student: A field experiment testing the effect of loss aversion theory to increase student participation in MOOCs”. The paper attempts to further examine (1) who should be counted when calculating retention rates and (2) what should be construed as “completion” to gain yet a better understanding of evaluating a successful MOOC. We hope to then attempt to look beyond these measures and (3) discuss tangible, impactful methods for motivating intended-completers towards whole-course completion. Early findings suggest significant results involving motivational weekly emails that include a customized course progress update in two different formats (Vazquez, Fein, Owens-Nicholson, Mock & Woodruff, in preparation).

Feedback Strategies

Using assessment feedback to improve student learning outcomes has been a widely used teaching and learning strategy for decades. “Feedback processes facilitate the regulation of learning and enable students to measure their performance against their aims” (Espasa & Meneses, 2010, p. 278). Although the type and timing of feedback continue to be debated (Skinner, 1968, Kulhavy, 1977, Kulik & Kulik, 1988), many educators and educational researchers agree on its utility for enhancing learning -- moving away from past drill and practice model research (with no feedback given), and focusing on newer models that include the provision of feedback to assist in diagnosing misconceptions (Cole & Todd, 2003). A significant meta-analysis of 53 research studies comparing immediate and delayed feedback posited that immediate feedback was most effective in three situations (1) quiz instruments, (2) acquisition of test content, and (3) memorization of lists (Kulik & Kulik, 1988, Cole & Todd, 2003). Highly cited studies such as Chickering and Gamson (1991) and Chickering and Ehrmann (2008) highlight feedback as one of the key elements in quality teaching in higher education (Espasa & Meneses, 2010). “Feedback can be offered individually -tailored to the work of each student - or in groups (by means of a general communication to an online classroom), or by providing a model answer for students against which they can check their own work” (Espasa & Meneses, 2010, p. 280).

In 2010, in the journal, *Higher Education*, Anna Espasa and Julio Meneses released a study entitled "Analysing Feedback Processes in an Online Teaching and Learning Environment: An Exploratory Study". They concluded, which is consistent with a review of the literature, that "most studies conducted in this area do not provide empirical results or go beyond theoretical formulations and neither analyse the specific characteristics of feedback when they promote the regulation of learning" (2010, p. 278). This is the case, for example, with Nicol and Macfarlane-Dick (2006), who proposed seven principles for good feedback, and Gibbs and Simpson (2004), whose "interest was in the importance of feedback as an influential mechanism in learning" (Espasa & Meneses, 2010, p. 278). In online learning environments, three general feedback dimensions have been proposed by Susanne Narciss and Katja Huth et al. (Narciss 2004, 2008; Narciss et al. 2004; Narciss and Huth 2004, 2006): the functional dimension, the structural dimension and the semantic dimension" (Espasa & Meneses, 2010). The semantic dimension, refers to the "feedback content or the significance of statements made in the feedback" (Espasa & Meneses, 2010). Literature (see, for example: Kulhavy and Stock 1989; Mason and Brunning 2001; Mory 2004; Narciss 2004; Tunstall and Gipps 1996) suggests that the semantic dimension of feedback is comprised of four sub-dimensions (Espasa & Meneses, 2010, p. 280):

- Information on errors made. For example, "answers 2 and 4 are incorrect, please review and resubmit"
- Information about the correct answer or final solution. For example: "the answer is incorrect, it should be 6.26".
- Information about guidelines and strategies to improve work. For example: "Review the second part of the study material again to better understand orientation within organisations".

- Information about additional resources as an aid to future learning. For example: "If you would like to learn more about the subject of orientation within organisations consult the Educaweb web page: http://www.educaweb.com"

According to Kulhavy and Stock, the first two sub-dimensions of semantic feedback make up the *verification* component of feedback because they allow students to obtain information on the correctness of their response. The latter two sub-dimensions, linked to improving the assignment in hand and providing more in depth subject matter information, belong to the *elaboration* component of feedback because they allow students to obtain information on how to improve the learning process (1989; Shute, 2007). Kulhavy and Stock (1989) and Mason and Brunning (2001) remind us that "feedback must integrate information both for verification and elaboration in order to ensure the success of the teaching and learning process" (Espasa & Meneses, 2010, p. 281). The literature concludes, as it does in many other research studies (Egan and Akdere 2005; Goodyear et al. 2001; Williams 2003), that "the training of university teachers in asynchronous and written contexts should undoubtedly take into account developing strategies for providing teachers with knowledge on the types and characteristics of feedback as a tool to promote the regulation of learning and good teaching practice, especially in online environments" (Espasa & Meneses, 2010, p. 290).

In Renee Cole and John Todd's study on web-based multimedia homework, immediate feedback was utilized with the goal of promoting learning and retention (Cole & Todd, 2003). Elaboration feedback was presented "to help students identify their own misconceptions, incomplete understanding of material, and areas where they needed additional help" (Cole & Todd, 2003, p. 1338). Multimedia was utilized to "more easily illustrate certain difficult concepts in general chemistry" (Cole & Todd, 2003, p. 1338), based on two meta-analyses where feedback administered through the use of computers had presented a modest effect on student learning (Schimmel, 1983 & Azevdeo & Bernard, 1995) with effect sizes between 0.35 and 0.80. The study was set up as follows:

"When the student answered a question using one of these misconceptions, the feedback to that question pointed out the inconsistency or error and encouraged the construction of a more scientifically acceptable conception. The feedback was not available until after the student had responded to the question, thus preventing pre-search availability. We included graphical representations of matter in many questions as well as dynamic browser plug-ins and videos in a few questions to probe students' reactions to the media. Homework assignments were accessible to students through WebCT using primarily multiple-choice and matching questions. The questions on the homework assignments were randomly drawn from a specified set of questions testing the same concept. Graphics and interactive plug-ins were often used to accommodate learning styles other than those that rely solely on reading and calculations. Finally, students received a different set of questions for their second attempt rather than being given a second chance at the questions they received for their first homework attempt" (Cole & Todd, 2003, p. 1340).

Although the literature had suggested that the inclusion of immediate feedback might have a positive effect, Cole and Todd found that there was no measurable quantitative effect on the students' learning outcomes (2003). All fourteen students "indicated that they appreciated and enjoyed multimedia videos and animations while they were learning chemistry concepts", particularly the dynamic three-dimensional display of molecular structures that would have otherwise been shown as a static image diagram, but only the low-GALT (Group Assessment of

Logical Thinking) students liked receiving the immediate feedback and preferred the online homework assignments" (Cole & Todd, 2003, p. 1341-1342).

With a low sample size of only 14, the authors end their research discussion by suggesting "additional study is needed to assess whether more dynamic and interactive assignments, with a greater number of graphics and animations, will be more effective in promoting student learning. Interactive tutorials are also being developed that should have a greater impact on student learning than homework problems alone" (Cole & Todd, 2003, p. 1342).

Valerie Shute's research on formative feedback highlights that, similar to the timing of the feedback (immediate vs. delayed), while there is a lot of research showing the learning benefits of elaboration feedback, (e.g., Albertson, 1986; Grant, McAvoy, & Keenan, 1982; Hannafin, 1983; Moreno, 2004; Pridemore & Klein; 1995; Roper, 1977; Shute, 2006), other studies report that increasing the amount of feedback information has no effect on learning or performance (e.g., Corbett & Anderson, 1989, 1990; Gilman, 1969; Hodes, 1985; Kulhavy, White, Topp, Chan, & Adams, 1985; Merrill, 1987) (Shute, 2007).

As higher education's work with online learning moves from experimental to mainstream, part of what is needed to ensure that the *quality* of the learning be at the strategic forefront relates to universities continuing to explore what we know about multimedia as a medium and feedback as a pedagogical strategy in this new space. The experiments in this dissertation can play a vital role in the work towards understanding, prioritizing and implementing quality instructional design in online settings.

CHAPTER III. RESEARCH METHODOLOGY

Research Design

For this dissertation study I selected an experimental design. Experimental design includes considered attention to internal validity, which is important in a study where one hopes to determine whether or not certain treatments *cause* various potential outcomes (i.e. I wanted to be able to manipulate the variables that might be causal). In order to co-create a world-class learning experience for Illinois students and faculty, it is vital that my work and the work of the Center for Innovation in Teaching & Learning utilize sound research. An experimental design is essential for determining whether treatments are worthy of use in our current practice. Even if I had discovered that this line of inquiry had no significant impacts, the research would still be useful for moving online education forward in an extremely new field setting.

To determine learning performance, subjects in the Fall 2015 University of Illinois Microeconomics MOOC were randomly assigned to receive one of four different types of quiz feedback on each of three different course modules. Each quiz involved eight total questions; two questions (Question A-First Attempt and Question B-Second Attempt) each from the first four behaviors in Bloom's cognitive taxonomy. Bloom's taxonomy is a framework for categorizing educational goals originally created by Benjamin Bloom and colleagues in 1956. In 2001, "a group of cognitive psychologists, curriculum theorists and instructional researchers, and testing and assessment specialists published a revision of the Taxonomy with the title "A Taxonomy for Teaching, Learning, and Assessment" (Bloom's, 2015, para. 7).

Students then took a post-quiz measuring learning satisfaction, learning engagement and perceived learning effectiveness.

The outcome measures were as follows:

1. Learning Performance: How a student performs post-incorrect answer (Question A-First Attempt) on Question B-Second Attempt after a particular treatment in their practice quiz
2. Learning Engagement
3. Learning Satisfaction
4. Perceived Learning Effectiveness

Controls were implemented by random assignment to one of the four groups for each module with the control offering no treatment.

Recent offerings of the microeconomic principles MOOC have had between 4,000 and 10,000 participants and this course was selected intentionally to provide the study with a much larger sample size than previous studies examining feedback in online education such as Cole & Todd, 2003 et al. With a much stronger sample size, some uneven attrition between the groups did not hamper the experiment.

Data collection took place October through December 2015 during the second eight-weeks of the Fall 2015 semester as part of practice quizzes in weeks three, four and five of the eight-week Microeconomic Principles (https://www.coursera.org/course/microecon) course. After each quiz, students took a post-quiz survey.

In early 2016 I ran a Cronbach's Alpha reliability test and a Principle Components Factor (validity) Analysis on the Learning Engagement, Learning Satisfaction and Perceived Learning Effectiveness instruments to describe variability among observed, correlated items. Post-validity testing, I utilized a mixed model analysis of variance (ANOVA) to run models and analyze for significant differences among group means and their associated treatment. A more common "repeated measures" ANOVA, where each respondent is in the same set one time, independently, was not appropriate here. For this study, each respondent could be in the set multiple times due to (1) each A/B Question representing a different level of Bloom's taxonomy, (2) different treatments being possible for each module and (3) the opportunity to answer Question A-First Attempt correctly and not receive a treatment. Because each respondent did not have an equal experience, utilizing the mixed model ANOVA was a better test than the repeated measures ANOVA.

Controls were in place that used the subject ID number as a random factor variable in the model so I could determine if any respondents were vastly different than others (i.e. to identify outliers, etc.) and to ensure the p-values were calculated correctly. All subject ID entries where there was a treatment (i.e. Question A-First Attempt was incorrect) were used.

Example:

- Person 1 participates in practice quizzes for Module 3 and 4, but not 5 thus producing 8 entries for the model (4-12 are possible depending on how many module practice quizzes are completed).
- Person 1 answers Question A-First Attempt correctly 3 times and incorrectly 5 times.
- Person 1 would receive 5 treatments and then have to answer a Question B-Second Attempt 5 times.
- Person 1 will have 5 unique entries in the data set.

Process for sample selection and assignment to condition

There were 14,628 participants in the Fall (October) 2015 offering of Microeconomic Principals with 4,254 (29.1%) “active” participants defined here as having logged into the course at least one time and still active by week 3. 391 active participants partook in at least one practice quiz. Each participant who took a practice quiz and missed Question A-First Attempt was randomly assigned to receive one of four different types of quiz feedback treatments before having an opportunity to answer Question B-Second Attempt on the same topic. Any participant who (1) quit without answering at least one question or (2) attempted the same module quiz more than one time (duplicates) was eliminated from the sample. In addition, I could not look at any A/B question pair where the participant got Question A-First Attempt correct because they did not receive a treatment; so anyone who got all of the A Questions correct were removed from the analyses. After I eliminated duplicates and correct answers, my data included 295 unique respondent samples (see Table 10) with 357 usable records.

Interventions

According to Kulhavy and Stock, the first two sub-dimensions of semantic feedback make up the *verification* component of feedback because they allow students to obtain information on the correctness of their response. The latter two sub-dimensions, linked to improving the assignment in hand and providing more in depth subject matter information, belong to the *elaboration* component of feedback because they allow students to obtain information on how to improve the learning process (1989). Kulhavy and Stock (1989) and Mason and Brunning (2001) remind us that feedback must integrate information both for verification and elaboration in order to ensure the success of the teaching and learning process" (Espasa & Meneses, 2010, p. 281).

