EXAMINING THE RELATIONSHIP BETWEEN SELF-REGULATED LEARNING PROCESSES AND PERSISTENCE TO GOALS IN MASSIVE OPEN ONLINE COURSES

by

Maha Al-Freih
A Dissertation
Submitted to the
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of
Doctor of Philosophy
Education

Committee:

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Date: ______________________________ Summer Semester 2017
George Mason University
Fairfax, VA

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Dedication

To my beautiful children, Rudy and Rayan.
I hope this work inspires you to follow your dreams, just as you have inspired me to keep going through the good times and bad.

To my parents, for being the best role models.
Your quest for knowledge and search for a better life for my siblings and me has laid the foundation on which I stand today.

To Dr. Nada Dabbagh, for your unwavering support and encouragement over the years.
This work would not have been possible without you.

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Completing this doctoral dissertation has been a life-changing experience for me, one of struggle, perseverance, and growth. There are a number of people in my life who not only made this journey possible, but one of success and joy. For that, I would like to thank them.

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Abstract

EXAMINING THE RELATIONSHIP BETWEEN SELF-REGULATED LEARNING PROCESSES AND PERSISTENCE TO GOALS IN MASSIVE OPEN ONLINE COURSES

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The proliferation of Massive Open Online Courses (MOOCs) and other forms of informal online learning has created many opportunities for learning outside of the formal educational structure (Kop & Fournier, 2010). As of 2015, the number of people who signed up for these courses has risen from an estimated 16-18 million to over 35 million compared to the previous year (Shah, 2015). Despite this rise in enrollment, MOOCs still suffer from exceedingly high dropout rates (Jordan, 2015; Kizilcec, Piech, & Schneider, 2013; Koller, Ng, Do, & Chen, 2013). However, Research suggests that the flexibility and lack of learner-support structures that are typically in place in traditional learning environments coupled with the absence of financial or academic consequences for dropping out of MOOCs indicates that learners' motivational beliefs and Self-Regulated Learning (SRL) strategies become even more critical for learners' success and persistence in MOOCs (Hood, Littlejohn, & Milligan, 2015; Kop & Fournier, 2010;

Little, 2013). This dissertation study adds to the literature at the intersection of SRL in informal online learning settings such as MOOCs and participants' persistence to goals. Specifically, this study explored the relations between MOOC learners' motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value), use of SRL strategies (i.e. time management, effort regulation, peer learning, and help seeking), and self-reported persistence to goals and whether these motivational belief and SRL strategy factors can predict self-reported persistence to goals in MOOCs.

Study participants (N = 111) filled out a survey following their last engagement with a MOOC entitled Humanizing Online Instruction (HumanMOOC) that was offered on the Canvas Open Network in the fall of 2016. Correlation analysis results were mostly consistent with the social-cognitive framework of SRL. That is, motivational beliefs variables were found to be significantly and positively related to the use of a number of SRL strategies, and the use of those SRL strategies were in turn significantly and positively related to learners' persistence to goals in the HumanMOOC. Further, the hierarchical regression analysis indicated that the proposed regression model provided a statistically adequate fit for the data obtained and accounted for 32% of the variance in learners' persistence to self-set goals in the HumanMOOC, with time management emerging as the strongest positive predictor of persistence to goals. Educational design implications, recommendations for future research directions, and study limitations are also discussed.

Chapter 1: Introduction

In the fall of 2008, a new online course called Connectivism and Connective Knowledge (CCK08) was offered through the Learning Technologies Center and Extended Education at the University of Manitoba and facilitated by George Siemens and Stephen Downes. This course was offered for credit to 25 paying students and was also open for registration at no cost to those interested in participating informally but not in obtaining credit (Fini, 2009). Over 2,200 registered for this course, which led to the emergence of a new model for educational delivery in the e-learning landscape, *MOOC*. The term MOOC was coined to describe this course which highlights the key components of this new model: *Massive,* that is there is no limit on attendance; *Open,* free of charge and accessible to anyone with an Internet connection; *Online,* delivered via the Internet; *Courses,* structured around a set of goals in a specific area of study (Fini, 2009; Osvaldo, 2012). This new e-learning course not only stood out as a new model because of its scalability to a mass audience and open access, but it also challenged many of the conventions we had about formal learning (i.e. role of faculty, curriculum design, and accreditation) (McAuley, Stewart, Siemens, & Cormier, 2010).

This first MOOC was based on the connectivist pedagogy that emphasizes the learning journey defined by the connections learners create between resources and with peers, rather than learning content (Meinel, Totschnig, & Willems, 2013; Siemens, 2004, 2006). This new learning model that defines the early MOOCs consisted of:

- High levels of learner control and autonomy over learning resources, level of participation, modes, and places of interaction;
- Weekly synchronous sessions with facilitators and guest speakers;
- A daily email newsletter as a regular contact point for course participants that includes a summary of Moodle forums, course participant blogs, Twitter discussions related to the course, and Rich Site Summary (RSS) harvesting (gRSShopper) to track participants' blogs;
- Emphasis on social systems as effective means for learners to self-organize and navigate through complex subject areas;
- The criticality of "creation" in which learners create digital artifacts (blogs, concept maps, videos, podcasts) that recenters course discussion to a more personal basis (McAuley et al., 2010).

Since CCK08, numerous MOOCs have been offered following the same format and pedagogical principles such as Critical Literacies MOOC in 2009, Education Futures MOOC and Personal Learning Environments and Knowledge MOOC in 2010, and EduMOOC and Learning Analytics MOOC in 2011.

Variants on these courses emerged in 2011 with the launch of Stanford University course CS221: Introduction to Artificial Intelligence, taught by Sebastian Thrun and Peter Norvig, which attracted 160,000 learners from190 nations (Fazackerley, 2012; Schroeder & Levin, 2012). This was followed by other MOOC offerings from different elite universities in 2012 such as Harvard, Massachusetts Institute of Technology (MIT), and the Open University in the UK. As a result, a number of MOOC platform providers emerged including Coursera, edX, and Udacity. This variation of MOOCs, usually offered by prestigious universities, is predominantly associated with the cognitive-behaviorist approach to learning and teaching rather than connectivist pedagogy. Most of the discussions about MOOCs distinguish between these two formats, which are often referred to as connectivistMOOCs, or cMOOCs, and xMOOCs (Conole, 2013; Daniel, 2012; Haggard, 2013; Meinel et al., 2013; Osvaldo, 2012; Yuan & Powell, 2013). As of 2015, the number of people who signed up for these courses has risen from an estimated 16-18 million to over 35 million users compared to the previous year. This growth is also evident in the number of MOOCs offered, the breadth of topics covered in these new learning settings, and the number of universities collaborating to offer MOOCs across the globe (Evans, Baker, & Dee, 2016; Shah, 2015). Despite this rise in enrollment, MOOCs still suffer from exceedingly high dropout rates (Jordan, 2013; Kizilcec, et al., 2013; Koller et al., 2013).

While the problem of student retention and persistence is also an issue in online and distance learning (Angelino, Williams, & Natvig, 2007; Hart, 2012; Rovai, 2003; Xu & Jaggars, 2011, 2013), the dropout rate witnessed in MOOCs far exceeds that observed in formal online courses, with completion rates falling below10% in some MOOCs (Breslow et al., 2013; Hollands & Tirthali, 2014; Koller et al., 2013). For instance, in a review of enrollment and completion rates from 129 MOOCs offered on a range of MOOC providers, Jordan (2015) found that completion rates vary from 0.7% to 52.1%, with a median value of 12.6%, still significantly lower than completion rates reported for formal face-to-face and online courses. That being said, researchers are divided about the concept of completion in MOOCs. Some attempt to identify contextual, behavioral, and psychological factors associated with completion in MOOCs (Adamopoulos, 2013; Balakrishnan & Coetzee, 2013; Kizilcec, Perez-Sanagustin, & Maldonado, 2016; Nawrot & Doucet, 2014; Wang & Baker, 2015) while others question the validity of such measures in MOOCs especially since registration is free and there is no consequence to dropping out (Littlejohn, Hood, Milligan, & Mustain, 2016; Reich, 2014). In the middle of these two camps is a third that calls for the need to reconceptualize the traditional concept of retention and completion to fit this new context (DeBoer, Ho, Stump, & Breslow, 2014). This camp bases its argument on the fact that, unlike students in formal educational contexts, learners join MOOCs with varying goals and intentions that go above and beyond the goal of course completion (e.g. personal growth, professional development). This variation in goals along with the flexible and open access in MOOCs means that any measure of retention or persistence in MOOCs must take into consideration personal goals (Reich, 2014).