The 2010 Espasa & Meneses study set a solid foundation for the experiment conducted in this dissertation. Their study began to advance the discussion in regard to feedback in fully online educational environments and moreover justified the need for feedback by making clear the positive association between feedback and student satisfaction and performance (Espasa & Meneses, 2010). In the Espasa & Menendes study, the main feedback component was verification. In addition, even though the techno-pedagogical design of the subjects in their study was based on a continuous assessment process, their final results obtained did not implicitly contain the necessary formative component "which would allow students to improve their learning process" (Espasa & Meneses, 2010, p. 281).

The study in this dissertation takes the Espasa & Meneses research further by ensuring we have random samples and an appropriate sample of those who did and did not receive feedback as well as adding a variety of types of feedback. In addition, the study here contains a continuous formative assessment that includes both the verification component of feedback (allows students to obtain information on the correctness of their response) and in treatments 2 and 3, an additional elaboration component of feedback (allows students to obtain information on how to improve the learning process). Ensuring elaboration feedback was included in the research was vital for continuing previous inquiry on the effectiveness of this type of feedback (Shute, 2007 et al.)

Intervention Summary

The control and first treatment in our experiment involved the *verification* sub-dimension of semantic feedback. Treatments two and three, included both the *verification* and *elaboration* sub-dimensions of semantic feedback.

Correct/Incorrect
[Control]

The control group received feedback in the form of “Correct” or “Incorrect” and no other feedback.

Correct/Incorrect w/ Answer
[Treatment 1]

The first treatment received feedback in the form of “Correct” or “Incorrect” and feedback in the form of the correct answer.

Answer + Text Narrative
[Treatment 2]

The second treatment group received feedback in the form of “Correct” or “Incorrect”, received the correct answer and a text feedback narrative explaining the correct answer in more depth.

Answer + Video Narrative
[Treatment 3]

The third treatment group received feedback in the form of “Correct” or “Incorrect”, received the correct answer and a ~one-minute video feedback narrative explaining the correct answer in more depth.

A brief review of the first four levels of Bloom's cognitive taxonomy utilized in this study

Remembering (Knowledge)

Recall Facts and Basic Concepts

Example: What are the health benefits of eating apples?

Understanding (Comprehension)

Explain Ideas or Concepts

Example: Compare the health benefits of eating apples vs. oranges.

Applying (Application)

Use Information in New Situations

Example: Would apples prevent scurvy, a disease caused by a deficiency in vitamin C?

Analyzing (Analysis)

Draw Connections Among Ideas

Example: List four ways of serving foods made with apples and explain which ones have the highest health benefits. Provide references to support your statements.

Experimental design model specifications: Operationalization of variables

A dependent variable is a variable that depends on other factors. When one is examining the potential relationship between two items, a researcher's objective is to discover what causes the dependent variable to change. There were four dependent variables in my design: (1) Learning Performance, (2) Learning Engagement, (3) Learning Satisfaction and (4) Perceived Learning Effectiveness.

Learning Performance was measured as part of the practice quiz results (i.e. How a student performed on the practice quiz Question B-Second Attempt after a particular treatment). The other three dependent variables (learning satisfaction, perceived learning effectiveness and learning engagement) were measured during the post-quiz survey.

Between-subject variables are independent variables or factors where a different group of subjects is utilized for each level of the variable. In this experiment, I had three groups of between subject variables: (1) Treatment Factor Levels, (2) Bloom's Cognitive Behaviors, and (3) Course Module Number. The treatment factor levels measured were: (1) Experiment Control, (2) Treatment 1: Correct/Incorrect w/ Answer, (3) Treatment 2: Answer and a Text Narrative, and (4) Treatment 3: Answer and a Video Narrative. The Bloom's cognitive behaviors measured were: (1) Knowledge, (2) Comprehension, (3) Application and (4) Analysis. The course module number's measured were: (1) Module 3, (2) Module 4, and (3) Module 5. These three modules were measured because they were the three modules in the course that included practice quizzes and random treatments.

An independent variable is a variable that stands alone and is not changed by the other variables you are trying to measure. Covariates are variables that are potentially predictive of the outcome of the research. There were seven independent variables/covariates in this dissertation: (1) Age, (2) Sex, (3) Level of Education, (4) English proficiency: speaking, (5) English proficiency: reading, (6) English proficiency: writing and (7) English proficiency: understanding spoken English.

The independent variables/covariates were also measured during the post-quiz survey.

Table 1: Visual of the operationalization of variables

<u>Between Subjects</u>	**Correct/Incorrect Only [Control]**	**Correct/Incorrect w/ Answer [Treat 1]**	**Answer + Text Narrative [Treat 2]**	**Answer + Video Narrative [Treat 3]**
Blooms Taxonomy				
Knowledge				
Comprehension				
Application				
Analysis				
	<u>Dependent</u>			
	Learning Engagement	Learning Engagement	Learning Engagement	Learning Engagement
	Learning Satisfaction	Learning Satisfaction	Learning Satisfaction	Learning Satisfaction
	Perceived Learning Effectiveness	Perceived Learning Effectiveness	Perceived Learning Effectiveness	Perceived Learning Effectiveness
	Learning Performance	Learning Performance	Learning Performance	Learning Performance
<u>Independent</u>	(1) Age, (2) Sex (Factor), (3) Level of Education,	(4) English proficiency: speaking, (5) English proficiency: reading,	(6) English proficiency: writing and	(7) English proficiency: understanding spoken English.

Table 2: Design Visualization Example

Mixed Model ANOVA

Person*	Attempt ID#	Module	Potential Treatment	Blooms	Ques A	Ques B	Treatment Yes/No*
1	1	3	2	1	I	C	Yes
1	2	3	2	2	C	C	No
1	3	3	2	3	I	I	Yes
1	4	3	2	4	C	C	No
1	5	4	4	1	C	C	No
1	6	4	4	2	I	C	Yes
1	7	4	4	3	I	C	Yes
1	8	4	4	4	I	I	Yes
1	9	5	1	1	C	C	No
1	10	5	1	2	C	C	No
1	11	5	1	3	C	C	No
1	12	5	1	4	I	C	Yes
2	13	3	2	1	I	C	Yes
2	14	3	2	2	C	C	No
2	15	3	2	3	I	I	Yes
2	16	3	2	4	I	C	Yes
…		…	…	…	…	…	…

*Only incorrect answers on Question A-First Attempt received a treatment before Question B-Second Attempt. Students who input a correct answer on Question A-First Attempt, still received Question B-Second Attempt with no treatment in between.

I – Incorrect
C - Correct

CHAPTER IV. DATA ANALYSIS

Data Analysis: Participants

There were 14,628 participants in the Fall (October) 2015 offering of Microeconomic Principals with 4,254 (29.1%) “active” participants defined here as having logged into the course at least one time and still active by week 3. 391 active participants partook in at least one practice quiz. Response rates, defined here as the number of learners who took the quiz divided by the number of active learners that week, (which is a fairer response rate than number of learners who took the quiz divided by total course enrollees that week) are as follows:

- Quiz 3: 285/4,254 = 6.7%
- Quiz 4: 216/3,034 = 7.1%
- Quiz 5: 196/2,620 = 7.5%

Of the active participants, I eliminated cases for two reasons: (1) the student quit without answering at least one question or (2) it was not their first attempt at the quiz (duplicates). In addition, I could not look at any A/B question pair where the participant got Question A-First Attempt correct because they did not receive a treatment; anyone who got all of the A Questions correct were removed from the analyses. After I eliminated duplicates and correct answers, my data included 295 unique respondents (see Table 10) with 357 usable records.

Participants in the study were 59.9% Male and 40.1% Female and 76.1% held a minimum of a Bachelor’s degree, while 23.9% had less than a Bachelor’s level education (see Tables 3-9). 74.7% of the student participants in my study were non-native English speakers.

81.6% self-reported as having at least "Good" English reading ability, 57.1% at least "Good" English writing ability, 70.7% at least a "Good" understanding of spoken English and 55.5% having at least "Good" English speaking ability.

Table 3: Participant's Sex (Dem2)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F Female	79	26.8	40.1	40.1
	M Male	118	40.0	59.9	100.0
	Total	197	66.8	100.0	
Missing	9 No answer	98	33.2		
Total		295	100.0		

Table 4: Participant's Education Level (Dem8)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	12 Secondary/high school or less	20	6.8	10.2	10.2
	13 Some college but less than a 4-year degree	27	9.2	13.7	23.9
	16 Bachelor's Degree/4-year college degree	77	26.1	39.1	62.9
	18 Post-graduate or Master's degree	61	20.7	31.0	93.9
	20 Doctoral Degree	12	4.1	6.1	100.0
	Total	197	66.8	100.0	
Missing	9999 No answer	98	33.2		
Total		295	100.0		

Table 5: Whether a Participant is a Native Speaker of English or Not (Dem3)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0 No	148	50.2	74.7	74.7
	1 Yes	50	16.9	25.3	100.0
	Total	198	67.1	100.0	
Missing	9999 No answer	97	32.9		
Total		295	100.0		

Table 6: Participant's English Reading Ability (Dem4)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.0 Very poor	1	.3	.7	.7
	2.0 Poor	2	.7	1.4	2.0
	3.0 Fair	18	6.1	12.2	14.3
	3.5	4	1.4	2.7	17.0
	4.0 Good	87	29.5	59.2	76.2
	4.5	2	.7	1.4	77.6
	5.0 Equal to a native speaker	33	11.2	22.4	100.0
	Total	147	49.8	100.0	
Missing	9997.0 Skip: Native Speaker	50	16.9		
	9998.0 Unknown: Did not answer Native Speaker question	97	32.9		
	9999.0 Non-native speaker, unknown ability	1	.3		
	Total	148	50.2		
Total		295	100.0		

Table 7: Participant's English Writing Ability (Dem5)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.0 Very poor	2	.7	1.4	1.4
	1.5	2	.7	1.4	2.7
	2.0 Poor	11	3.7	7.5	10.2
	2.5	3	1.0	2.0	12.2
	3.0 Fair	44	14.9	29.9	42.2
	3.5	3	1.0	2.0	44.2
	4.0 Good	63	21.4	42.9	87.1
	4.5	1	.3	.7	87.8
	5.0 Equal to a native speaker	18	6.1	12.2	100.0
	Total	147	49.8	100.0	
Missing	9997.0 Skip: Native Speaker	50	16.9		
	9998.0 Unknown: Did not answer Native Speaker question	97	32.9		
	9999.0 Non-native speaker, unknown ability	1	.3		
	Total	148	50.2		
Total		295	100.0		

Table 8: Participant's Understanding of Spoken English (Dem6)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.0 Very poor	1	.3	.7	.7
	1.5	2	.7	1.4	2.0
	2.0 Poor	12	4.1	8.2	10.2
	2.5	2	.7	1.4	11.6
	3.0 Fair	24	8.1	16.3	27.9
	3.5	1	.3	.7	28.6
	4.0 Good	70	23.7	47.6	76.2
	4.5	1	.3	.7	76.9
	5.0 Equal to a native speaker	34	11.5	23.1	100.0
	Total	147	49.8	100.0	
Missing	9997.0 Skip: Native Speaker	50	16.9		
	9998.0 Unknown: Did not answer Native Speaker question	97	32.9		
	9999.0 Non-native speaker, unknown ability	1	.3		
	Total	148	50.2		
Total		295	100.0		

Table 9: Participant's English Speaking Ability (Dem7)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1.0 Very poor	4	1.4	2.7	2.7
	2.0 Poor	19	6.4	13.0	15.8
	2.5	2	.7	1.4	17.1
	3.0 Fair	38	12.9	26.0	43.2
	3.5	1	.3	.7	43.8
	4.0 Good	56	19.0	38.4	82.2
	4.5	1	.3	.7	82.9
	5.0 Equal to a native speaker	25	8.5	17.1	100.0
	Total	146	49.5	100.0	
Missing	9997.0 Skip: Native Speaker	50	16.9		
	9998.0 Unknown: Did not answer Native Speaker question	97	32.9		
	9999.0 Non-native speaker, unknown ability	2	.7		
	Total	149	50.5		
Total		295	100.0		

Table 10: How many A Questions were missed (could be up to 12)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	67	22.7	22.7	22.7
	2	76	25.8	25.8	48.5
	3	56	19.0	19.0	67.5
	4	45	15.3	15.3	82.7
	5	19	6.4	6.4	89.2
	6	19	6.4	6.4	95.6
	7	9	3.1	3.1	98.6
	8	1	.3	.3	99.0
	9	3	1.0	1.0	100.0
	Total	295	100.0	100.0	

Data Analysis: Instrumentation

In addition to learning performance, measured by how often a student answered Question B-Second Attempt correct after missing Question A-First Attempt given a different treatment, the three additional variables we tested were learning engagement, learning satisfaction and perceived learning effectiveness. These instruments were based on validated items utilized in previous experiments by Paul Jen-Hwa Hu and Wendy Hui in their 2012 journal article entitled "Examining the role of learning engagement in technology-mediated learning and its effects on learning effectiveness and satisfaction". Hu and Hui were examining the role of learning engagement in technology-mediated learning and its effects on learning effectiveness and satisfaction. Early results showed that learning engagement was potentially one of the outcome measures associated with perceived learning effectiveness (2012). The Hu/Hui means are on a seven-point scale.