Several theories exist to explain this steep dropout rate witnessed in MOOCs. The scalability of MOOCs means that learners must go through the course with minimal, if any, interaction with MOOC instructors. This, coupled with the lack of predetermined structures of formal higher education courses, renders learners' ability to manage and regulate their own learning crucial in order to persist and achieve their personal goals in MOOCs (Hood, et al., 2015; Little, 2013). Several scholars have suggested that Self-

Regulated Learning (SRL) skills, that is learners' ability to take an active role in their learning by employing specific learning strategies to achieve their goals (Pintrich, 2000a; Zimmerman, 2000a), may be particularly important for students participating in online courses (Dabbagh & Kitsantas, 2004; Kitsantas & Dabbagh, 2010; Rovai, 2003). Further, some researchers assert that the ability to regulate and manage one's learning might have a greater impact on learning in informal settings where there is less external control and incentive (Fontana, Milligan, Littlejohn, & Margaryan, 2015; Kop, 2011; Schulz & Roßnagel, 2010; Sitzmann & Ely, 2011). According to Schulz and Roßnagel (2010), the hallmark of intentional informal learning is that "learners (rather than some instructor) are in charge of their learning by setting their learning goals, by monitoring their learning progress, and by choosing the time and place of learning" (p. 383). These skills and processes are consistent with the processes exhibited by highly self-regulatory learners (Pintrich, 2000a; Zimmerman, 2000a). Although SRL has been extensively examined in the context of formal online learning and has been linked to an increase in learners' achievement and persistence (Cheng & Chau, 2013; Hu & Driscoll, 2013; Tsai, Shen, & Fan, 2013; Tseng, Liang, & Tsai, 2014), it has not been investigated thoroughly within the context of MOOCs and informal learning. Given the informal nature of learning in a MOOC that occurs completely online and the unique challenges faced by learners participating in these online settings, researchers caution against simply transferring our insights about factors that drive motivation and persistence in formal learning settings to MOOCs and call for the need to examine this issue in this new context (DeBoer et al., 2014; Fontana et al., 2015; Greene, 2014; Hood et al., 2015; Kop, 2011; Littlejohn et al., 2016; Rovai, 2003).

Clearly, there is a need to examine SRL within the unique context of MOOCs in order to gain a better understanding of the processes that are more relevant and crucial for success and persistence in this new context. Thus, the purpose of this study was to examine the relationship between specific motivational beliefs and SRL skills and participants' persistence to self-set goals in MOOCs while taking into account the unique characteristics that distinguish MOOCs as a learning environment from formal online courses as well as MOOC participants' needs and learning experience compared to that of traditional students. The following section provides an overview of MOOC history and development as well as a general description of MOOC participants' demographics and goals for signing up for such courses.

Problem Background

History and development of MOOCs. While MOOCs are a relatively recent e-learning model, they have quickly gained popularity, expanded, and evolved. Early MOOCs were based on the connectivist pedagogy, which integrates principles explored by chaos, network, and self-organization theories and emphasize learners' autonomy, diversity, and connectedness with peers and learning artifact through technologies (Dabbagh et al., 2016; Mackness, Mack, & Williams, 2010). While these MOOCs provide a predefined timeline, weekly topics, and activities, there are no expectations for participation and learners are encouraged to self-organize and participate according to their personal interests and goals using different social media tools. In cMOOCs, the control and responsibility for learning shifts from the instructor to the learner, and learning becomes a process of knowledge creation and sharing rather than consumption (McAuley et al., 2010). On the extreme end of the continuum is the MOOC model that emerged in 2011 and is offered by elite universities. These MOOCs are an extension of the traditional classroom where experts transmit knowledge to learners, usually through recorded video lectures and peer or automated graded assignments. These types of MOOCs are usually more structured and contained within a learning management system and focus on content production and delivery at scale. Most of the discussions about MOOCs distinguish between these two formats, which are often referred to as connectivist MOOCs, or cMOOCs, and xMOOCs (Daniel, 2012; Meinel et al., 2013; Odom, 2013; Yuan & Powell, 2013). The introduction of xMOOCs in 2011 increased the debate of whether MOOCs can in fact support effective learning, and some have even gone as far as to compare xMOOCs to the traditional instructivist correspondence courses (Bousquet, 2012; Boxall, 2012; Mackness, Waite, Roberts, & Lovegrove, 2013; Stine, 2013). However, some researchers argue that this kind of classification is simplistic and does not pay attention to the nuances of different types of MOOCs (Baker & Surry, 2013; Bayne & Ross, 2014; Conole, 2013, Ho et al., 2014).

Siemens (2013) adds a third class of MOOCs, called quasi-MOOCs. These environments provide learners with loosely linked open educational resources that are not necessarily packaged as a course but are rather intended to support specific tasks such as those of the Khan Academy and MIT's OpenCourseWare. Conole (2013) also proposed a set of 12 dimensions that can be used to classify MOOCs and asserts that this framework gives a better indication of the nature of the different MOOCs: the degree of openness, the scale of participation (massification), the amount of multimedia use, the amount of communication, the amount of collaboration, the type of learner pathway, the level of quality assurance, the degree to which reflection is encouraged, formality (formal vs. informal), the level of assessment, autonomy, and diversity.

Further, Lane (2012) asserts that all MOOCs have three elements: network, task, and content. However, MOOCs can be classified based on which of these elements are dominant. In network-based MOOCs, such as those original cMOOCs taught by George Siemens, Stephen Downes, and Dave Cormier, the emphasis is on the social construction of knowledge and networks as opposed to the acquisition of skills or transmission of content. These MOOCs are based on the connectivist pedagogy. Task-based MOOCs emphasize skills development by requiring participants to complete certain tasks. The social aspect of learning in these environments is important but secondary. Hence, these MOOCs reflect a mix of instructivist and constructivist pedagogical principles. The third type of MOOCs according to Lane is content-based. In a content-based MOOC, content acquisition triumphs networking and task completion and in doing so, tends to use an instructivist or behaviorist pedagogy.

Finally, Baker and Surry (2013) provide a taxonomy that can be used to identify, differentiate, and classify the various types of open education structures and concepts that have emerged in the last few years including MOOCs called Open Education Design (OED). The three major categories of OED are Alternate Education Models, Topic Focus Models, and Traditional Education Models.

Different MOOCs fall under different categories of OED. Alternate Education Models contains three subcategories, namely Open University Models, Peeragogy Models, and Mass Delivery Models. According to Baker and Surry, Udacity, Coursera, and other institutional MOOCs (xMOOCs) fall under the latter subcategory and aim at reaching as many learners as possible and custom generate their content specifically for each course. Topic Focus Models are categorized by free access to resources and connections that are usually aggregated in a central place with varying levels of structure flexibility. Hence, two main subcategories fall under this model, Well Structured Designs and Ill Structured Designs. Well Structured Designs provide learners with a clear path through content, a specific definition for success, and a set of objectives to be reached. An example of a MOOC that falls under this subcategory is MOOC MOOC, which is a mini-micro-meta MOOC about the development of MOOCs and has run four iterations in August 2012, January 2013, June 2013, and recently in January 2014 ("MOOC MOOC," n.d.). Ill Structured Designs are more flexible in that learners are not required to follow a specific path but the modules and content are provided as a scaffold for learning and learners are encouraged to form their own goals and create their own spaces using different tools. cMOOCs are prime examples of such designs. Finally, the Traditional Education Models encapsulate those courses that are designed to replicate a traditional or standard education structure. The subcategory that is of interest here is the Anchored Open Courses in which these courses are an extension of higher education courses from notable universities what are often referred to as xMOOCs such as Stanford's AI MOOCs.

Clearly, not all MOOCs are alike and the acronym itself is open to interpretation (Bayne & Ross, 2014; Glance, Forsey, & Riley, 2013; New, 2013). By analyzing MOOCs based on their underpinning learning theory (Meinel et al.; Odom, 2013), degree of openness (Baker & Surry, 2013), or a combination of different elements (Conole, 2013), MOOCs overlap and can be grouped in different ways. However, there are common defining characteristics among these different types of MOOCs as they are generally accessible to any learner worldwide regardless of age, education level, demographic, or previous experiences. Further, they carry no fees, there are no prerequisites other than Internet access and interest, no predefined expectations for participation, and no formal accreditation (McAuley et al., 2010). As a result of this free and open access, these courses attract a large number of registrants with varying goals and abilities as described in the following section.

MOOC learners. Case studies and recent reports about MOOC participants share a common conclusion: There are considerable differences across and within courses and countries in average participant demographics, learning goals and objectives, technology skills, self-organization skills, learning styles, and time availability (Carson, 2014; Cross, 2013; Fini, 2009; Gaebel, 2013; Ho et al., 2014; Ho et al., 2015; Koller et al., 2013; Kop, Fournier, & Mak, 2011; Stine, 2013).