Hu & Hui's Learning Satisfaction items

<u>Learning satisfaction (LS)</u>

<u>LS-1: I like the idea of learning Photoshop in a lab like this.</u>
<u>LS-2: Learning Photoshop by taking a lab like this is a good idea.</u>
<u>LS-3: My learning experience in this lab is positive.</u>
<u>LS-4: Overall, I am satisfied with this lab.</u>
<u>LS-5: My learning in this lab is pleasant.</u>
<u>LS-6: Learning Photoshop in a lab like this is enjoyable.</u>
<u>LS-7: As a whole, the lab is effective for my learning Photoshop.</u>

There were 212 participants in the study and we see that the average person scored 5.05, 4.74 and 4.62 for LS, PLE and LE respectively (see Table 11 below).

Conversion of my 5-point means (see Table 11) to a seven-point scale would look like this: LS – 5.35, PLE - 4.82, LE – 4.872.

Table 11: Comparison of Mean scores between Hu/Hui and Fein

Measured Construct	Hu/Hui	Fein
Learning Satisfaction (LS)	5.05	5.35
Perceived Learning Effectiveness (PLE)	4.74	4.82
Learning Engagement (LE)	4.62	4.872

Hu/Hui shows similar means to my data despite wording and response changes. As stated above, the original instruments utilized a 7-point agree/*disagree* scale (i.e. something was good or not good) and I converted the scale to 5-point *item-specific* scale (i.e. how good an item is). Questions with item-specific response options assist participants in avoiding acquiescence and minimizes participant's cognitive burden (Saris, Krosnick, Revilla, & Shaeffer 2010).

Table 12: Means and Standard Deviation for the Instruments in Fein. 5-Point Scale.

Report

	LS	PLE	LE1
Mean	3.8158	3.4474	3.48
N	277	278	260
Std. Deviation	.64958	.68921	.836

A version of these instruments were also used in Ioana Topala and Simona Tomozii's 2014 studies "Effective Learning and Learning Satisfaction, In An Academic Context Discussion Concerning An Integrating Model" and "Learning satisfaction: validity and reliability testing for students' learning satisfaction questionnaire (SLSQ)."

In the Topala and Tomozii study, a sample of 80 students, ages ranging from 25 to 57, participated in the initial study and the instrument consisted of 26 items graded on a six-point Likert scale (2014). The study was attempting to measure the level of satisfaction that students feel regarding different aspects of learning (Topala & Tomozii, 2014). “The reliability coefficient was calculated by introducing all 26 items of the scale. The value of the global Cronbach's alpha, .947, showed a good level of internal consistency for the SLSQ” (Topala & Tomozii, 2014, p. 384).

My learning satisfaction instrument is more parsimonious including only 6 items while still showing a good Cronbach’s Alpha of .823 for Learning Satisfaction (see Table 13). The reduction in items was intentional as I was conscious of not making the end of quiz questionnaire too long.

By seeing these Cronbach scores in two different recent studies, I can say that these questions measure the same concepts in both studies.

Table 13: Cronbach’s Alpha for Fein

Measure	Cronbach’s Alpha	N of Items
Learning Satisfaction (LS)	.823	6
Learning Engagement (LE)	.650	4
Perceived Learning Effectiveness (PLE)	.860	6

Data Analysis: Limitations of the Study

My response rate across the three modules was 7.1% and would have been higher if we could have inserted the practice quiz links in the syllabus. Instead, due to a Coursera platform limitation, I had to display the links on the announcements page. In addition, Coursera's quizzing tool did not allow the branching I required so students had to be sent out of the learning management system to Survey Gizmo to complete the post-quiz surveys. Finally, it is important to note that the practice quizzes were optional.

Within the practice quizzes, I could not control for frequency of quiz attempts. I selected the first attempt to ensure the students had not experienced the questions or treatment prior.

For my final analysis, I eliminated cases for two reasons: (1) the student quit without answering at least one question or (2) it was not their first attempt at the quiz (duplicates). In addition, I could not look at any A/B question pair where the participant got Question A-First Attempt correct because they did not receive a treatment; anyone who got all of the A Questions correct were removed from the analyses.

Learning satisfaction, perceived learning effectiveness and learning engagement were measured during a post-quiz survey which would have been measured for each module if a participant had at least one entry for each of the three modules. This could have presented a fatigue factor for those participants.

CHAPTER V. RESEARCH FINDINGS

Examining Learning Performance

The data show a number of important findings that help us better understand learning and instructional improvement in the massive, open, online space. To begin, I ran a logistic regression test in order to determine if my model was much better than chance at predicting correct subsequent answers. The results for correct subsequent answers show that the model is much better than chance ($P < 0.05$) (See Table 14). Not only is the whole model a significant predictor of getting B correct, but each term is also significant individually (for Module, Bloom's level and treatment group).

Table 14: Tests of Model Effects

Tests of Model Effects

Source	Type III Wald Chi-Square	df	Sig.
(Intercept)	11.165	1	.001
RandomGroup	25.228	3	.000
Module	26.386	2	.000
Bloom	32.562	3	.000
RandomGroup * Bloom	26.720	9	.002

Dependent Variable: Question B-Second Attempt
Model: (Intercept), RandomGroup, Module, Bloom, RandomGroup * Bloom

The most important finding in my experiment to elucidate high utility instructional design practices in MOOCs revealed a substantial difference in learning performance between students who received either multimedia elaboration feedback or text elaboration feedback. When compared against the control group (who received no feedback), after missing Question A-First Attempt, in any module, in any Bloom's category, **students who received multimedia feedback (treatment 3) were 5.3 times more likely (see Table 15: Treatments and Impact on Learning Performance) to get Question B-Second Attempt correct than those who did not receive any feedback (control group).** Students who received text feedback (treatment 2) were 3.4 times more likely (see Table #12: Treatments and Impact on Learning Performance) to get Question B-Second Attempt correct than those who did not receive any feedback (control group).

Table 15: Treatments and Impact on Learning Performance

Treatment	**Description**	**Odds of answering Question B-second attempt correct.**	**Significance**
Control	No feedback	---	---
Treatment 1	Feedback = "Correct" or "Incorrect"	.488	.110
Treatment 2	Treatment 1 + Elaboration Text Narrative	3.385	.002
Treatment 3	Treatment 1 + Elaboration Video Narrative	5.255	.000

55.4% of students got Question B-Second Attempt correct overall after missing Question A-First Attempt.

44.2% of students who received treatment 1 (Correct/Incorrect w/ Answer) answered Question B-Second Attempt correctly compared to 61% of students who received treatment 2 (Answer and a Text Narrative) and 65.7% students who received treatment 3 (Answer and a Video Narrative). (See Table 16: Percentages of correct answers by treatment group: Summary).

Table 16: Percentages of correct answers by treatment group: Summary

Treatment	% of Question B-Second Attempt Answered Correctly	
Treatment 1 (Correct/Incorrect w/ Answer)	**44.2%**	
Treatment 2 (Answer and a Text Narrative)	**61.0%**	
Treatment 3 (Answer and a Video Narrative).	**65.7%**	

Another extremely interesting instructional improvement research finding related to learning performance was an examination of whether or not taking a practice quiz is a useful activity in the MOOC setting. Inserting practice quizzes is an increasingly common practice in online instructional design, but does take more work on the part of the instructor and design team. The findings here suggest that utilizing practice quizzes as a pedagogical strategy in MOOCs is worth the time and effort.

(For reference, see Table 2: Design Visualization Example, page 44) Students (defined here as learners who took at least one of the final quizzes in Modules 3, 4 or 5) who never attempted a practice quiz had an overall course score of 47.2%. A one-way ANOVA shows a significant difference ($p = .000$) and we can compare the *no practice quiz* score to the students who we know took *multiple practice quizzes*. **Participants who took a practice quiz multiple times achieved an overall course score of 74%, which is far higher than the 47.2% totaled by the no practice quiz attempts group.**

Table 17: Overall course scores for practice quiz takers

# of Practice Quiz attempts	Overall Course Score %	
Did not attempt a practice quiz	**47.2%**	
Took 1 practice quiz	**60.7%**	
Took multiple (2 or more) practices quizzes	**74.0%**	

Analyzing this further, participants who attempted two practice quizzes (N = 57) had an overall course mean score of 60.5%. The 27 students who practiced at least five times achieved a certificate-qualifying score of 77%.

Table 18: Correlation between numbers of quizzes taken and final score percentage

**. Correlation is significant at the 0.01 level (2-tailed).

Correlations

		Number of times Practice Quizzes taken	Final Score Percentage
Number of times Practice Quizzes taken	Pearson Correlation	1	$.508^{**}$
	Sig. (2-tailed)		.000
	N	967	967
Final Score Percentage	Pearson Correlation	$.508^{**}$	1
	Sig. (2-tailed)	.000	
	N	967	967

Examining the other learning measures

As discussed in chapter three, before examining the other measures via the validated instruments from past research, it was important to run standard reliability tests to ensure the fit of the instruments. I ran Cronbach's Alpha (corrected for number of items to avoid unnecessarily high values) and a Factor Analysis on the Learning Engagement, Learning Satisfaction and Perceived Learning Effectiveness instruments in order to describe variability among observed, correlated items.

The Cronbach's Alpha for Learning Satisfaction (LS) showed a good fit at .823. The Cronbach's Alpha for Perceived Learning Effectiveness (PLE) was also high at .860. I was able to create indices for these two measures. Cronbach's for Learning Engagement (LE) was low at .650 so I chose the strongest individual question (LE1) to represent that scale as there was not a good index for the LE measure.

Table 19: Cronbach's Alpha and Means for LS, LE and PLE

Mean scores can range from 1 to 5 where 5 is a high amount of learning satisfaction, perceived learning effectiveness and learning engagement and 1 is a low amount of these measures.

Measure	Cronbach's Alpha	N of Items	N of People	Mean
Learning Satisfaction (LS)	.823	6	277	3.82
Learning Engagement (LE)	--	1	278	3.45
Perceived Learning Effectiveness (PLE)	.860	6	260	3.48

Next, I ran a principal components factor analysis with a Varimax (orthogonal) rotation on the Learning Engagement, Learning Satisfaction and Perceived Learning Effectiveness instruments (See Table 20: Factor Analysis), which maximizes the sum of the variances or tries to find components/factors that are as uncorrelated with each other as is possible. The factor analysis showed that most of the learning satisfaction (LS) and perceived learning effectiveness (PLE) items loaded on the same factor with learning engagement items loading on a second factor. Even though, LS and PLE loaded on the same factor theoretically, to match prior literature, it made sense to keep those as separate instruments. Additionally, Cronbach's alpha showed no individual items that detracted from the overall reliability on those two instruments.

Table 20: Factor Analysis
Rotated Component Matrix[a]

	Component		
	1	2	3
LS1	.833		
LS2	.409		.704
LS3			.795
LS4	.440	.404	
LS5	.807		
LS7		.574	
LE1		.640	
LE2		.704	
LE3			.581
LE4		.769	
PLE1	.724		
PLE2	.738		
PLE3		.572	
PLE4	.739		
PLE5	.661		
PLE6	.793		

Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 5 iterations.

Despite the significant findings related to learning performance, multimedia and text quiz feedback did not change student perceptions of their engagement and/or satisfaction with learning the material. It is quite interesting actually that the student learners did not believe that the feedback treatments that they received helped them learn more effectively – nor did they believe the feedback created a more satisfying learning situation, yet we can see that the treatments *did* effect performance quite positively. It is possible that this relates to the common social psychological bias, the overconfidence effect, where a person's subjective confidence in his or her judgments is reliably greater than the objective accuracy of those judgments (Dobelli, 2013).

Examining Blooms taxonomy

As part of the research questions examining instructional improvement in MOOCs, I worked with Dr. Vazquez to intentionally design the quiz questions to represent any one of the first four levels of the oft-cited Bloom's taxonomy. For the purposes of this study, we used the original taxonomy (See Figure 1). I wanted to know if questions that required higher levels of understanding would affect the impact of a particular feedback treatment in the experiment (i.e. How much interaction is there between the treatment groups and Bloom's taxonomy behaviors?).

I found that, generally, there were some interesting differences between the Bloom's taxonomy levels when controlling for treatment. After missing Question A-First Attempt, on any module, in any Bloom's category, students receiving any feedback (treatments 1, 2 or 3) were 1.6 times more likely to get Question B-Second Attempt correct than those who did not receive any feedback (control group). After missing Question A-First Attempt, on any module, in any Bloom's category, students receiving ANY *elaboration* feedback (treatments 2 and 3) were 2.1 times more likely to get Question B-Second Attempt correct than those who only received *verification* feedback (control and treatment 1). Similar to the learning performance findings, the more elaborate the feedback, the better students performed across all levels of Bloom.

Other potentially significant findings from examining the impact of the differences between Bloom's levels were that when holding treatment and module constant students were 2.9 times more likely to answer Question B-Second Attempt correct when their Question A-First Attempt was a Bloom's level 2 "Understanding" question. In addition, they were 1.6 times more likely to answer Question B-Second Attempt correct when their Question A-First Attempt was a Bloom's level 3 "Applying" Question A-First Attempt 1.5 times more likely to answer Question B-Second Attempt correct when their Question A-First Attempt was a Bloom's level 4 "Analyzing" question.

Table 21: Bloom's Variables: Any Treatments

Coefficients from a logistic regression where the dependent variable is getting Question B-Second Attempt correct and the independent variables are module, bloom's level and any treatment

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Module			25.236	2	.000	
	Module(4)	.488	.197	6.155	1	.013	1.629
	Module(5)	.807	.164	24.049	1	.000	2.240
	Bloom			32.230	3	.000	
	Bloom(2)	1.059	.187	31.923	1	.000	2.884
	Bloom(3)	.483	.220	4.816	1	.028	1.620
	Bloom(4)	.413	.189	4.741	1	.029	1.511
	Any Treatment	.471	.177	7.092	1	.008	1.601
	Constant	-.976	.208	21.995	1	.000	.377

a. Variable(s) entered on step 1: Module, Bloom, Feedback.

Table 22: Bloom's Variables: Elaboration Treatments

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Module			25.567	2	.000	
	Module(4)	.508	.200	6.445	1	.011	1.661
	Module(5)	.821	.167	24.259	1	.000	2.272
	Bloom			31.403	3	.000	
	Bloom(2)	1.056	.190	30.981	1	.000	2.874
	Bloom(3)	.478	.223	4.621	1	.032	1.614
	Bloom(4)	.392	.192	4.181	1	.041	1.481
	Elaboration Treatments	.764	.144	27.980	1	.000	2.146
	Constant	-1.018	.172	35.240	1	.000	.361

a. Variable(s) entered on step 1: Module, Bloom, Feedback2.

Table 23: How many different modules each participant took a practice quiz for.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	166	56.3	56.3	56.3
	2	81	27.5	27.5	83.7
	3	48	16.3	16.3	100.0
	Total	295	100.0	100.0	

Examining the modules

To test for the effect of module, I wanted to examine whether or not the treatment's significance varied across different modules. I found that students who completed the quiz in Module 5 were 2.3 times more likely than students in Module 3 to get Question B-Second Attempt correct. I hypothesize this is possibly due to the fact that students who persist in the course are doing a better job with the material, but it could also be due to progressive learning from module 3 to 4 to 5 (i.e. the more foundational knowledge you have the easier it is to master the concepts later in the course). Even amongst the participants who took all three quizzes, they performed better in module 5, which means that it is likely that students were becoming more comfortable with topics progressively as they moved through the course.

Examining English language ability

Another interesting observation from the data that related to instructional improvement in MOOCs were whether or not the English reading, writing, speaking and understanding ability had a significant effect on learning performance. As discussed earlier, this is an important question as one of the perceived primary benefits of MOOCs and the idea of creating massive, open, online courses is that they can scale to include a global audience. If the elaboration feedback had less of an effect on students who are non-native English speakers, instructional designers would have to consider this when designing instructional material in these settings.

What I found was that English reading, writing, speaking and understanding ability does not have a significant effect on whether or not a person got Question B-Second Attempt correct.

Table 24: English ability variables

These variables are measured on 5 point scale where 5 is a high self-assessed abilities and 1 is a low self-assessed ability. Native vs. Non-Native is a dummy variable where 1 equals a native speaker.

Variables	Significance	Odds of Getting Question B-Second Attempt correct
Reading	.883	.989
Writing	.636	1.030
Understanding Spoken English	.617	.967
Speaking	.891	.992
Native vs. Non-Native	.333	1.197

Despite non-native English speaking students actually performing as well their peers given any feedback treatment (see Table 25: Non-Native vs. Native Getting Question B-Second Attempt correct), under all conditions, the native English students perceived that they would do worse on the quizzes (independent of treatment). When looking at the correlations (See Table 27: English Ability Correlations) all of the questions related to English ability were very correlated with each other and negatively correlated with the Perceived Learning Effectiveness (PLE) index. What this tells us is that the higher your self-assessed abilities are at English reading, writing, speaking and understanding, the lower your perceived learning effectiveness (i.e the better you speak English the less effective you believed, on average, *any* feedback treatment would be). This is discussed further in Chapter six.

Table 25: Non-Native vs. Native Getting Question B-Second Attempt correct

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Dem3(1)	.180	.186	.939	1	.333	1.197
	Constant	.236	.093	6.420	1	.011	1.266

a. Variable(s) entered on step 1: Dem3.

Table 26: Descriptives

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound	Min	Max
0 No	303	3.4971	.63438	.03644	3.4254	3.5688	1.33	5.00
1 Yes	115	3.1838	.90518	.08441	3.0166	3.3510	1.00	5.00
Total	418	3.4109	.73149	.03578	3.3406	3.4812	1.00	5.00

Table 27: English ability correlations

	Dem 4: Reading English	**Dem 5: Writing English**	**Dem 6: Understanding Spoken English**	**Dem 7: Speaking English**	**PLE**
Dem 4: Reading English	Pearson: 1 N = 626				
Dem 5: Writing English	Pearson: .921*** N = 626	Pearson: 1 N = 626			
Dem 6: Understanding Spoken English	Pearson: .915*** N = 626	Pearson: .908*** N = 626	Pearson: 1 N = 626		
Dem 7: Speaking English	Pearson: .897*** N = 623	Pearson: .928*** N = 623	Pearson: .945*** N = 623	Pearson: 1 N = 626	
PLE	Pearson -.143*** N = 416	Pearson -.133*** N = 416	Pearson -.138*** N = 416	Pearson -.128*** N = 416	Pearson: 1 N = 626

Examining the demographics

Another measure that I wanted to examine was the data related to whether or not other demographic factors had a significant effect on learning performance. This is also an important question given the target of MOOCs and its intended global audience. What would the effect of feedback be on students from a variety of backgrounds, namely age, gender and level of education? Once again, understanding these similarities and differences will be important for instructional designers to consider for pedagogical design in these settings.

What I discovered was that age, gender and level of education had no impact on getting Question B-Second Attempt correct net of the effects of treatment, module, and Bloom's level.

Table 28: Demographic variables

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Module			19.910	2	.000	
	Module(4)	.756	.258	8.602	1	.003	2.129
	Module(5)	.811	.201	16.294	1	.000	2.251
	RandomGroup			17.094	3	.001	
	RandomGroup(2)	.032	.264	.015	1	.903	1.033
	RandomGroup(3)	.501	.249	4.062	1	.044	1.651
	RandomGroup(4)	.940	.272	11.963	1	.001	2.560
	Bloom			25.004	3	.000	
	Bloom(2)	1.159	.238	23.731	1	.000	3.186
	Bloom(3)	.292	.270	1.174	1	.279	1.339
	Bloom(4)	.340	.227	2.232	1	.135	1.405
	Age	-.003	.008	.117	1	.732	.997
	Male(1)	.214	.184	1.353	1	.245	1.238
	Dem8	.010	.043	.051	1	.821	1.010
	Constant	-1.134	.694	2.672	1	.102	.322

a. Variable(s) entered on step 1: Module, RandomGroup, Bloom, Age, Male, Dem8.

CHAPTER VI. CONCLUSIONS, DISCUSSION AND SUGGESTIONS FOR FUTURE RESEARCH

Conclusions and Design Recommendations

Conclusions on the Hypothesis: Learning Performance

(H1) *Designing and implementing a MOOC featuring multimedia quiz feedback options will have a positive impact on measures of (1) learning engagement, (2) learning satisfaction, (3) perceived learning effectiveness and (4) learning performance.*

"People learn more deeply from words and graphics than from words alone. This assertion can be called the multimedia principle, and it forms the basis for using multimedia instruction—that is, instruction containing words (such as spoken text or printed text) and graphics (such as illustrations, charts, photos, animation, or video) that is intended to foster learning (Mayer, 2009, p. 223)." My hypothesis predicted that designing and implementing a MOOC featuring multimedia quiz feedback options would have a positive impact on a variety of measures including (1) learning engagement, (2) learning satisfaction and (3) perceived learning effectiveness (4) learning performance. I will begin by discussing learning performance.

When compared against the control group (who received no feedback), after missing Question A-First Attempt, on any module, in any Bloom's category, students who received multimedia feedback (treatment 3) were 5.3 times more likely (see Table 29) to get Question B-Second Attempt correct than those who did not receive any feedback (control group). Students who received text feedback (treatment 2) were 3.4 times more likely (see Table 29) to get Question B-Second Attempt correct than those who did not receive any feedback (control group). Treatment 1 (where students received feedback in the form of "correct" or "incorrect" were even less likely (.488) to answer Question B-Second Attempt correctly then those who received no feedback at all (control). This provides additional information that it is likely that the text and video elaboration feedback was a key component in the learning performance.

Table 29: Treatments and Impact on Learning Performance

Treatment	Description	Likelihood of answering Question B-second attempt correct.	Significance
Control	No feedback	---	---
Treatment 1	Feedback = "Correct" or "Incorrect"	.488	.110
Treatment 2	Treatment 1 + Elaboration Text Narrative	3.385	.002
Treatment 3	Treatment 1 + Elaboration	5.255	.000

Consistent with Mayer's research and the research surrounding the cognitive theory of multimedia learning (Mayer & Bove, 1996, Harp & Mayer, 1998, Moreno & Mayer, 2000, Mayer & Jackson, 2005, Mayer, 2009), I found that learners in the Fall 2015 MOOC offering of "Microeconomic Principles" were able to build meaningful connections, defined here as good retention and good transfer performance (Mayer, 2009, p. 3), when presented with words and pictures as reflected in their performance on the practice quizzes.

This finding has a number of implications for instructional design. I organize these below as **Design Principles** and **Design Principle Implementations**. Design Principles are useful design conclusions and Design Principle Implementations are recommendations to practitioners based on these conclusions.

Design Principle #1:

First, we see that designing assessment feedback to only include verification (acknowledgement of only a correct or incorrect answer) feedback does not produce any positive impact on performance and should not be considered as a helpful treatment for students other than to simply verify for progress.

Design Principle #2:

Secondly, utilizing any type of instant *elaboration* feedback has an immediate impact on student performance. A text narrative providing the student with additional information about the misunderstood subject matter produces better student performance results, up to 3.4 times better than a student who received no help during a quiz.

Design Principle #3:

Third, designing quiz feedback to instantly (dynamically) deploy a multimedia video that covers the topic has the greatest impact on learning performance. Students who have the opportunity to learn the concept visually through the use of pictures, video and audio performed 5.3 times better than a student who received no help during the quiz.

There are a number of follow-up studies that will need to be conducted (these are discussed later in the dissertation), but these are important findings in a quasi-new delivery format that is still finding its bearings. The findings are particularly significant in the MOOC space where scale is observed as an advantage despite its nuanced challenges. In a course with tens of thousands of learners it is not possible for the instructor, or even teaching assistants and community forum managers, to provide real-time content feedback. Spending more time on the already detailed design process for MOOCs would only be worthwhile if we had empirical evidence of actual impact on learner performance. It would seem then that writing quiz assessments to include multimedia elaboration feedback is worth the extra time and effort. This treatment can now be seen as one of a host of emerging design solutions in the massive space that promotes learning while embracing the scale of the course environment.

Design Principle Implementation #1:

In writing quiz assessments that include multimedia elaboration feedback it is possible that the necessary quiz feedback could be added in stages as it does take additional commitment on the part of the instructor and/or instructional designer. One might begin by adding text feedback and then as a secondary step at a later date, the development team (designers, instructors, other subject matter experts, etc.) could record and deploy the multimedia/video feedback. At a minimum, examining the results of this study would suggest that instructional designers and faculty strongly consider taking the time to add instant elaboration feedback to their course quiz and, potentially, exam assessments.

Design Principle Implementation #2:

Another design recommendation that emerged from my findings that also provides an answer to research question 1.2 (What impact, if any, does the number of times a student attempts the practice quiz have on the learning performance?) suggests that utilizing practice quizzes as a pedagogical strategy in MOOCs is also worth the time and effort. Students who attempted multiple practice quizzes finished with an average course score of 74% compared to students who did not attempt any practice quizzes and finished the course with an average score of 47.2%.

As institutions move towards programs and courses that need to have the ability to scale without compromising quality, a two-fold design strategy that may increase learning performance might be to (1) create practice quizzes before each module exam and encourage the students to attempt the practice quiz more than once. (2) Create and dynamically deploy multimedia feedback videos to assist students when they are not grasping a particular concept within the practice quiz.

Conclusions on the Hypothesis: Other Learning Measures

As part of the study and in addition to learning performance, I also wanted to examine student perceptions of their learning engagement, learning satisfaction and learning effectiveness. Would multimedia quiz feedback, or any feedback change student perceptions of their engagement and/or satisfaction with learning the material? Do students believe that particular feedback treatments make the learning more effective? In my limited study of these measures, the answer is no, there were no significant effects on these perceptions in any of the treatments. One interesting finding, however, related to a crosstab I ran examining perceived learning effectiveness and English language ability.