Koller et al. (2013) argue that learners join Coursera MOOCs with varying intents and that these motives or objectives can be deduced from their behavior and interaction with course content, with the most obvious distinction being between *browsers* and *committed learners*. According to Koller at al., browsers are those who sign up for a

MOOC but never participate and engage with a MOOC or only show up for a week or two before disengaging. Committed learners on the other hand can be divided into three main groups. *Active participants* are those who complete all the assignments and work necessary to earn a statement of accomplishment. *Passive participants* are those who engage with MOOC content mainly through watching lecture videos but have limited interaction with other course components such as discussion forums, homework, and quizzes. Finally, *community contributors* are those who actively participate in the course mainly through the contribution of new content. These varying intentions and objectives are also evident in a survey conducted by researchers at Duke University which indicated that learners' motivation to participate in a MOOC varies and typically falls into one of four categories:

- To support lifelong learning, with no expectations for completion or achievement.
- For fun, social experience, and intellectual stimulation.
- Convenience, often in conjunction with barriers to traditional education options.
- To explore online education. (Belanger & Thornton, 2013)

Similarly, Littlejohn et al. (2016) examined the goals and motivations of 362 participants in an Introduction to Data Science MOOC offered on the Coursera platform. The researchers found that learners' primary motivations for participating in the MOOC were relevance to work, professional development and to expand their skill set, an enjoyment for learning, and to support career development and advancement. Qualitative analysis of the goals led to the emergence of four categories: general learning and development, development of specific know-how, to achieve a certificate, and to complete all the assignments.

In addition, a report conducted jointly by institutional units at Harvard and MIT describes the 597,692 unique MOOC participants in terms of demographics across the first year of HarvardX and MITx courses (6 HarvardX courses and 11 MITx courses) that were released on the edX platform following its first year of launch (Ho et al., 2014). The researchers found that the most typical formal course registrant, a male with a bachelor's degree who is 26 years or older, only accounted for 31% of the total population. Consequently, the researchers argue that the diversity of registrants makes it impossible to describe a singular profile and that those differences are what define MOOC registrants. These differences, the researchers assert, far exceed differences in residential universities. Furthermore, this report examined registrants in term of course activity and patterns of participation (only registered, only viewed, only explored, and certified) and found that registrants register for courses with different intentions, and as such, are engaging with courses in different ways. In a following and more recent report (Ho et al., 2015) on edX MOOCs and including an additional year of data with a total of 1.7 million participants, the researchers revisit some of these earlier findings. The researchers conclude, based on survey data collected from 35 edX courses, that only about 19%-57% of MOOC registrants sign up with the intention of earning a certificate. However, the researchers argue that certification in MOOCs is not indicative of learning, as there are other valid patterns of participation in MOOCs, regardless of certification or completion, that provide better metrics for understanding participants' intentions. Finally, the researchers examined the expectation that MOOC certification rates would grow exponentially from year one to year two of Harvard and MIT courses on the edX platform and concluded that this expectation did not hold true, confirming the diversity of MOOC participants' goals and objectives that goes beyond certification and course completion. This diversity of MOOC participants in terms of backgrounds, goals, and behaviors has rendered the traditional definition of terms such as "students," "learning," "completion," "retention," and "certification" outdated in this new context and many researchers have begun to argue that these terms should not be assessed in the conventional sense (DeBoer et al., 2014; Ho et al., 2014: Ho et al., 2015; Milligan, Littlejohn, & Margaryan, 2013; Reich, 2014).

Other models of participation patterns in MOOCs have been explored in the literature including Clow's (2013) funnel of participation as a metaphor to explain the steep drop-off in activity and different participation modes exhibited by MOOC participants; Hill's (2013) five emerging student patterns emerging from Coursera-style MOOCs of *no-shows*, *observers*, *drop-ins*, *passive participants*, and *active participants*; and Milligan et al.'s (2013) three types of behavioral engagement of *active*, *lurking*, and *passive participation* in cMOOCs. This change in participants' behavior within and between courses adds to the difficulty of identifying a demographic profile of a MOOC participant at any given moment (Cross, 2013).

In summary, MOOCs' design and delivery vary as do participants' demographics, goals, and behaviors. Given the scalability and open access of these courses, providing personalized experiences or direct instructor support for those struggling or showing signs of disengagement is not feasible in their current form (Little, 2013; Park, Cha, & Lee, 2016). This can be a source of many of the practical and psychological challenges, with the signature critique being their low completion rates (Bali, 2014; Daradoumis, Bassi, Xhafa, & Caballé, 2013; Fini, 2009; Glance et al., 2013; Reich, 2014). Little (2013) summarizes some of these challenges facing MOOC learners as being related to the chaotic nature of learning in a MOOC, the need for a certain level of digital literacy, the time and effort commitment needed on part of participants, and the need for strict self-regulation especially in terms of defining goals. These challenges are consistent with current findings about MOOC learners' experience. For instance, Daradoumis et al. (2013) argue that the lack of adaptability of these courses to individual needs and learning styles can be a source of frustration with these learning environments. In addition, research shows that while some learners who are more autonomous and confident thrive in this informal distributed learning environment, others feel overwhelmed by the number of participants and resources available and require more coordination and direction to assist them in their learning journey (Kop, 2011; Kop & Fournier, 2010). Clearly, learners' ability to independently regulate and manage their own learning in MOOCs is critical for successful and effective learning (Hood et al., 2015). Understanding the key SRL processes that are more relevant in a MOOC context is crucial in order to develop design interventions that support learners with varying goals and self-regulatory abilities to succeed and persist (Dabbagh & Kitsantas, 2005; Littlejohn et al., 2016). However, another challenge facing MOOC researchers and designers is the ability to identify these varying personal goals in order to make accurate inferences about completion rates and effective MOOC design strategies that can support learners' achievement of those goals (Reich, 2014). In the following sections, a review of the current research practices on learners' retention and persistence in MOOCs and how the conceptual framework guiding this research can help address some gaps in current research practices is presented.

Current state of research on MOOC persistence and retention rates. While the issue of high dropout rates in MOOCs has been, and still is, of wide interest and concern, determining the magnitude of the problem and accurately measuring dropout rates is not an easy task. These early numbers reported on MOOC retention and persistence rates are what can easily be measured at scale, and thus based on the fraction of individuals of those who initially enroll in a MOOC and successfully complete it to the standards specified by the instructor (Koller et al., 2013). However, many researchers argue that using the traditional definition of retention that is used in the formal education structure, where students tend to have a common goal of earning credits and degrees, can be misleading in a MOOC context (DeBoer et al., 2014; Ho et al., 2014; Ho et al., 2015; Kizilcec et al., 2013; Koller et al., 2013). In a MOOC where there are minimal, if any, academic or financial consequences for dropping out combined with the varied motivation and objectives for signing up for a MOOC (e.g. sampling a course or interest in developing specific skills for personal or professional growth), such metrics offer little insight in terms of evaluating the success and effectiveness of a MOOC (DeBoer et al., 2014; Ho et al., 2014; Ho et al., 2015; Koller et al., 2013). With a common consensus emerging in the field regarding the heterogeneity of MOOC participants' goals and objectives as well as patterns of behavioral engagement and interaction in MOOCs, researchers began to examine participants' completion rates and persistence in a more contextualized manner that captures this variation, which is generally achieved in three main ways. The first method is by limiting analysis to those who sign up for a MOOC and indicate in a precourse survey an intention to complete all course activities or earn a certificate (Reich, 2014). While this method gives a more accurate picture about persistence rates, it excludes the experience of those who sign up for a MOOC for other purposes such as developing specific work-related skills. The second method is by redefining persistence in terms of length or types of interactions that are relevant within a specific MOOC (e.g. percentage of videos watched or assignments submitted) (Kizilcec et al., 2016). The drawback of this method is that it assumes that all learners engage in a MOOC in a unified way to reach these varied goals, overlooking current research that shows the different patterns of interaction with content and other participants. And lastly, the third method used is by inferring participants' intentions from their behavior and actions within a MOOC (Koller et al., 2013). However, this analysis operates on the premise that every participant engaged with the MOOC in a certain way because they intended to, without actual input from participants to confirm such assertion, which adds little to our understanding about those who might be gradually disengaging or interacting with a MOOC because of difficulty in managing their learning or decrease in their motivation (Ho et al., 2015).

Reframing the completion/retention/persistence rate debate. As mentioned previously, the relatively low completion rate of MOOC participants has been a central criticism in the popular discourse (Balakrishnan & Coetzee, 2013; Jordan, 2013, 2015; Reich, 2014). In these discussions, the terms retention, persistence, certification, and course completion are often used interchangeably (Jiang, Williams, Schenke, Warschauer, & O'Dowd, 2014; Liyanagunawardena, Parslow, & Williams, 2014; Reich, 2014). This has also been an issue in traditional university and community college literature (Hagedorn, 2005; Reason, 2009; Wild & Ebbers, 2002). However, according to Hagedorn (2005), the National Center for Education Statistics defines "retention as an institutional measure and persistence as a student measure" (p. 6). This sentiment is shared by Reason,

> colleges and universities *retain* students. Institutional retention rates, the percentage of students in a specific cohort who are retained, are often presented as measures of institutional quality. Persistence, on the other hand, is an individual phenomenon—students *persist* to a goal. (2009, p. 660)

Reason goes on to explain that students' goals may not be to complete a program or earn a degree, and thus, retention and persistence can be viewed as two distinct measures. In other words, individual students might persist toward their goals without being retained to graduation or program completion. Reason argues that persistence measures focus our attention on individual students' goal attainment rather than the institution's goal of keeping students. This is especially true for community college students, which led Wild and Ebbers (2002) to argue for the need for new theories on community college students' persistence and retention that take into account the characteristics that distinguish between community colleges and their students and traditional universities. These include, according to Wild and Ebbers, the heterogeneity of community college students' goals, especially when it comes to the development of practical work place skills, as well as work and family demands. They argue, "One definition of retention applied in community colleges is phrased as a persistence rate, and it may be helpful for purposes of definition in that it begins to consider goals other than graduation rates" (p. 506). Based on these differences between community college and traditional university students, the researchers recommend that any definition of community college retention should include the following factors: (a) initial identification of the student's goal, (b) periodic verification or adjustment of the goal, and (c) persistence of the student toward the goal.