When looking at the correlations (See Table 27), all of the questions related to English ability were highly correlated with each other and negatively correlated with the Perceived Learning Effectiveness (PLE) index. This pattern of findings indicates that the higher one's self-assessed abilities are at English reading, writing, speaking and understanding, the lower one's perceived learning effectiveness (i.e. the better you know English the less effective you believed any feedback would be). The students in the Microeconomics MOOC, particularly those who speak, read, write and comprehend English well, did not believe that any particular feedback treatment would improve their learning. As we know from the results, this was not the case – despite students *believing* quiz feedback would not help them, we know that across all modules and Bloom's question-types, multimedia and text elaboration feedback helped them perform significantly better.

Research Questions

1.1. *How much interaction is there between the treatment groups and Bloom's taxonomy behaviors?*

1.2. *What impact, if any, does the number of times a student attempts the practice quiz have on the learning performance?*

1.3. *Do English language ability and/or other key demographic measures impact any treatment effects?*

Conclusion on Research Question 1.1: Bloom's Taxonomy

Similar to the learning performance findings, the more elaborate the feedback, the better students performed across all levels of Bloom. Across all treatments and modules, students were most likely (2.9 times) to answer Question B-Second Attempt correct when their Question A-First Attempt was a Bloom's level 2 "Understanding" question. They were 1.6 times more likely to answer Question B-Second Attempt correct when their Question A-First Attempt was a Bloom's level 3 "Applying" Question A-First Attempt 1.5 times more likely to answer Question B-Second Attempt correct when their Question A-First Attempt was a Bloom's level 4 "Analyzing" question. These findings will need to be explored further in subsequent research. It may be useful then to be aware that, based on these early findings, the greatest learning performance benefits are realized when the quiz questions are written to achieve understanding or comprehension through explaining ideas or concepts (e.g. asking students to compare the health benefits of eating apples versus eating oranges).

Design Principle #4:

What instructional improvement techniques does this data offer to designers? Since we know that multimedia elaboration feedback increased performance 5.3 times across all question levels of Bloom's taxonomy, I conclude that elaboration feedback, particularly in a multimedia format can help students learn to remember, understand, apply, and analyze the material they are interacting with.

Design Principle Implementation #3:

As suggested above, instructional designers may recommend that faculty focus initial quiz questions that align with the 'Understanding' behavior level of Bloom's taxonomy since results show that questions focused on this level of Bloom's taxonomy are somewhat more effective, independent of treatment.

Conclusion on Research Question 1.3: English Language Ability and Demographics

In addition to the conclusions I discussed above concerning the general overconfidence of English language learners who did not believe any feedback treatment would assist them, I also reported that English reading, writing, speaking and understanding ability does not have a significant effect on whether or not a person got Question B-Second Attempt correct.

This was another extremely important finding as a documented benefit to the achievable scale at which MOOCs can foster high quality learning is that this scalability often occurs with a global reach. Reaching a global audience in online education is nothing new, but to reach global learners at this scale, from 217 different countries in a just a few dozen courses, is a game-changer. Knowing that there are learning performance benefits through multimedia feedback even if you are from a non-English speaking country and lack English language abilities is truly significant for the overall impact and educational reach of this medium (See Appendix C).

Design Principle #5:

If the text and multimedia elaboration quiz feedback had less of an effect on students from non-native English speaking countries, instructional designers would have to consider this when developing feedback treatments in these settings. Only 29% of Illinois MOOC students reside in the United States, the United Kingdom and Canada, so it is most significant that no design alterations need to occur for learners in the other 214 countries – the data show that, on average across learners, there are learning performance benefits from multimedia feedback.

Design Principle #6:

Similar to English language learning ability, the fact that the learning performance results were independent of age (See Appendix D), gender and level of education is important. For practical instructional design application, one can proceed in deploying these treatments in all appropriate courses knowing that the learning benefits will be inclusive. The significance here can be highlighted by examining the data, for example, 24% of Illinois MOOCs learners are over the age of 40 and almost 10% are over the age of 50 (see Appendix D: Illinois MOOC Learners Age Distribution). All age groups benefited from multimedia quiz feedback. The same is true across gender and level of education.

Additional Conclusions

Impact of Multimedia on Cost and Quality

The gains in learning performance are deeply encouraging, but at what cost? Multimedia and video treatments can be expensive. Do we need to spend more money to produce better learning gains? One of the ideas behind this study was to help administrators understand whether adding multimedia was worth the cost. Higher Education needs data to better understand when and when not (and why) to utilize this medium – particularly in the MOOC space, where due to the number of participants in the course, some level of multimedia *must* be deployed. The highest quality “Hollywood-style” media can be extremely expensive and the industry has reported some MOOCs from The Massachusetts Institute of Technology (MIT) and EdX costing over $250,000 to produce (Peterson, 2013). Given that the current hourly rate for media production is anywhere between $100 and $600 per hour depending where the service provider is located, an important question to ask is whether or not students can achieve the same learning performance with good quality DIY video. After all, many faculty, instructors and designers are carrying an HD camcorder around with them in their pocket – we call these mobile phones. This ever-present availability eliminates enormous former barriers; the understaffed equipment office formerly in charge of handling cumbersome media check-out, maintenance and ongoing training. Today, a faculty member can discuss a particular learning topic utilizing high definition video in less than five minutes. There are myriad free apps to then edit, optimize and publish the video. The multimedia used in my experiment was instructor-produced with an iPad ©. While the quality of the video was far from the exemplary multimedia a professional team can produce in the studio, it was more than acceptable and enough to net the results found in this dissertation showing significant learning gains. I have yet to perform a specific A/B comparison, however. A comparison of multimedia, studio-quality versus self-created quality, in both quiz feedback and lecture settings, would be very valuable for carrying forward the instructional improvement research in this dissertation.

After a multitude of conversations with peer universities, fellow administrators and third-party educational service providers, I am convinced now more than ever that this is an important question to explore as this topic is particularly important for land grant public institutions like the University of Illinois where, due to state budget issues, keeping expenditures under control and explicitly strategic is paramount.

To that end, in the near future, I will be once again partnering with Dr. Jose Vazquez to discover what we can learn about the quality of course video and what interaction it might have with the learning performance gains I observed in this dissertation. If the cost to produce Massive, Open, Online Courses can be reduced, it could allow institutions to create more courses in new areas of global educational need while achieving the same learning gains – after all, one of the important original tenants of online education for the masses was the promise that higher education could realistically achieve high quality education at scale for the good of the world in areas impractical, or impossible, to reach otherwise. In an effort to keep both free education and revenue generation at the apex of their mission, Coursera has recently worked with their partners, including the University of Illinois, to segment their offerings into "Standard" and "Premium" where standard offerings are open, free or very low cost and do not carry a credential (or academic credit) and premium offerings (can be for-credit), are priced at an appropriate market cost, are credentialed, and include additional content, assessments and interaction. Understanding the quality and cost balance will solidify when and why certain design decisions are made and where on the online education continuum (instructional design, multimedia, student services, branding, marketing, etc.) a university should allocate their limited resources. Institutional policy can then be formed to protect high quality teaching and learning and ensure the institution is both broadening access and being fiscally responsible.

<u>Impact on the Cognitive Theory of Multimedia Learning</u>

The cognitive theory of multimedia learning (CTML) centers on the idea that learners attempt to build meaningful connections between words and pictures and that they learn more deeply from multiple media than they could have with words or pictures alone. In his book Multimedia Learning (2009), Richard Mayer discusses twelve principles that shape multimedia design. Each of these twelve principles (Mayer, 2009) support CTML by carrying out the theoretical function they serve:

Principles for reducing extraneous processing

1. Coherence Principle – People learn better when extraneous words, pictures and sounds are excluded rather than included.
2. Signaling Principle – People learn better when cues that highlight the organization of the essential material are added.
3. Redundancy Principle – People learn better from graphics and narration than from graphics, narration and on-screen text.
4. Spatial Contiguity Principle – People learn better when corresponding words and pictures are presented near rather than far from each other on the page or screen.
5. Temporal Contiguity Principle – People learn better when corresponding words and pictures are presented simultaneously rather than successively.

Principles for managing essential processing

6. Segmenting Principle – People learn better from a multimedia lesson is presented in user-paced segments rather than as a continuous unit.
7. Pre-training Principle – People learn better from a multimedia lesson when they know the names and characteristics of the main concepts.
8. Modality Principle – People learn better from graphics and narrations than from animation and on-screen text.

Principles for fostering generative processing

9. Multimedia Principle – People learn better from words and pictures than from words alone.
10. Personalization Principle – People learn better from multimedia lessons when words are in conversational style rather than formal style.
11. Voice Principle – People learn better when the narration in multimedia lessons is spoken in a friendly human voice rather than a machine voice.
12. Image Principle – People do not necessarily learn better from a multimedia lesson when the speaker's image is added to the screen.

My study focused on Mayer's ninth principle, the multimedia principle, by providing a feedback treatment in the form of words and pictures, rather than just words alone. The results demonstrated that the fostering of generative cognitive processing (i.e. helping the learner to recognize the material in a way that makes more sense) was helpful in improving student's learning performance. My findings also provide an opportunity to discuss two other principles that may be worth examining further in future studies: the modality principle and the personalization principle.

The modality principle suggests that people learn better from graphics and narrations than from animation and on-screen text, that is, graphics and narrations without on-screen text help the learner manage essential processing or build more helpful representations of the content. The idea is that having the spoken words on-screen contributes to cognitive overload and that faculty can help students better manage their learning by not duplicating the information across both the visual and auditory channels. In my study the videos were captioned, which is standard practice to ensure that students who may have auditory disabilities can participate without disclosure. My results call into question the modality principle and the idea that on-screen text overloaded the learner enough to affect their performance – at least in this field setting, this did not occur.

The personalization principle suggests that people learn better from multimedia lessons when words are in conversational style rather than formal style. Dr. Vazquez is quite conversational in his presentation of the feedback in the video treatments. I did not compare this conversational style against multimedia treatments that were presented more formally, but given the fact that learning performance was significantly better after the multimedia treatment, I believe it would be worth examining whether or not a conversational style truly fosters better generative cognitive processing and whether or not that might be something that practitioners could suggest as a design recommendation in the online space.

<u>Modules</u>

As discussed Chapter V: Research Findings, students were more likely to perform better on Question B-Second Attempt in Module 5 than in the earlier modules. The likeliest explanation for this is due to the progressive learning that occurs from module 3 to 4 to 5 (i.e. the more foundational knowledge you have the easier it is to master the concepts later in the course). Even amongst the participants who took all three quizzes, they performed better in module 5, which means that it is more likely that students were becoming more comfortable with topics progressively as they moved through the course. Some courses are designed with more progressive elements than others, often accompanied by scaffolding supports. In a course where there are prerequisite topics that naturally build on each other, it would be good practice for the course design to feature quiz-based elaboration feedback.

Design Principle Implementation #4:

The data show that scaffolding the learning may be particularly helpful to include from the beginning of a course as learning performance can improve progressively as the student becomes more comfortable with the subject matter.

Suggestions For Future Research

Although I am extremely pleased with the results and conclusions of this initial research examining instructional improvements in massive, open, online courses, there are a number of suggestions for future research that could strengthen the learning impact across this new educational modality.

Instant feedback

In reading the literature concerning feedback strategies, there remain debates on the impact of delayed versus immediate feedback (Kulhavy, 1977, Kulik & Kulik, 1988, 1991). For the purposes of the experiment within this dissertation, I selected immediate feedback as it seemed more appropriate for the audience, scope and setting of instructional improvement in the MOOC space. Quite possibly, to achieve maximum impact on learning performance there may be a need for both immediate and delayed feedback. Many researchers agree that both types of feedback are vital (Cole & Todd, 2003), but I was not able to explore this question in the context of this dissertation.

Learning performance gains in traditional online, blended learning and face-to-face

Although the focus of this dissertation is instructional improvement in the massive, open, online space, there is good reason to hypothesize that the learning performance gains related to multimedia feedback can be achieved in other teaching modalities. Any course that (1) provides quizzes as part of the learning assessment strategy and (2) offers these to students via an online learning management system, may benefit from improved student performance when integrating instant, multimedia elaboration feedback. Certainly this would be possible in traditional (non-massive) online courses and blended structures where all or at least half of the materials are provided online. Setting this up in a strict face-to-face course setting may be more difficult, although it is becoming more and more common for wholly face-to-face courses to at least utilize an online learning management system as a central file and assignment submission repository. Even minor use of a learning management system would allow for the creation of online quizzes and the subsequent deployment of instant, multimedia elaboration feedback.

Other assessment types

One question I may have answered through examination of the results in this dissertation relates to whether or not instant feedback would have the same impact in a final quiz setting as it did in a practice quiz setting (when applied identically). Results should prove to be similar as, to avoid any repetition bias; I took a student's first pass at the practice quiz, which most closely simulates the setting on an actual quiz when a student is often only allowed one attempt, but this is something that could benefit from additional examination. Does the length of the assessment have an impact on performance? Would performance gains be sustainable across a longer final practice exam? These are questions that could be addressed in follow-up studies. This might be particularly impactful for MOOCs in the computational and technological sciences where exams are commonly utilized as a form of summative learning assessment.

Adaptive Learning

An increasing focus of federal research dollars, personalized and adaptive learning have captivated a growing audience of researchers and practitioners – not to mention a host of private for-profit companies. Thought of as an extension of differentiated learning, personalized learning incorporates data from an individual's personal learner profile. The more data points available, the more customized a learning experience can be. "Personalized learning refers to instruction in which the pace of learning and the instructional approach are optimized for the needs of each learner" (U.S. Department of Education, 2016). In differentiated and personalized learning, however, paths are pre-defined for different learner types.

Adaptive learning uses data and algorithms to create unique student pathways that help customize content and control the learning pace. "Digital learning systems are considered adaptive when they can dynamically change to suit the learning in response to information collected *during* the course of learning rather than on the basis of preexisting information such as a learner's gender, age, or achievement test score" (U.S. Department of Education, 2016). The results of this dissertation suggest that multimedia elaboration feedback interventions *during* practice quizzes increase learning performance on a particular topic.

Future research in this area could include dynamic tracking of how many first attempt questions were missed and the subsequent design an algorithm to adapt the multimedia feedback to be more or less (1) frequent and/or (2) comprehensive based on that real-time data. This line of inquiry could follow what is being defined as "linear but adaptive within competencies." "In this scenario the teacher sets up a series of major topics or competencies that will be covered in order. Within each item in that sequence, a knowledge map is defined upon which the adaptive engine operates. This provides the teacher with a mid-point between the traditional time-based, highly controlled course with which most faculty are familiar and the fully adaptive learning experience" (Moore, 2016, para. 10). Utilizing the findings here create a useful foundation for future research on adaptive learning in the MOOC space.

MOOCs: Where are we headed?

Five years ago, Harvard professor, Clayton Christensen, ended his highly influential book *The Innovative University* by reminding the reader that despite all of the disruption, an institution's most valuable asset remain its faculty and in some cases the physical campus. He encouraged universities to measure their success not just against other institutions, but rather to examine how well they are meeting the needs of their students, governments and other constituencies (Christensen & Eyring, 2011). Yet he was also brutally honest.

"Now, however the external pressures on universities require many to respond in ways that go beyond incremental, across-the-board budget reductions. The viability of the whole institution is at risk, and with it the ability of individual faculty members to make the kinds of contributions for which they joined the academy. Realizing their collective and individual ambitions will require all members of the university community to consider changes in the ways they pursue the mission of higher education" (Christensen & Eyring, 2011, p. 380).

In the 2012 rush to be first to market, while instructional quality was surely considered, pedagogical strategy was secondary to institutions "getting on the train" and not being left behind in what promised to be a game-changing paradigm. Many early MOOCs utilized lecture capture and other less-desirable instructional treatments. The sheer speed at which the initial MOOC explosion occurred did not allow enough time for thinking and rethinking instructional design in this space. The haste at which higher education moved to attempt to embrace this movement was not completely negative, however. Today, the hype has settled and there is a willingness at top universities to ensure good pedagogy is the primary consideration. Many experts across the academy give credit to MOOCs for accomplishing something that traditional online education had not been able to achieve in over twenty years of innovation. George Siemens, the proclaimed Grandfather of MOOCs and known skeptic of MOOC proliferation recently stated, “With the development of MOOCs--and I’ll put it squarely on MOOCs--we’ve seen a conversation on teaching and learning in higher education, across institutions and various faculty that have never had this conversation.” (Chung, 2015). The reach of the MOOC hype and hyperbole *did* have an impact. Coupled with continued advances in educational technology, such as new efforts in augmented and virtual reality, and higher education’s refocusing on teaching and learning – as a disruption – was underway.

One of the changes to higher education that Christensen urges faculty and administrators to embrace is the rise of multiple-modality teaching and learning. Continuing and correspondence education is nothing new, but this expansion of the breadth and depth of technology and the widespread and growing availability of connectedness is a new paradigm in what is possible for post-secondary education. Massive open, online courses take the scale to new heights without the previous restrictions that would automatically decrease quality. In our efforts to embrace this change for the good of higher education and the students that choose to attend our institutions, it is essential that we be able to understand, prepare and lead in the coming years. Conducting research on the new possibilities and potential pedagogical improvement strategies in this new space will be a key to achieving viable change for individual faculty and the entire institution. So where are we headed?

More research on teaching and instructional improvement

As we move further beyond the initial inflated expectations, past the disillusionment that was the result of a narrow focus on defining completion and into productive research that will inform high quality instructional improvement in this area, funding will be a key factor. Large foundations have been pushing learning outcomes assessment and MOOCs will be a continued area of focus. The Gates Foundation recently hired SRI Education to evaluate the educational technology investments that it has made. Among the findings: "Online courses in which students' dominant role was solving problems or answering questions had more positive effects than those where most of the students' time was spent reading text or listening to lecture videos" (Watters, 2015, para. 88). This particular study sought to "understand what is required for technology applications to produce positive student impacts at scale and analyzed the features of 137 different courses from 12 major postsecondary courseware-related projects (Means, Peters, & Zheng, 2014). These types of longitudinal studies that examine scale will be more common moving forward. Research that specifically emphasizes the manner in which students engage with multimedia may be particularly important in continuing to understand instructional improvement strategies in the MOOC space. Based on the above findings, we may need to better understand, for example, what the effects of multimedia are in a passive lecture setting versus deployment as feedback in a quiz setting.

Possibly the most important outcome so far of the MOOC revolution is that it has driven the conversation about teaching and learning back to the forefront. Designing courses to offer more than rote memorization is something that higher education has been grappling with for the better part of a century (United States OOE, 1921). In just the past five years, in large part due to the surge in massive, open, online courses, the academy has been more willing to spend time and money on research in the area of instructional improvement. A revealing finding from Josipa Roksa, co-author of the heralded book *Academically Adrift: Limited Learning on College Campuses,* says that faculty members no longer dismiss concerns about teaching (Young, 2015).

The MOOC providers are conducting research alongside their partner universities in this area. Similar to the study within this dissertation, the massive amount of data generated from MOOCs provide new opportunities for pedagogical research and new examinations of teaching methods. A recent study in this space from MIT found that shorter video "lectures" are more effective than longer ones. EdX President Anant Agarwal reports that their research concludes that the ideal length of each multimedia segment is six minutes (Guo, 2013).

Personalized or adaptive learning is another area of ripe for research and MOOCs are a leading platform for this work. Technology investors at a 2015 National Education Association panel wisely cautioned colleges and universities to not "put all their eggs in one basket", as they forecasted that MOOCs won't be an effective digital strategy on their own (Mathewson, 2015, para. 4). What they did agree on, however, was that online education of this kind can and should be used for gaining a better understanding of the possibilities for personalized learning. The primary benefit being that universities could then better track learning outcomes based individual online activity that would in turn create usable data analytics that would assist institutions in tailoring their online courses to meet students' unique individual needs (Mathewson, 2015).

Better Student Outcomes

Earlier in this dissertation, when examining the history of MOOCs and the MOOC movement, I discussed how MOOCs can be evaluated successfully when retention rates are scientifically measured appropriately using student motivation and intention as a quantifiable metric in the equation. Data using these new measures are already starting to show retention improvements as a benefit from appropriate criteria, a greater focus on teaching and learning, enhanced online student support services and the value of tangible credentials such as a specialization certificate. As recently as July 2015, completion rates for Coursera MOOCs were hovering around 4%, by March 2016, rates had more than tripled to almost 15% (Coursera Confidential, 2016). The University of Illinois has played a significant role in working with Coursera to improve these completion rates by recommending design and student service improvements such as: enhanced discussion forums allowing students to better organize sub-forums, integrating in-browser coding tools such as ‘Jupyter’ and a learner dashboard so students can self-monitor their course progress and performance (Coursera Confidential, 2016). Better retention can also impact student outcomes further down the lifecycle and new data suggest that MOOC learners are starting to see tangible career benefits. Of the 52% of Coursera learners surveyed who self-identified as taking a course to ‘advance their career’, 87% of them reported a career benefit. Some of these benefits would be categorized as “career development” such as, being better equipped for their current job (62%) or improved candidacy for a new job (43%), other benefits were definitive “career improvements” such as finding a new job (26%) or receiving a raise or promotion (6%) (Coursera Confidential, 2016). Yet this remains an area ripe for additional exploration. While the definition of “completion” is and should be under continued discussion, a 15% rate clearly offers ongoing opportunities to further improve student outcomes.

Upskilling

Similar to the idea that the academy must keep moving teaching well beyond sole reliance on repetitive lecture strategies, designing learning for adult working professionals must remain a tried and true focus for institutions of higher education. Andragogy or the method and practice of teaching adult learners, has been a staple of continuing education units for decades. Today though, the audience for these teaching and learning practices are larger than ever before and only expanding. On-the-job skills, particularly in the STEM areas, are changing faster than traditional colleges can produce new programs. Udacity has recently partnered with several top universities to serve working adults in highly technical fields and have coined the phrase "upskilling" (Young, 2015). This upskilling is also present outside of the United States. Two MOOCs from the UK that teach adult learners highly needed English skills, entitled ‘Understanding IELTS’, (on the FutureLearn platform), has had 700,000 students sign up for the two offerings in just the last year (Chappell, 2016).

“The British Council has been stunned by the popularity of the MOOC – and says the biggest reason for the success lies, not in what it [the British Council] did in developing the course, but in what the students have been doing themselves” (Chappell, 2016, para. 37).

Anna Searle, Director of English at the British Council, says: “A lot of people said to us at the beginning: ‘Online learning? A MOOC for English? Are you serious!? I don’t think that can work. How can you teach English through a MOOC?’” (Chappell, 2016, para. 38).

"And what we found is that the students taught each other, mentored each other. [They] used the tools, used the techniques, used the materials – but they built the communities." (Chappell, 2016, para. 39).

A bright future for MOOCs are their potential to effectively become an important update of traditional colleges' extension and continuing education programs (Young, 2015).

Marketing

For many top institutions, marketing is a foreign concept. Most of these great institutions have existed for a century or more, sometimes two, and need no introduction. Every spring X thousand students apply, Y students are accepted and the cycle repeats. In large part this has not changed for residential students, at least not at the major research universities. However, as colleges and universities seek to expand their audience beyond a bound geographical location where most of the audience already has formulated an opinion on the institution, marketing and branding have become a vital strategy. In 2012, the first year the University of Illinois launched a MOOC, the exposure created for the institution (and faculty) were equivalent to being featured on the cover of the *New York Times* or a major research journal. With more than 165,000 students in his Android © MOOC, Dr. Lawrence Angrave and many others in similar situations acknowledged that they had just taught more students in one course that they had previously taught or would ever teach in all of their other course sections for the remainder of their lives. Since 2012, higher education has become even more saturated with MOOC and traditional online offerings and the new frontier requires market speed and differentiation. Today's students are savvy consumers and increasingly used to the customizable options available to them on services such as Netflix. Kristina Alexanderson lists five key areas for MOOCs in 2016 and writes,

"I'm not predicting MOOCs will disappear. I think what the above indicates is that MOOCs will need to be targeted to meet very specific aims and audiences. Whether this more finessed approach is viable with the external, commercially driven enterprises who rely on a continual intake of new courses and learners remains to be seen…they will need to adapt to meet the goals of the sector, and reflect on those initial claims" (2015, para. 3).

How marketing and market demand will continue to affect higher education is still unknown, but MOOCs have played an enormous role in the conversation.

Credentialing and Academic Credit

The Georgia Institute of Technology was the first to offer a MOOC-based program for credit when, in a 2014 partnership with Udacity, they launched a Computer Science degree. The University of Illinois became the first to do so in partnership with Coursera in 2016 with the unveiling of the online Master's of Business Administration, branded the "iMBA". Academic credit is still the coin of the realm and as a reflection of that reality, MOOC providers have worked closely with their partner institutions to do something very traditional; offer degrees. These degrees do not look like traditional degrees, though. Once again, due to new possibilities with technology along with new research on pedagogical strategies in these spaces, there are a number of innovative experiments being conducted that would allow for multiple audiences to access the content from many different entry points (See Figure 4).

Figure 4: iMBA Options

In the University of Illinois' iMBA alone, there are six different options to persist. Options 1, 2 and 4 are non-credit options that previously existed in the MOOC space, but options 3, 5 and 6 are new to the MOOC landscape and remain controversial. As stated earlier in this dissertation, teaching a course to tens, sometimes hundreds, of thousands of students for no credit and zero tuition was palatable for most higher education institutions. When academic credit is introduced, faculty senates and accrediting agencies start to get nervous. How can we be assured that appropriate academic rigor is in place to justify the awarding of university credit for a MOOC? Especially given the reports of poor completion rates? The definition and criteria of what constitutes a credit hour is still highly debated (Fabris, 2015), but also highly protected (Silva, White, & Toch, 2015). Institutions interested in offering credit for MOOC-based programs have had to and will have to document and assure proper quality checks that satisfy both faculty governance and regional accreditation.