Research on MOOC participants' retention and persistence is facing similar issues. The measures that are being used were developed for retention and persistence consideration in traditional university settings that may not provide the same insights needed to understand the needs and experiences of MOOC learners. For instance, one could argue that high attrition rates in traditional university settings could be indicative of problems with course/program design and delivery because students attrite despite the monetary and academic consequences of doing so. However, there are no such consequences in a MOOC context. Thus, one can argue that persistence toward goal could provide a better indication of MOOCs' effectiveness and efficacy because higher persistence to goals rates mean that learners are persisting toward their personal goals despite the lack of monetary or academic consequences for dropping out. While efforts have been made to provide operational definitions for persistence and retention in MOOC research to fit this new learning context, the basic traditional assumptions that underlie these measures are not being challenged. DeBoer et al. (2014) state:

> Reoperationalizing a variable involves updating its operational definition while leaving its conventional interpretations and uses intact. Reconceptualizing a variable may involve updating its operational definition, but more importantly, it involves updating or differentiating its intended uses and interpretations, often to suit a new educational context….We conclude by reflecting on nascent efforts to evaluate MOOCs, and we argue that these have largely involved reoperationalization and not reconceptualization of existing variables. (p. 74)

Following this line of reasoning, I believe that the opportunities and challenges presented in MOOCs require more than simple reoperationalization of variables. As such, any measure of persistence in MOOCs, if it is to be used as a proxy for its learning effectiveness and efficacy, should be examined in terms of personal goal attainment rather than completion or certification. Because individuals define their goals in MOOCs with no monetary or external incentive, using persistence to goals measures in this context could provide very helpful insights when it comes to understanding the learning experience of learners and the effectiveness of MOOC design and delivery in supporting learners' persistence toward these goals. The study detailed here is intended to offer a new contribution to the research literature on MOOC learners and their persistence to goals as an alternative way to look at completion rates in MOOCs that has not been examined in the literature to date.

Learning in a MOOC is fundamentally different from learning in formal online courses. The lack of direct instructor support and feedback, structure, or predefined expectation for how to engage or participate means that it is the learners' responsibility to set goals, work toward those goals by employing appropriate learning strategies, and evaluate their progress. One theory that addresses learners' ability to activate and sustain motivation, cognition, and behavior systematically oriented toward attainment of personal goals is SRL (Pintrich, 2000a; Schunk, 1990; Zimmerman, 2000a). In the following section, a review of this theoretical model and how it can be used to examine the issue of persistence to goals in MOOCs is presented.

The Social-Cognitive Model of SRL: A Conceptual Framework

The role of Self-Regulated Learning (SRL) to promote student engagement and academic achievement has been well researched. As a result, different definitions and frameworks of SRL processes and design strategies have been proposed by researchers reflecting different theoretical orientations (Cho, 2004; Efklides, 2011; Kitsantas & Dabbagh, 2010; Pintrich, 1995, 2000a; Zimmerman, 1990, 2000a, 2008). The most recent conceptualization of SRL is from the social-cognitive perspective that views SRL as being operated through three areas of psychological functioning: motivational (e.g. self-efficacy and task value), cognitive (e.g. learning strategies), and metacognitive (e.g. self-monitoring and reflection). According to this view, self-regulation is not limited to the cognitive processes and behaviors learners perform, but is also influenced by motivational and contextual factors. For instance, learners who are more motivated or interested in a task or feel more confident in their ability to learn will be more self-regulated (Pintrich, 2000a). A number of closely related models that are based on this view have been developed such as Zimmerman's three-phase model of forethought, performance, and self-reflection (2000a) and Pintrich's four-phase model of forethought, planning, and activation; monitoring; control; and reflection and reaction (2000a). Both models acknowledge the cyclical nature of SRL where motivational beliefs influence learners' adoption of cognitive and metacognitive processes and behaviors during different phases of the learning task and across tasks (Cleary, Callan, & Zimmerman, 2012; Zimmerman, 2011).

Specifically, this study examines the relations among motivation as a dimension of self-regulation of learning that encompasses different motivational factors including goal orientation, online learning self-efficacy, and online learning task value; SRL skills and behaviors and skills including time and environment management, effort regulation, help seeking, and peer learning; and persistence to self-set goals in a MOOC. Examining the issue of persistence to goals in MOOCs through the lens of the social-cognitive framework of SRL serves a number of purposes. This integrative model states that different motivational beliefs/feelings interact with each other as well as with other SRL processes. These sources of motivation include goal orientation, self-efficacy, and task value and interest. These motivational constructs not only play a vital role in initiating and sustaining learners' effort to self-regulate their learning, but also increase learners' attention, effort, and persistence on difficult learning tasks (Artino & Vermillion, 2007;

Cleary et al., 2012; Cleary, Dong, & Artino, 2014; Levy, 2007; Ramdass, & Zimmerman, 2011). However, the motivational factors that drive learning in informal settings are quite different than those in formal learning contexts (Kop, 2011). Further, Fontana et al. (2015) argue that while informal learning does involve a range of SRL subprocesses, they do not occur in discrete phases as described by SRL theories, but are rather dynamic and intertwined with work goals. While the role of these motivational factors has been examined in MOOCs and found to have an impact on learning (Hood et al., 2015), our understanding of how they influence learners' application of SRL strategies and choices in MOOCs is still limited. This perspective of SRL allows us to understand the relationship between motivational factors and SRL strategies and how that might influence learners' persistence to self-set goals in MOOCs.

Learning in a MOOC requires learners to be able to decide what, why, and when to learn which can lead to confusion and a sense of isolation, especially for learners who are not autonomous and lack the regulatory skills to persist in such learning environments (Daradoumis et al., 2013; Kop & Fournier, 2010; Mackness et al., 2010). Furthermore, MOOCs attract a large number of users and encourage the use of synchronous and asynchronous tools and social media, which can lead some learners to feel overwhelmed with the amount of resources and tools available. Holding strong goal intentions and positive motivational beliefs for learning does not necessarily lead to goal achievement if learners are unable to self-regulate during goal striving (Gollwitzer & Sheeran, 2006; Multon, Brown, & Lent, 1991). Hence the ability to actively manage internal (i.e. effort regulation) and external (help seeking, peer learning, time and study environment) resources becomes a critical factor in supporting learners' persistence and success in these online informal learning environments (Moore & Kearsley, 2011). While the motivational aspect of SRL answers the question of why some learners self-regulate, it does not answer the question of how or what specific SRL skills and behaviors they utilize as they actively engage in MOOCs to accomplish their learning goals. Using this framework allows us to examine how these motivational beliefs relate to learners' use of SRL strategies as they persist to accomplish their personal goals (Zimmerman, 2011).

Statement of the Problem

A common consensus in the literature regarding MOOCs is the challenges faced by educational designers, researchers, and instructors as a result of the overwhelming student-to-instructor ratio (Daradoumis et al., 2013; Fini, 2009; Glance et al., 2013; Kop et al., 2011). The novelty of minimal direct learner support coupled with the potential scale of enrollment offers new pedagogical challenges. These challenges are reflected in the current body of literature as it highlights some factors crucial for learners success and persistence in a MOOC such as participants' ability to build connections and create communities (Daradoumis et al., 2013; Kop et al., 2011) as well as their motivation and confidence (Kop & Fournier, 2010), ability to define clear goals (Kop & Fournier, 2010; Littlejohn et al., 2016; Milligan et al., 2013), manage their time effectively (Kop & Fournier, 2010; Nawrot & Doucet, 2014), and monitor their progress (Balakrishnan & Coetzee, 2013). These factors are aligned with self-regulated learning processes in online learning (Dabbagh & Kitsantas, 2004).

However, according to recent research, not all learners possess the knowledge management and self-regulatory skills to effectively customize and manage the learning experience they want (Beaven, Hauck, Comas-Quinn, Lewis, & de los Arcos, 2014; Dabbagh & Kitsantas, 2012). These challenges also hold true for MOOC learners as the unprecedented scale of enrollment and sheer range of diversity of MOOC learners raises concerns about isolation and lack of sophisticated support structure that caters to learners with varying abilities and goals (Beaven et al., 2014; Daradoumis et al., 2013; Glance et al., 2013; Kop et al., 2011; Milligan et al., 2013). This problem is exacerbated by the fact that direct one-on-one support from instructors or providing personalized experiences and support for those struggling to manage their learning or showing signs of disengagement is not feasible in their current form (Little, 2013; Park et al., 2016). Given the varying levels of skills and shifting motivations of MOOC participants combined with the different patterns of behavioral engagement present in MOOCs as indicated in the literature, measuring persistence using traditional metrics of course completion/certification or course interaction data can be misleading. Hence, persistence in this study is measured as the percentage of self-set goals achieved for registering for the MOOC as estimated by participants themselves. Although SRL has been extensively examined in the context of formal online learning, it has not been investigated thoroughly within the context of MOOCs and informal learning (Fontana et al., 2015). Given the unique challenges faced by MOOC learners and the heterogeneity of their goals and skills, examining motivational beliefs and SRL within the specific context of MOOCs is warranted (Broadbent & Poon, 2015; Greene, 2014; Hood et al., 2015). This study adds to the literature at the intersection of SRL in informal online learning settings such as MOOCs and participants' persistence to goals.