In the coming years, more universities will offer MOOC-based programs for credit because they offer three programmatic advantages that are unique to the massive space. The first advantage is pecuniary. Assuming the program meets all of the credit-worthy quality checks, MOOC-based programs allow institutions to scale to previously unreachable heights. This has a two-fold effect. First, programs can charge each student less tuition which is notable achievement given that tuition has done nothing but rise since the early 1980s – to the tune of four times inflation or 257% – while a typical family's income has only risen 16% during that same time period (US BOLS & The College Board, 2013). Second, charging less tuition per student, but having the capacity to admit more qualified students into a program without lowering admissions standards allows institutions that are constantly on the lookout to diversify their income-base to generate much-needed revenue.

The second advantage relates to globalization and cultural education. Recently, in the University of Illinois' offering of a MOOC on Global Postharvest Loss Prevention we were discussing with the instructor what it was like to teach a global course to an actual global audience. What he shared with our instructional design team nicely summarizes why the MOOC space is an amazing opportunity for higher education. Rather than students from the United States speculating or even reading about what issues southern Europe or Central India face with postharvest crop loss, they are actually able to discuss these issues *with* people who are dealing with those issues in those actual geographical locations – often in real-time. What better way for a farmer in Illinois or Iowa to learn a new strategy than from someone who is experiencing a similar issue in a similar climate on the other side of the Earth? The ability to leverage this massively diverse student body creates significant teaching and learning opportunities (and challenges) as higher education moves forward in this space.

The third advantage relates to stackable credentials. The term 'stackability' is currently a buzz term to suggest a program that is offered in layers, each one with the potential to stack on the other to generate a more valuable outcome or credential. True stackability would be difficult to achieve without the flexibility of a system that offers both non-credit and credit options in addition the ability to combine them for maximum learning impact. Think of the credit-portion of the course as the cake. The cake is the meat of the dessert and it would not be called 'cake' without it. The non-credit (MOOC material) portion is the frosting. Anyone can take the non-credit portion at any time (eat the frosting – go ahead!), but it's best consumed along with the for-credit activities (cake + frosting = yum). In order for a stackable program to function well, a good recipe is a critical mass of students in the non-credit, open space learning alongside and on the periphery of their for-credit peers, each participating to make a rich and unique learning environment. This is only possible in a massive, open space where the courses have been intentionally designed to leverage scale.

Final Arguments

While they have been highly controversial and much more research needs to be conducted before larger institutional strategies depend on them consistently, MOOCs are likely here to stay as part of (not the sole source of) an institution's educational innovation strategy.

"MOOCs haven't gone away. A growing number of colleges offer them — more than 400 institutions, including 22 of the top 25 most selective universities, according to Class Central, a blog that tracks MOOCs. Venture-capital firms have thrown hundreds of millions of dollars into companies making or supporting the free courses" (Young, 2015, para. 3).

As he continued his recent reflections, Professor George Siemens was sharing further on where higher education and MOOCs may be headed and suggested that perhaps the biggest legacy of MOOCs so far is that they have increased pressure on institutions to spend more money on teaching. Educational leaders such as Siemens would likely argue that spending on teaching improvement across the board is long overdue. "Universities ignored the early wave of innovation in education — at least the larger ones did," (Young, 2015, para. 8). He concludes by reminding all of us that we can no longer sit still. "Today's digital-native students demand new styles of instruction" (Young, 2015, para. 8). MOOCs are a part of meeting this demand.

Whether it be instructional cost, instructional quality, best and better instructional design techniques, understanding more about instructor feedback, adaptive learning, upskiling for career enhancement, or new ideas around academic credentialing, the implications for understanding learning in Massive, Open, Online Courses are substantial. The academy must embrace this new teaching and learning modality or suffer the consequences of our students and faculty not benefitting from the research and expertise emerging in this area. While convenience and expedience are not acceptable reasons for an age-old industry such as higher education to lean into understanding more about its future – better teaching and learning is. MOOCs are not *the only* treatment needed for the health and future of education, but they are *one of a number of* treatments that will continue to enhance education. Learning inquiry requires questioning, exploring, sharing, and exploring again in a beautiful, expressive loop. This dissertation argues that we need to understand more about massive, open, online courses and presents a number of findings related to understanding more about instructional improvement in this area. Today, we know a little more than we did yesterday.

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APPENDIX A: PRACTICE QUIZ QUESTIONS

Quiz Questions

3 quizzes, 8 questions each (2 of each from bloom objectives 1-4: knowledge, comprehension, application, analysis) + 3 check-in questions

Quiz 3: Price Controls

Bloom-1: Knowledge

Student Objective: Recall the definition of an effective price control

A-Question
For a price ceiling to be considered effective it must be set:
*a) below the equilibrium price
b) above the equilibrium price
c) at the equilibrium price
d) either above or below the equilibrium price

B-Question

When a price control is set below the equilibrium price we say it is:
*a) an effective price ceiling
b) a price ceiling
c) an effective price floor
d) a price floor

Bloom-2: Comprehension

Student Objective: Identify whether a price ceiling causes a shortage or a surplus.

A-Question
The equilibrium rent in the market for 1-bedroom apartments in your neighborhood is $800. If the government imposes a price ceiling of $400 in this market:

*a. Fewer people will rent apartments.
b. The same number of apartments will be rented
c. More people will rent apartments.
d. More people will be willing to rent apartments at every price.

B-Question

Suppose that the equilibrium price of a home solar energy system is $25,000, and the government places a price ceiling of $30,000. This price ceiling would:

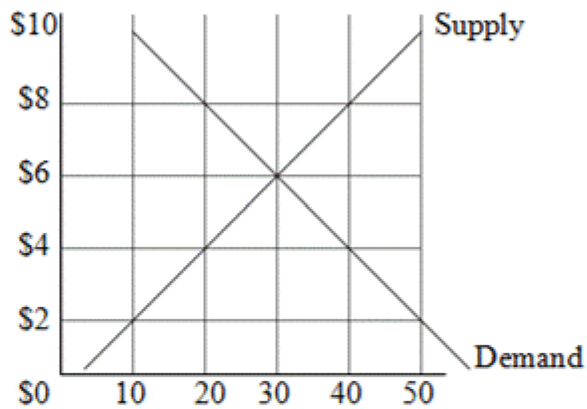
a) create a surplus of solar energy systems in the market
b) create a shortage of solar energy systems in the market
c) cause the demand for solar energy systems to decrease significantly
*d) cause no immediate effect on the price of solar energy systems

Bloom-3: Application

Student Objective: Compute the effect of a price control in the demand and supply diagram.

A-Question

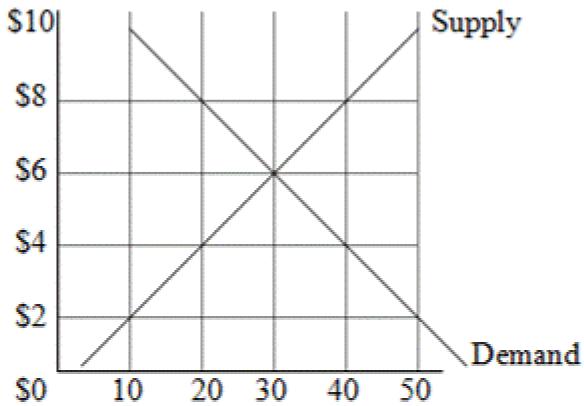
2. In the following diagram showing the demand and supply for baseball tickets, which of the following policies would create a shortage of 20 units?



a) a price floor of $8
b) a price ceiling of $8
*c) a price ceiling of $4
d) a price ceiling of $2

B-Question

2. In the following diagram showing the demand and supply for basketball tickets, which of the following policies would create a surplus of 20 units?



*a) a price floor of $8
b) a price ceiling of $8
c) a price floor of $4
d) a price ceiling of $4

Bloom-4: Analysis

Student Objective: Infer a price control based on its deadweight loss.

A-Question
Which of the following policies would most likely reduce deadweight loss in the market for oranges?

a) lowering an effective price ceiling from $2 to $1.50 per pound
*b) lowering an effective price floor from $3 to $2 per pound
c) raising an effective price floor from $3 to $4 per pound

B-Question
Which of the following policies would most likely increase deadweight loss in the market for grapes?

*a) lowering an effective price ceiling from $2 to $1.50 per pound
b) lowering an effective price floor from $3 to $2 per pound
c) raising an effective price ceiling from $3 to $4 per pound
d) none of the above would increase deadweight loss

Check-in Questions

1. Did you read/watch the in-quiz videos/text? (Only for treatments 2 and 3)
2. Did you try to find the right answer somewhere else?

3. Did you have any technical difficulties with the quiz feedback?

Quiz 4: Elasticity

ELASTICITY

Bloom-1: Knowledge

Student Objective: Classify elasticity based on price and quantity changes.

A-Question
If iTunes raises the price of its music downloads from $1.25 to $1.50, and subsequently the quantity demanded falls by 30%, music downloads from iTunes would be considered:

a) inelastic
*b) elastic
c) unitary elastic
d) perfectly elastic

B-Question

If Apple raises the price of its GPS apps from $3 to $5, and subsequently the quantity demanded falls by 20%, demand for GPS apps from Apple would be considered:

*a) inelastic
b) elastic
c) unitary elastic
d) perfectly elastic

Bloom-2: Comprehension

Student Objective: Estimate the change in quantity from a price elasticity and a percentage change in price.

A-Question
A popular clothing store estimates the price elasticity of its graphic t-shirts to be equal to 2. If the store discounts all of its graphic t-shirts by 10%, what would be the resulting effect on the quantity demanded?

a) An increase of 5%
b) A decrease of 5%

*c) An increase of 20%
d) A decrease of 20%

B-Question
A luggage store estimates the price elasticity of its carry-on cases to be equal to 3. If the store discounts its carry-on cases by 10%, what would be the resulting effect on the quantity demanded?

a) An increase of 3%
b) A decrease of 3%
*c) An increase of 30%
d) A decrease of 30%

Bloom-3: Application

Student Objective: Calculate price elasticity of demand when given the percentage changes.

A-Question
In the past year, the average price of skateboards has increased by 20%, and the quantity demanded has fallen by 10%. The price elasticity of demand for skateboards is:

*a) 0.5
b) 2.0
c) 10.0
d) 30.0

B-Question
In the past year, the average price of surfboards has increased by 10%, and the quantity demanded has fallen by 40%. The price elasticity of demand for surfboards is:

a) 0.25
*b) 4.0
c) 30.0
d) 50.0

Bloom-4: Analysis

Student Objective: Infer the price elasticity of demand by comparing the relationship between a change in price and a change in total revenue.

A-Question
If Harryonprice is considering raising its menu prices in order to earn more money, under what assumption about the cafafge in total revenue.ice elasticity of demand for surfboar

a) The customers are very elastic.
b) The customers are somewhat elastic.
c) The customers are somewhat inelastic.
*d) The customers are very inelastic.

B-Question

If HaleyonoBoba Tea Cafe is considering lowering its prices in order to earn more money, under what assumption about the cafafut the caf cafl revenue.ice elasticity of demand for sul?

*a) The customers are very elastic.
b) The customers are somewhat elastic.
c) The customers are somewhat inelastic.
d) The customers are very inelastic.

Check-in Questions

1. Did you read/watch the in-quiz videos/text? (Only for treatments 2 and 3)
2. Did you try to find the right answer somewhere else?
3. Did you have any technical difficulties with the quiz feedback?

Quiz 5: Production and Costs

Bloom-1: Knowledge

Student Objective: Define the long-run and short-run

A-Question
[Q#]The long run is a period of time in which
a. the firm will not be able to make a profit.
b. at least one input is fixed.
c. the firm is guaranteed to be able to make a profit.
*d. a firm can adjust the quantity of any input.

B-Question
[Q#]. The short run is the period of time in which
*a. at least one input is fixed.

b. a firm can adjust the quantity of any input.
c. the firm will not be able to make a profit.
d. the firm is guaranteed to make a profit.

Bloom-2: Comprehension

Student Objective: Distinguish the difference between fixed costs and variable costs.

A-Question
[Q#]Oscar has negotiated a lease for his sporting goods store in which he is required to pay $2,500 per month in rent. Oscar pays his staff $9 per hour to sell sporting goods and his monthly electricity bill averages $700, depending on his total hours of operation. Oscar's fixed costs per month equal:
*$2,500
$3,200
$700.
$3,209.

B-Question
Oscar has negotiated a lease for his sporting goods store in which he is required to pay $2,000 per month in rent. Oscar pays his staff $10 per hour to sell sporting goods and his monthly electricity bill averages $500, depending on his total hours of operation. Oscar's fixed costs per month equal:
*$2,000
$2,500
$500
$2,510

Bloom-3: Application

Student Objective: Solve for marginal cost when given data on employment, average product, and average fixed costs.

A-Question
[Q#]Austin's total fixed cost is $4,000. Austin employs 20 workers and pays each worker $120. and the marginal product of the last worker hired is 10. What is the marginal cost of the last unit produced by the last worker Austin hired?
*$12
$60

$120
$6

B-Question

[Q#]Austin's total fixed cost is $4,000. Austin employs 25 workers and pays each worker $110, and the marginal product of the last worker hired is 5. What is the marginal cost of the last unit produced by the last worker Austin hired?
*$22
$28
$110
$4

Bloom-4: Analysis

Student Objective: infer the relationship between marginal and average cost from the shape of the average total cost curve

A-Question
At quantities below the minimum-cost output,
*a. marginal cost is less than average total cost and average total cost is falling.
b. marginal cost is greater than average total cost and average total cost is falling.
c. marginal cost is greater than average total cost and average total cost is rising.
d. marginal cost is equal to average total cost.

B-Question

[Q#]At quantities above the minimum-cost output,
a. marginal cost is less than average total cost and average total cost is falling.
b. marginal cost is less than average total cost and average total cost is rising.
*c. marginal cost is greater than average total cost and average total cost is rising.
d. marginal cost is equal to average total cost.

Check-in Questions

1. Did you read/watch the in-quiz videos/text? (Only for treatments 2 and 3)
2. Did you try to find the right answer somewhere else?
3. Did you have any technical difficulties with the quiz feedback?

APPENDIX B: CONSENT FORM AND POST-QUIZ SURVEY

Consent Form

Your answers are confidential and will be in no way associated with your identity until after the course is completed.

Post-Quiz Survey

Dear Coursera Student,

While the computer is tallying up your practice quiz results, would you mind taking 5 minutes to complete a little survey? It will greatly help us analyze how we make the feedback during your quizzes better. Your answers will be kept strictly confidentially. You may skip any question you do not wish to answer.

Thank you!
Dr. José J. Vázquez-Cognet

- [ ] Sure! I will take the survey.
- [ ] No, thanks. Just show me my quiz score. [RESPONDENT SKIPPED TO END]

Questions about the feedback you received on this quiz when you chose an incorrect answer:
[QUESTIONS PRESENTED IN RANDOM ORDER]

LS1

Overall, how helpful was the feedback you received during this quiz?

- [ ] Not at all helpful
- [ ] Slightly helpful
- [ ] Moderately helpful
- [ ] Very helpful
- [ ] Extremely helpful

LS2

How much do you like receiving feedback like this during a quiz?

- [ ] I don't like it at all
- [ ] I like it a little
- [ ] I moderately like it
- [ ] I like it very much
- [ ] I like it extremely well

LS3

What do you think of receiving feedback like this during a quiz?

☐ It is a very bad idea ☐ It is a somewhat bad idea ☐ It is neither good nor bad ☐ It is a somewhat good idea ☐ It is a very good idea

LS4

How negative or positive was your learning experience during this quiz?

☐ Very negative ☐ Somewhat negative ☐ Neither negative nor positive ☐ Somewhat positive ☐ Very positive

LS5

Overall, how satisfied are you with the feedback you received during this quiz?

☐ Not at all satisfied ☐ Slightly satisfied ☐ Moderately satisfied ☐ Very satisfied ☐ Extremely satisfied

LS7

How enjoyable was your learning during this quiz?

☐ Not at all enjoyable ☐ Slightly enjoyable ☐ Moderately enjoyable ☐ Very enjoyable ☐ Extremely enjoyable

LE1

How engaged with the topic of price controls did you feel while you were taking this quiz?

Not at all engaged | Slightly engaged | Moderately engaged | Very engaged | Extremely engaged

LE2

How much effort did you put into taking this quiz?

No effort at all | A little effort | A moderate amount of effort | A large amount of effort | An extreme amount of effort

LE3

How do you feel about the length of this quiz?

It was much too long | It was a little too long | It was just right | It was a little too short | It was much too short

LE4

How absorbed or involved did you feel while you were taking this quiz?

Not absorbed at all | A little absorbed | Moderately absorbed | Very absorbed | So absorbed I forgot everything around me

PLE1

How effective was the quiz feedback in helping you learn the fundamental aspects of price controls?

Not at all effective | Slightly effective | Moderately effective | Very effective | Extremely effective

PLE2

How adequate was the feedback in this quiz in providing you with resources to learn about price controls?

Not at all adequate | Less than adequate | Adequate | More than adequate | Much more than adequate

PLE3

How well did this quiz do in allowing you to practice what you learn?

☐ Not well at all ☐ Slightly well ☐ Moderately well ☐ Very well ☐ Extremely well

PLE4

How much did your understanding of price controls improve as a result of the feedback in this quiz?

☐ It did not improve at all ☐ Improved a little ☐ A moderate amount ☐ Improved a lot ☐ Improved an extreme amount

PLE5

How much did the feedback in this quiz help you appreciate the importance of price controls?

☐ It did not help at all ☐ Helped a little ☐ A moderate amount ☐ Helped a lot ☐ Helped an extreme amount

PLE6

How much did the feedback in this quiz help you understand the fundamentals of price controls?

☐ It did not help at all ☐ Helped a little ☐ A moderate amount ☐ Helped a lot ☐ Helped an extreme amount

Last Page of Questions!

About you:

In what year where you born?:

Your sex?

- Male
- Female

Are you a native speaker of English?

- Yes [RESPONDENT SKIPPED TO EDUCATION QUESTION]
- No

Please rate your English ability in the following areas:

	Very poor	Poor	Fair	Good	Equal to a native speaker
Reading English					
Writing English					
Understanding spoken English					
Speaking English					

What is the highest level of education you have <u>completed</u> so far?

- Secondary/high school or less
- Some college but less than a 4-year degree
- Bachelor's Degree/4-year college degree
- Post-graduate or Master's degree
- Doctoral Degree

☐ Something else *(Please specify:)*: __________

APPENDIX C: APRIL 2016 ILLINOIS MOOC LEARNERS HOME COUNTRY

Current Illinois MOOC Learners Home Country, April 2016

		Frequency	Valid Percent
Valid	**Total**	199947	100.0000
	United States	46586	23.2992
	India	24580	12.2933
	United Kingdom	6938	3.4699
	China	6903	3.4524
	Brazil	6756	3.3789
	Canada	6006	3.0038
	Russian Federation	5245	2.6232
	Spain	4422	2.2116
	Mexico	4121	2.0610
	Germany	3647	1.8240
	France	3594	1.7975
	Australia	3537	1.7690
	Singapore	3349	1.6749
	Ukraine	2922	1.4614
	Egypt	2831	1.4159
	Italy	2520	1.2603
	Viet Nam	2424	1.2123
	Colombia	2346	1.1733
	Netherlands	2319	1.1598
	Nigeria	2036	1.0183
	Philippines	2031	1.0158
	Taiwan	2016	1.0083
	Turkey	1877	0.9387
	Peru	1726	0.8632
	Greece	1670	0.8352
	Pakistan	1660	0.8302
	Portugal	1653	0.8267
	Poland	1597	0.7987
	United Arab Emirates	1580	0.7902
	Hong Kong	1548	0.7742
	South Africa	1471	0.7357
	Romania	1430	0.7152
	Saudi Arabia	1378	0.6892
	Indonesia	1342	0.6712
	Malaysia	1198	0.5992

Switzerland	1165	0.5827
South Korea	1163	0.5817
Thailand	1110	0.5551
Japan	1063	0.5316
Belgium	902	0.4511
Israel	899	0.4496
Iran	892	0.4461
Ireland	891	0.4456
Argentina	847	0.4236
Bulgaria	827	0.4136
Denmark	796	0.3981
Chile	784	0.3921
Bangladesh	732	0.3661
Sweden	718	0.3591
Hungary	673	0.3366
Czech Republic	672	0.3361
Lithuania	654	0.3271
Morocco	633	0.3166
Ecuador	624	0.3121
New Zealand	610	0.3051
Serbia	581	0.2906
Kenya	548	0.2741
Venezuela	531	0.2656
Croatia	530	0.2651
Austria	509	0.2546
Kazakhstan	508	0.2541
Finland	500	0.2501
Ghana	483	0.2416
Belarus	461	0.2306
Norway	392	0.1961
Costa Rica	350	0.1750
Dominican Republic	346	0.1730
Latvia	306	0.1530
Slovakia	302	0.1510
Guatemala	296	0.1480
Georgia	283	0.1415
Slovenia	269	0.1345
Qatar	265	0.1325
Azerbaijan	255	0.1275
Jordan	254	0.1270
Lebanon	254	0.1270

Jamaica	253	0.1265
Estonia	251	0.1255
Sri Lanka	249	0.1245
Trinidad & Tobago	240	0.1200
Panama	214	0.1070
Armenia	208	0.1040
Nepal	204	0.1020
Mongolia	189	0.0945
Puerto Rico	187	0.0935
Albania	184	0.0920
Kuwait	178	0.0890
Bolivia	177	0.0885
El Salvador	169	0.0845
Uruguay	167	0.0835
Tunisia	165	0.0825
Algeria	156	0.0780
Cyprus	150	0.0750
Moldova	146	0.0730
Uganda	145	0.0725
Myanmar	139	0.0695
Luxembourg	132	0.0660
Sudan	132	0.0660
Ethiopia	131	0.0655
Tanzania	129	0.0645
Cameroon	126	0.0630
Cambodia	123	0.0615
Macedonia	119	0.0595
Honduras	116	0.0580
Bahrain	105	0.0525
Oman	105	0.0525
Mauritius	104	0.0520
Zimbabwe	104	0.0520
Syria	101	0.0505
Nicaragua	95	0.0475
Bosnia & Herzegovina	94	0.0470
Malta	91	0.0455
Côte D'Ivoire	90	0.0450
Palestine	90	0.0450
Haiti	88	0.0440
Paraguay	82	0.0410
Barbados	79	0.0395

Senegal	74	0.0370
Iraq	72	0.0360
Kyrgyzstan	69	0.0345
Rwanda	68	0.0340
Macao	64	0.0320
Zambia	63	0.0315
Afghanistan	61	0.0305
Uzbekistan	58	0.0290
Botswana	55	0.0275
Montenegro	50	0.0250
Iceland	44	0.0220
Somalia	44	0.0220
Mozambique	43	0.0215
Saint Lucia	41	0.0205
Bahamas	37	0.0185
Angola	35	0.0175
Belize	35	0.0175
Namibia	33	0.0165
Madagascar	32	0.0160
Maldives	31	0.0155
Yemen	29	0.0145
Dominica	28	0.0140
Malawi	28	0.0140
Congo-Kinshasa	27	0.0135
Guyana	27	0.0135
Benin	26	0.0130
Grenada	24	0.0120
Brunei	21	0.0105
Suriname	21	0.0105
Fiji	20	0.0100
Bhutan	19	0.0095
Burkina Faso	19	0.0095
Antigua & Barbuda	18	0.0090
Aruba	18	0.0090
Cape Verde	18	0.0090
Cayman Islands	18	0.0090
Curaçao	18	0.0090
Liberia	18	0.0090
Libya	18	0.0090
Laos	17	0.0085
Gambia	16	0.0080

Lesotho	16	0.0080
Djibouti	15	0.0075
Sierra Leone	15	0.0075
U.S. Virgin Islands	15	0.0075
Saint Vincent & the Grenadines	14	0.0070
Swaziland	13	0.0065
Papua New Guinea	12	0.0060
Réunion	12	0.0060
Tajikistan	11	0.0055
Cuba	10	0.0050
Guinea	10	0.0050
Isle Of Man	10	0.0050
Martinique	10	0.0050
Monaco	9	0.0045
Niger	9	0.0045
Bermuda	8	0.0040
Guam	8	0.0040
Mali	8	0.0040
Seychelles	8	0.0040
Burundi	7	0.0035
Congo-Brazzaville	7	0.0035
Mauritania	7	0.0035
Solomon Islands	7	0.0035
French Polynesia	6	0.0030
Jersey	6	0.0030
Togo	6	0.0030
Vanuatu	6	0.0030
Gibraltar	5	0.0025
Guadeloupe	5	0.0025
New Caledonia	5	0.0025
Saint Kitts & Nevis	5	0.0025
San Marino	5	0.0025
Andorra	4	0.0020
British Virgin Islands	4	0.0020
Gabon	4	0.0020
Kosovo	4	0.0020
Liechtenstein	4	0.0020
Faroe Islands	3	0.0015
Guernsey	3	0.0015
Sint Maarten	3	0.0015
Timor-Leste	3	0.0015

Turks & Caicos Islands	3	0.0015
Åland Islands	2	0.0010
Bonaire, Sint Eustatius & Saba	2	0.0010
Equatorial Guinea	2	0.0010
French Guiana	2	0.0010
Mayotte	2	0.0010
Northern Mariana Islands	2	0.0010
South Sudan	2	0.0010
Anguilla	1	0.0005
Eritrea	1	0.0005
Federated States of Micronesia	1	0.0005
Greenland	1	0.0005
Marshall Islands	1	0.0005
Montserrat	1	0.0005
Saint Martin	1	0.0005

APPENDIX D: APRIL 2016 ILLINOIS MOOC LEARNERS AGE DISTRIBUTION

Current Illinois MOOC Learners Age groups by decade, April 2016

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	14-19	232	2.1	2.1	2.1
	20-29	4704	41.9	42.5	44.6
	30-39	3389	30.2	30.6	75.1
	40-49	1697	15.1	15.3	90.5
	50-59	757	6.7	6.8	97.3
	60-69	252	2.2	2.3	99.6
	70-79	43	.4	.4	100.0
	80-89	5	.0	.0	100.0
	Total	11079	98.6	100.0	
Missing	System	161	1.4		
Total		11240	100.0		