Purpose of the Study

The purpose of this study is to explore the relations between MOOC learners' motivational beliefs, use of SRL strategies, and self-reported persistence to goals in a MOOC. In addition, this study examines whether motivational beliefs and use of SRL strategies can predict self-reported persistence to goals in MOOCs. The specific motivational beliefs and SRL strategies that are examined are in line with the processes that have been deemed in the literature as relevant to participants' success and persistence in MOOCs (Balakrishnan & Coetzee, 2013; Kop & Fournier, 2010; Milligan et al., 2013; Nawrot & Doucet, 2014). In this study, the motivational beliefs are examined as a dimension of the social-cognitive framework of SRL and include goal orientation, online learning self-efficacy, and online learning task value. The SRL strategies examined include time and study environment, effort regulation, peer learning, and help seeking.

Significance of the Problem

The low completion rates in MOOCs lead some to question the learning effectiveness of these new learning environments (Kolowich, 2013). This line of reasoning is derived from the theory that MOOC certificates are evidence of learning (Ho et al., 2015). While these metrics are useful for examining online course quality in formal courses, they can be misleading in an informal online learning context where there is low barrier to entry and no monetary or academic consequences for dropping out (DeBoer et al., 2014; Ho et al., 2015). Further, despite the low completion rates evident in MOOCs, recent reports show that the number of people who sign up for these courses has doubled in 2015 (Shah, 2015). This is indicative of the fact that users see value in these learning environments that may be hard to detect using a simple measure of completion or certification (DeBoer et al., 2014; Ho et al., 2015).

The significance of this study can be recognized in two main ways. First, as a response to the need for new approaches that can be used to capture and measure MOOC effectiveness, several new outcome measures have emerged that capture useful and contrasting dimensions of MOOC completion and efficacy (DeBoer et al., 2014). However, researchers in this newly developed field of study are encouraged to experiment and adopt new approaches to defining and measuring course efficacy and effectiveness (Ho et al., 2015). It is hoped that this study can add to this much-needed area of research by employing a new outcome measure that examines completion rates, as a proxy for MOOC effectiveness, in terms of participants' ability to persist and complete self-set goals. Second, research indicates that interventions targeting SRL are more effective when they are designed with contextual influences considered as opposed to the development of interventions that are designed to be applied to any domain or learning environment (Cleary et al., 2012; Dabbagh & Kitsantas, 2005, 2009). Thus, by adding to the literature about the interactive relations among motivational beliefs and SRL strategies crucial for success in informal online learning settings such as MOOCs, researchers and instructional designers can use these findings to improve the design of MOOCs and develop interventions that can increase participants' motivation and support their use of SRL processes effectively, and in turn, increase their chances of success and persistence in these settings.

Research Questions

- Is there a relationship between MOOC participants' motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value), use of SRL strategies (i.e. time and study environment, effort regulation, peer learning, and help seeking), and their self-reported persistence to goals in MOOCs?
- After controlling for MOOC experience, do motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value) and use of SRL strategies (i.e. time and study environment, effort regulation, peer learning, and help seeking) predict self-reported persistence to goals in MOOCs?

Term Definition

MOOC: The term MOOC was coined to describe a new type of online course which highlights the key components of this new model: *Massive*, that is there is no limit on attendance; *Open*, free of charge and accessible to anyone with an Internet connection; *Online*, delivered via the Internet; *Courses*, structured around a set of goals in a specific area of study (Fini, 2009; Osvaldo, 2012).

Persistence to Goals: Persistence is the behavior of continuing action despite the presence of obstacles (Rovai, 2003). Persistence to goals in this study is measured as the percentage of self-set goals for registering for a MOOC that participants have successfully achieved. This percentage ranges from 0% to 100%, and is estimated by participants of this study based on their personal goals.

Self-Regulated Learning: "An active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features of the environment" (Pintrich, 2000a, p. 453).

Goal Orientation: The purpose or reason for why learners set specific achievement goals as well as the standards and criteria for evaluating their performance and success on learning tasks (Pintrich, 2000b).

Online Learning Self-Efficacy: The extent to which participants feel confident in their ability to learn the material presented in a self-paced, online format (Artino & McCoach, 2008).

Online Learning Task Value: Participants' judgments of how interesting, useful, and important the online course is to them (Artino & McCoach, 2008).

Time and Study Environment: Participants' ability to manage and regulate their time and study environment including scheduling, planning and managing their study time, and setting where they do their course work (Pintrich, Smith, García, & McKeachie, 1993).

Effort Regulation: Participants' ability to persist and control their effort and attention in the face of distractions and uninteresting tasks (Pintrich et al., 1993).

Peer Learning: Participants' ability to collaborate with other learners to clarify course materials and reach new insights (Pintrich et al., 1993).

Help Seeking: Participants' ability to seek and manage the support of others including peers and instructors (Pintrich et al., 1993).

Chapter 2: Literature Review

Even with MOOCs' relatively recent existence, the issue of low completion rates in MOOCs has been a topic of much research and debate. In these discussions, several terms are used interchangeably such as completion rates, certification rates, retention, and persistence (Jiang et al., 2014; Liyanagunawardena et al., 2014; Reich, 2014). The lack of unified definition and assumptions that underlie these variables are cause for concern, especially for a developing field of research, as it makes it difficult to reach common understanding on these issues and how to solve them. Some researchers have even gone as far as to argue for the need to reconceptualize outcome variables (e.g. achievement, retention, and curriculum) by updating the way they are interpreted and used to fit this new learning context (DeBoer et al., 2014). Engaging in a MOOC is the result of choices made by individual learners for different purposes that extend beyond MOOC completion and certification. Hence, using traditional retention measures—the number of learners who sign up for a MOOC and complete it by engaging in all activities or earning a certificate of completion—as an outcome variable to evaluate MOOC effectiveness is misleading and can lead to false conclusions. This research is guided by the premise that course completion or certification rates should not be of concern in this new learning environment, but rather how adequate the MOOC environment is in supporting participants as they achieve their goals, which takes into account the goal of certification and completion (Heutte, Kaplan, Fenouillet, Caron, & Rosselle, 2014). Learners' persistence in this context is defined as learners' accomplishment of self-set goals despite the presence of obstacles (Rovai, 2003). While such definition would require additional information from users about these goals and their progress, it would provide a more valid measure of MOOC effectiveness that can lead to reliable conclusions about learning design interventions and improvements (DeBoer et al., 2014; Heutte et al., 2014).

Examining learners' persistence to goals in MOOCs requires an understanding of these goals and objectives. Consequently, this literature review begins by examining the question: How do learners engage in MOOCs and why? This is followed by a review of primary student persistence theories and models. A discussion of research follows, as it pertains to research on learners' persistence in online learning environments and in MOOCs specifically. Following this is a review of SRL models and review of research on SRL in online learning environments and MOOCs, with a focus on the social-cognitive model of SRL, which is being used to examine the issue of persistence to goals in MOOCs in this study. Finally, a review of selected literature at the intersection of SRL and persistence in online learning and MOOC environments will be presented.

How Do Learners Engage in a MOOC and Why?

Research interest in MOOCs is rapidly growing, but the field is still relatively new and in its early stages. Given the scalability of these courses, most of the questions being investigated are those that can be measured at scale using learning analytics and clickstream data such as progression, completion rates, and behavioral engagement trajectories (Anderson, Huttenlocher, Kleinberg, & Leskovec, 2014; Coffrin, Corrin, de

Barba, & Kennedy, 2014; Kizilcec et al., 2013; Koller et al., 2013; Liyanagunawardena, Adams, & Williams, 2013; Seaton, Bergner, Chuang, Mitros, & Pritchard, 2014). For instance, Kizilcec et al. (2013) used K-clustering techniques to identify prototypical behavioral engagement trajectories as longitudinal interaction patterns with video lectures and assessment in three computer science MOOCs. Using the learning analytic methodology, the researchers consistently identified four prototypical engagement patterns for learners' interaction with the course: *completing*, *auditing*, *disengaging*, and *sampling*. Completers are those learners who completed most of the assessment offered in the class regardless of how well they performed. Auditors are those who mostly engaged with the course by watching video lectures. Disengaging learners are those who engaged with assessment at the beginning of the MOOC but showed dramatic decrease in engagement, which happened mostly during the first third of the MOOC. Finally samplers are those who watched some of the video lectures and explored the course material briefly. MOOC participants were also asked to fill out a survey that included questions about age, gender, employment status, highest degree achieved, work experience, overall experience with the MOOC, and intentions for enrolling in the MOOC. In these three MOOCs, participants' age ranged between 18 and 65+ with most of them either working full-time or being an undergraduate or graduate student. In terms of intentions for registering for the MOOC, the most cited reasons in all three courses were because they found it fun and challenging and because they were interested in the topic. Further, for completing learners, the reason for enrolling to enhance their resume was high in all three courses. Thus, even though credentialing was important to many participants, far more were enrolled in these MOOCs for other reasons such as intellectual stimulation. Finally, in terms of experience, both completers and auditors indicated high levels of overall experience compared to disengaging and samplers. This, the researchers argue, indicates that auditing represents an alternative and valid pattern of behavioral engagement with MOOCs for meeting learners' needs.

In another attempt to use the learning analytics approach to understand patterns of learning behaviors in MOOCs, Coffrin et al. (2014) conducted a series of repeated analyses on data from two MOOCs developed at the University of Melbourne: Principles of Macroeconomics and Discrete Optimization. These MOOCs were chosen because even though the same team developed them, the MOOC structure, implementation, and assessment were entirely different. For instance, Principles of Macroeconomics was an introductory course with minimal prerequisites presented in a linear structure while Discrete Optimization was a graduate-level course with material presented in an open curriculum structure. This allowed the research team to generate insight about how course structure might influence learners' behavioral engagement in MOOCs. Completion rates in these two MOOCs were 3% and 5% when calculated in the traditional sense of the fraction of learners who signed up for the MOOC and completed all assignments. However, the researchers found that the number of learners who only watched the videos was far greater than those who attempted the assignments. Using the subpopulation of learners who attempted any assignment to calculate completion rates, the completion rates of these MOOCs increased to 18.1% and 12% respectively.

In terms of patterns of learning behaviors, the researchers were able to use weekly participation data to identify three mutually exclusive groups. The first group is *auditors*, referring to learners who watched videos in any given week but did not engage with the assignments. *Active learners* are those who engage with the assignments in any given week. And finally *qualified learners* refers to learners who watched a video or attempted an assignment in a given week, but also participated in the assignments during the first two weeks and scored 60% or higher. The reason for establishing the last group is because the researchers found an association between performance in the first two weeks and overall success in the MOOC, indicating that those learners have substantial prior knowledge and have invested time and effort required to complete the assignments. Interestingly, despite the significant differences between the two MOOC formats and structure, both exhibited a similar proportion of student subgroups as well as patterns of behavioral engagement and performance. For instance, the percentage of qualified learners in both MOOCs was maintained over time, unlike the proportion of active users that decreased steadily. A final and interesting analysis conducted by the research team was to examine the extent to which learners took advantage of the open course structure using temporal visualization techniques. The authors found similar differences between qualified and nonqualified learners in terms of video viewing and assignment submission patterns in both MOOCs. In both MOOCs, the number of nonqualified learners was greater. However, qualified users took greater advantage of the open nature of the course as evident by their switching habits between video topics and repeated revision of their assessments.

Anderson et al. (2014) analyzed interaction data generated by users in six Stanford MOOCs offered on Coursera: three successive offerings of Machine Learning (ML1-3) and three of Probabilistic Graphical Models (PGM1-3) to develop a conceptual framework for understanding how users currently engage with MOOCs. Based on the total volume of lectures consumed and number of assignment questions completed, they were able to identify five behavioral engagement styles. *Viewers* are those who primarily watch lectures and hand in minimum if any assignments. *Solvers* are those who mainly hand in assignments for a grade but view few if any lectures. *All-rounders* are those who balance video watching activity with assignment submissions. *Collectors* are those who download materials and lectures but do not hand in any assignments. Unlike viewers, it is not clear whether collectors actually use the material they download. And finally *bystanders* are those who register for the MOOC but their total activity is below a very low threshold. In looking at the final grades, the researchers note that a large number of users receive a score of zero in these courses. However, they argue that when this issue is viewed in terms of behavioral engagement styles, the final score of zero does not indicate lack of learning or effort because many of those who receive a zero are viewers who spend a considerable amount of time watching lectures and engaging with material but do not submit assignments.

While these studies identify high-level patterns and bring some valuable insight about a whole cohort of MOOC learners and their actions, they provide minimal understanding about how learners' dispositions and choices and how different factors (i.e. demographics, skills, motivation) shape their experience and behavioral engagement

(Coffrin et al., 2014; Hew, 2015; Hood et al., 2015; Veletsianos, Collier, & Schneider, 2015). Some researchers suggest that the high dropout rates witnessed in MOOCs might be the result of the variability not only in learners' demographics and background, but also in their perspectives and motivations for enrolling in a MOOC, and call for the need to examine issues of behavioral engagement from a learners' perspective (Hood et al., 2015; Liyanagunawardena et al., 2013; Yousef, Chatti, Wosnitza, & Schroeder, 2015). In order to determine types of behavioral engagement and factors mediating different types of behavioral engagement in a MOOC, Milligan et al. (2013) used semistructured interviews with 29 participants in the 35-week Change11 MOOC. These 1-hour interviews explored issues related to the nature of learners' participation in the MOOC such as motivation, planning strategies, their learning networks, and use of different tools to support their learning, as well as their perception of their own participation in the MOOC. This data was then analyzed to determine patterns of behavioral engagement and factors mediating engagement in the course. Analyzing interview questions about each participant's motivation, behavior, and learning network enabled the researchers to identify three distinct levels of behavioral engagement including *active participant*, *lurker*, and *passive participant*. Active participants were those who maintained active social media accounts as a way to not only consume content and broadcast ideas, but also to connect with other course participants and discuss course topics with them. Those participants were highly motivated to persist through the course and overcome some challenges that would be considered hindrance to participation for others. Lurkers were also active in following the course, however, they were not actively engaging in developing a network and connecting with other. Even so, those participants indicated that lurking was an active choice they made and were satisfied with their experience and engaged with the course. This group was more complex than the others identified in this study as different factors (e.g. confidence) seemed to mediate their behavior. Accordingly, three different lurking behaviors were identified within this group. The first were those who did not engage with any network whether internal or external to the MOOC. According to this group, the lack of engagement with others was not a result of disinterest in the MOOC or lack of engagement with course content, but rather lack of interest in engaging with others, indicating that this type of behavioral engagement is compatible with their needs. The second subgroup was those who engaged with external networks but not with networks within the MOOC community. Those participants indicated that they wanted to gain practical skills to apply to their practice and thus were more likely to share their knowledge with external networks such as those at their institutions. The final subgroup was those who passively followed internal MOOC networks but did not actively contribute to them. For those, confidence seemed to be a factor mediating their behavior. For instance, some indicated that they did not believe they knew enough about the topic being discussed to contribute while others saw this as a step to gain experience to be able to participate more actively in future MOOCs. The last group was passive participants, with their frustration or dissatisfaction with the MOOC being what united them. Some reasons for their frustration included their preference for a more structured MOOC and their lack of knowledge on how to connect with other participants.

Milligan et al. (2013) identified three key factors that impact learner engagement and shape their behavior, namely motivation, prior experience, and confidence. The researchers noted that, unlike passive participants, participants who were active and engaged in the course described clear aims and objectives associated with their participation. Furthermore, because learning in a MOOC is fundamentally different from learning in a formal course, having prior experience seemed to influence the level of participation and behavioral engagement in the course. Confidence in one's ability to navigate the MOOC also influenced the level of participation as passive learners seemed frustrated with the need for critical literacy and autonomy to choose where, when, how, and with whom to learn. The researchers suggest that identifying novice MOOC participants and providing them with additional support as well as encouraging them to articulate clear goals and objectives for participation can increase motivation and help remedy some of these challenges.

DeBoer, Stump, Seaton, and Breslow (2013) examined the variability in students' location and behaviors as well as their reasons for joining MIT's 6.002x: Circuits and Electronics MOOC, a computer science and electrical engineering course offered to sophomores at MIT which was made available to anyone interested. Over 150,000 participants registered for this MOOC, however, the sample for this study included those participants who were given an exit survey using matrix sampling in which participants were given a random selection of questions from the survey. Data for this study included participants' point of access determined by their IP address and an exit survey administered to participants. The researchers found that individuals accessed the course from almost every country in the world. However, there was great variability in performance, time spent on the MOOC site, and certification rates. Although a statement on the MOOC site recommended that students have prerequisite knowledge in the area, about 2.4% reported having only attained elementary/primary school- or secondary/high school-level education. As expected, this group of participants had the lowest mean score in the MOOC, however, the range of scores indicates that some individuals within this group did in fact perform very well.

Participants were also asked about their offline collaboration activities. Although the majority indicated that they worked completely on their own, about 20.25% indicated that they had worked with experts or other students in the course. Those students earned significantly higher scores than other students in the course. Lastly, participants were asked about their motivation to join the course. The majority indicated that their primary reason for enrolling was driven by a desire to gain knowledge and skills, followed by a desire for personal challenge. Based on these findings, DeBoer et al. (2013) argue that while background knowledge in the content area was an important factor in predicting student success, their success was also related to the time and effort expended by participants as can be seen in the variability in final scores among those with only elementary/primary school- or secondary/high school-level education. Accordingly, the authors suggest that deeper exploration of the needs of those students and how additional scaffolding to support their learning is warranted. In addition, the authors note that the significant differences in final scores between those who collaborated with others and those who completed the course on their own suggests that supporting student-to-student interaction in the design of a MOOC might improve the learning experience and learners' success in MOOC.

Using in-depth interviews with 18 participants who had previously participated in MOOCs, Zheng, Rosson, Shih, and Carroll (2015) investigated users' motivation to register for a particular MOOC, their learning perceptions, and behavioral patterns. Using grounded theory and axial coding to analyze the interview transcripts, the researchers were able to identify four broad motivations for joining a MOOC: fulfilling current needs such as complementing other formal courses they are taking or for professional development, preparing for the future such as enhancing future employability, satisfying curiosity, and connecting with people. Participants were also asked about how they perceive the MOOC and how they engage with it. A common way participants engage with MOOCs is by treating it as a regular school class. Those participants have a self-mandated schedule and usually watch videos, take notes, complete quizzes and assignments, and participate in forums at a fixed time each week. In some cases, participants did not care whether they completed all course requirements but rather perceived the MOOC as a resource to satisfy a current need such as understanding a specific concept. Further, some participants indicated that they joined the MOOC for their entertainment value at no cost such as history, music, or art MOOCs. Those participants typically engaged with the MOOC by watching the videos in their spare time without completing quizzes and assignments. Finally, a number of participants indicated that interacting with others was how they learned in a MOOC, but because the MOOCs in which those participants engaged with did not support such interaction they had to take the initiative to either organize a study group or join one or use external collaborative tools such as Google Docs to work with other participants. Further, given the massive number of students registered and the difficulty in getting direct and timely feedback from MOOC instructors, participants used outside resources such as a simple Google search or Q&A platforms to ask questions.

In order to cluster and analyze MOOC stakeholders' (i.e. students and professors) perspectives and objectives for joining MOOCs, Yousef et al. (2015) designed a survey consisting of questions related to participants' demographics, experience in technology-enhanced learning environments, and the main open-ended question "What are your goals/objectives when participating in MOOCs?" Seventy-six professors from Europe, the United States, and Asia who had taught MOOCs, and 82 students from 41 different countries who had participated in MOOCs, responded to the survey. Their responses were analyzed using inductive category development analysis and the cluster coding similarity approach. Eight clusters were identified: blended learning, instructional design and learning methodology, flexibility, high quality content, lifelong learning, network learning, openness, and student-centered learning. Similarity computation to find correlations between clusters was performed, which resulted in two bigger clusters. One reflects the characteristics of xMOOCs (i.e. blended learning, flexibility, high-quality content, and instructional design and learning methodologies clusters). The other reflects the characteristics of cMOOCs (i.e. lifelong learning, network learning, openness, and student-centered learning).

The highest number of participants indicated that lifelong learning was their main objective for participating in MOOCs followed by instructional design and learning methodology and high quality content. The researchers attribute the finding that lifelong learning is the main objective for most MOOC participants to their demographics as they found that 82% were over the age of 30, with 46% of those being over the age of 40. This cluster reflects the advantages that MOOCs provide for those who are working full time and join MOOCs for personal or professional interest as opposed to obtaining an official academic degree. The second cluster, instructional design and learning methodology, represents those who join or offer a MOOC to experiment with or learn about new pedagogical and technological designs that can engage learners in courses and MOOCs. The third cluster, high-quality content, was mostly associated with those who engaged with xMOOCs and indicated that their main objective was to learn and gain experience from the world's leading universities. Blended learning also appeared as a cluster in this analysis and reflects participants' interest in MOOCs to enhance their classroom learning experience such as integrating MOOCs with traditional formal classes. A fifth cluster, flexibility, also emerged in the analysis. This cluster represented those who engage with MOOCs for their flexibility in terms of access to information and resources at a time and place convenient to them. The student-centered learning cluster refers to those participants who indicated their objective for joining a MOOC was because it provides a space for learners to be active in their learning process and self-regulate in a semistructured learning environment as opposed to an organized formal course. Network learning also appeared as a cluster. Participants in this cluster indicated that their main objective for joining MOOCs is to work with others by sharing goals, ideas, resources, activities, and taking responsibility for their learning. Finally, openness as a cluster represented those who engaged with MOOCs to access the open educational resources available for free with no entry requirements in terms of age, location, and educational level. Based on this analysis, Yousef et al. (2015) argue that while most MOOC implementations follow the more structured xMOOC format, the number of respondents whose goals were related to cMOOCs was slightly higher. Accordingly, they suggest that focusing on the implementation of MOOCs that combine elements of cMOOCs (i.e. student-centered, open) as well as xMOOCs (i.e. structured, high quality content) might be more effective in meeting the goals and needs of a wide range of participants.

Hew (2015) argues that MOOC completion rates might not be an appropriate metric to measure MOOC effectiveness because some continue to engage with a MOOC with no intention of completing the assignments. As such, Hew sought to identify the factors that students consider important in terms of their perceived ability to promote a satisfying or engaging learning experience in MOOCs based on participants' review comments about three highly rated MOOCs on CourseTalk, an open and public MOOC review and rating site. Using the inductive iterative coding method to allow common themes to emerge from the data, 965 reviews were analyzed. Out of those 965 participants, 908 completed at least one of the MOOCs, 53 were still taking it, and 14 partially completed or dropped out. Five design factors that participants perceived as engaging emerged: (a) authentic problem-centric learning, (b) instructor accessibility and passion, (c) peer interaction, (d) active learning, and (e) course resources to address participant learning needs. Based on his analysis, Hew proposed a framework to promote learners' engagement in MOOCs that includes three closely related propositions. First, instructors must be experts in the courses they teach and have genuine enthusiasm and interest in the topic they teach. Second, instructors must design MOOCs that help leaners build a sense of competence in the topic such as designing authentic problems for learners to engage with, monitor students' learning, and provide additional support and scaffolding for learners with wide array of learning preferences and skills. And finally, instructors must be willing to engage and interact with MOOC participants in such a way that learners feel instructors' interest in their progress.

Finally, in order to gain a deeper understanding about learners' experiences and activities in MOOCs, Veletsianos et al. (2015) used a semistructured interview protocol with 13 participants who had attended at least 3 weeks in at least 1 MOOC. Participants' ages ranged between 25 and 67 and they were from the United States, the UK, Canada, India, El Salvador, Ireland, and the Netherlands. All participants had completed at least 1 MOOC and were at the time enrolled in another MOOC. Those participants were asked to describe their day-to-day experience and activities in a MOOC.

Using constant comparative method analysis, participants described the following types of activities: activities that are digital such as support groups on social networking sites, activities that are not digital such as taking notes on paper, activities that are social such as discussing MOOC experiences with others, and activities that are individual such as locating a study space at home. However, three activities and experiences in particular were consistently described in detail by all participants: interaction on social network sites outside the MOOC platform, note taking, and content consumption. In terms of social interactions, participants indicated that these interactions occurred before, after, or during a MOOC and included both digital interactions with other participants via emails, Facebook, or Twitter, and face-to-face interactions with a MOOC study group that some participants create or discussions of MOOC-related topics with family and friends outside the MOOC. In addition, note taking seemed to be a study habit that all participants shared except for one. Note taking was either done digitally or on paper for personal or professional reasons. Surprisingly, none of the big MOOC platforms support integrated note-taking tools. Finally, content consumption seemed to be influenced by contextual factors related to work and family responsibilities or course design issues. These factors influenced the time they spent on the MOOC as well as the way they engaged with course material such as video lectures.

Based on their analysis, Veletsianos et al. (2015) argue that learning and participation in MOOCs can be understood along a digital-analog continuum as well as a social-individual continuum. For instance, note taking can be considered a digital social activity when shared and discussed with others as well as an analog individual activity, while watching video lectures can be understood as a digital individual activity. Further, participants in this study acknowledged the importance of the social interactions that happened outside the MOOC platform with other MOOC learners. Those participants showed agency as well as comfort with the literacies required to navigate multiple platforms to engage in such discussions. However, the researchers point out that not all learners have the confidence and digital literacies needed to perform these activities.

Finally, given the importance of note taking for participants of this study, the researchers suggest that integrating note-taking tools or including strategies for effective note taking in a MOOC platform might prove useful in supporting the learning experience of MOOC participants.

There is no doubt that only a small percentage of MOOC participants complete all MOOC activities or earn certificates and badges. However, most of the earlier studies limited their focus to classification or outcomes that can be measured at scale and did not account for the unique context of MOOCs (e.g. free and open access and low consequences to dropping out) and variation in participants' goals and objectives. Studies that accounted for these variations indicate that personal goals vary considerably and this variation does in fact shape participants' engagement behavior (Milligan et al., 2013; Zheng et al., 2015). For instance, participants who join MOOCs for professional purposes might not be active in the MOOC or submit assignments, but rather take what they need from the MOOC and share with colleagues at their institutions (Milligan et al., 2013). The validity of such engagement behavior is supported by participants' satisfaction with their experiences regardless of completion or certification (Kizilcec et al., 2013; Milligan et al., 2013). On the other hand, some participants do express frustration with their experience indicating that additional support might be needed for some participants to increase engagement and support persistence in MOOCs (DeBoer et al., 2013; Milligan et al., 2013; Zheng et al., 2015). The implications of these findings are twofold. First, they highlight the need to move away from traditional definitions of persistence to a more contextual definition that takes into account participants' goals and needs. Second, given this unique context and characteristics of MOOC participants, factors that have been found to support persistence in formal online learning contexts may not readily transfer to a MOOC setting as the long history of research on learners' persistence indicates that simple changes in learners' demographics (Bean & Metzner, 1985) or context of learning (i.e. face-to-face vs. online) (Kember, 1995; Rovai, 2003) lead to changes in factors influencing persistence as can be seen in the following section.

Persistence Theories and Models

Student persistence is one of the most widely studied areas in higher education and now spans more than five decades. When the issue of student persistence first appeared in higher education literature, it was theorized to be related to individuals' psychological attributes, skills, and motivations that drive behavior. These early studies were descriptive in nature and lacking in terms of understanding the longitudinal process of interaction that happens between individuals and institutions that can lead to different forms of dropout behaviors (Spady, 1970; Tinto, 1975). As a response to this gap in our understanding of the interaction between individuals and their context, a number of researchers began to develop and test more complex models using multivariate statistical techniques such as Spady's widely cited model of persistence (1970, 1971). Although the issue of student persistence had been examined and studied at the time, Spady's model was the first to consider the complex and interdisciplinary nature of student dropout that is a result of the interaction between the individual student and the college environment (i.e. courses, faculty, other students). This model was based on Durkheim's theory of suicide (1951) and how it relates to the concept of social integration, which states that the tendency of an individual to commit suicide increases as their moral consciousness and collective affiliation decreases. According to Spady, the social conditions that lead to suicide can parallel those that lead to the decision to drop out: holding values and orientations that are incongruent with those of the immediate social system or the lack of consistent interaction and support from others.

Spady's model (1970) consisted of five independent variables: grade performance, intellectual development, normative congruence, friendship support, and social integration. In his model, the first four variables influenced the fifth, social integration. However, Spady argued that the relationship between social integration and the decision to drop out is indirect for a couple of reasons: First, one's satisfaction with the college experience depends on the social and academic rewards they receive, and second, one's ability to sustain their commitment to the college requires a sense of integration and positive rewards. Thus, Spady adds two intervening variables that flow from the integration process to his model: commitment to the college and satisfaction with the experience. Spady (1971) then tested this model in a longitudinal study of 683 students who entered the College of the University of Chicago as freshman in September 1965. Based on the complex relationships that emerged empirically from the analysis, Spady made some modifications to the model by adding a separate component called structural relations and friendship support. A further modification reflected the significant interactions found for women only, men only, or both.

Building on Spady's theory, Tinto developed what he referred to as a predictive, rather than Spady's descriptive, theory of dropout behavior (1975). According to Tinto's model, student persistence can be viewed as a longitudinal process of interactions between the student and the academic and social systems of the college. Viewed like this, individuals enter a higher education institution with a variety of attributes, family backgrounds, and prior schooling experiences, all of which influence the individual's goals and commitment to the institution. Once in college, it is the individual's integration in college that most directly predicts their continuance and persistence at that college. Central to this theory is the concept of academic and social integration. Tinto measured successful academic integration by grade point average (GPA) and evaluated social integration, as it pertains to student persistence in college, by the development and frequency of positive formal and informal encounters with peers, faculty, and administrative personnel and involvement in extracurricular activity. These social interactions lead to varying degrees of friendship support, faculty support, and collective affiliations. Measuring student persistence in terms of social and academic integration highlights the need, as emphasized by Tinto, to distinguish between academic dismissal and voluntary withdrawal. Hence, while academic dismissal is strongly associated with grade point average, voluntary withdrawal is not. In fact, voluntary withdrawals generally show both higher academic performance and higher levels of intellectual development than do the average persisters but lack the social and intellectual congruency with the institutional system. Tinto also acknowledged the influence of external factors on reshaping individuals' original goals and commitments as well as their persistence in college. These modifications to goals and commitment happens as they perform cost-benefit analyses to determine whether an alternative form of investment of time, energy, and resources will yield greater benefits, relative to costs, than will staying in college.

Despite its impact, Tinto's integration model (1975) has limited applicability as it was developed with residential universities and students of majority background in mind (Bean & Metzner, 1985; Kember, 1995; Tinto, 2007). For instance, Bean and Metzner (1985) highlighted the gap in research on nontraditional student attrition and argued for the need to conduct studies that are based on a theory, do not emphasize social integration, include variables from the students' external environment, and use multivariate research design. As a response, Bean and Metzner developed a model to describe the attrition process of nontraditional students. According to Bean and Metzner, three factors distinguish traditional from nontraditional students: age, residence, and enrollment status. These three factors render the role of social integration, which plays a central role in Tinto's model (1975), less relevant to the process of nontraditional students. For instance, nontraditional students are usually older, part-time, and commute to class, and thus less susceptible to the socialization influence of attending college because of their maturity and limited time spent interacting with faculty and other students. While the role of socialization is less influential in the process of nontraditional student attrition, Bean and Metzner argue that there are other elements from previous models of traditional student persistence that must not be ignored such as background and academic variables. These relationships were maintained in their model.

In analyzing previous models of traditional student attrition as well as reviewing the literature on nontraditional students and behavioral theories, Bean and Metzner

(1985) were able to identify the following factors that directly and indirectly affect persistence:

- Defining and background variables. The three defining variables include age, enrollment status, and residence. In addition, four background variables, educational goals, high school performance, ethnicity, and gender, are included at this stage in the model.
- Psychological outcomes. Psychological variables in this model include utility, satisfaction, goal commitment, and stress. These variables are a result of academic and environmental variables, which in turn indirectly affect dropout through intent to leave.
- Intent to leave. Intent to leave indicates a student's intention to leave the institution before graduation. In this model, intent to leave is best predicted by psychological outcomes and actual dropout is best predicted by intent to leave.
- Academic variables. These variables include study skills and habits, absenteeism, course availability, academic advising, and major certainty. In this model, these variables are expected to have an indirect effect on dropout through GPA, intent to leave, and psychological outcomes, especially satisfaction.
- Environmental variables. These are the factors that institutions have little control over but directly affect students' decisions to drop out such as finances, hours of employment, opportunity to transfer, and family

responsibility. These variables also have an indirect effect on attrition through the psychological outcome variables.

- Academic outcome. This represents students' current GPA which has two effects, a direct effect on dropout as well as an indirect effect on dropout through intent to leave.

Although this model does provide a more appropriate lens through which to understand learners' persistence in MOOCs given that most MOOC participants are working adults (Online Course Report, 2016; Wang & Baker, 2015), it does not address the geographic separation of teacher-student and student-student that needs to be considered in an open learning context (Kember, 1995). Furthermore, in reviewing models that address the process of attrition in open and distance learning courses (e.g. Kennedy and Powell (1976) and Powell, Conway, and Ross (1990)), Kember (1995) argues that they suffer from either one of two major deficiencies: (a) the framework is narrow in that it excludes variables external to the institution, and/or (b) they have not been empirically tested.

Given the absence of a strong theoretical foundation upon which to base a model describing the attrition process of adult students in distance and open learning, Kember (1995) adapts Tinto's model (1975) as a starting point for the development of a model in this new context. Similar to Tinto's model, Kember's longitudinal model consists of four core elements: entry characteristics, social integration, academic integration, and outcome. However, that is where the similarities between the two models end. Kember redefines the concept of social and academic integration to suit the characteristics of adult open learning students, who are mainly mature working adults who spend little if any time on a physical campus. According to Kember, academic integration refers to all aspects of a course (i.e. packaging of the course, tutoring) and all elements of interaction between the student and the institution whether academic, administrative, or social in nature. Social integration, on the other hand, refers to the degree to which the student is able to integrate the demands of a course with their preexisting commitments of work, family, and social life.

Kember's model begins with students' entry characteristics that influence persistence through social and academic integration variables. According to Kember, entry variables such as educational qualification, family status, and employment are not good predictors of final outcome, however, they do influence integration variables and direct students toward one of two tracks: either a positive or negative track. The positive track contains factors that lead to higher levels of social integration (i.e. enrollment and study encouragement from employers, family, and friends and peers) as well as academic integration (i.e. learning approach, motivation, language ability, and student's course evaluation and feedback). The lack of social and academic integration, however, leads the student down what Kember referred to as the negative track. Those who were unable to integrate course requirements into their social context tend to attribute it to elements within their social environment such as insufficient time, unexpected events, or other life distractions. If students continue on this path, they move to the academic incompatibility stage, characterized by a surface approach to learning, extrinsic motivation, and negative course evaluation.

Regardless of which track a student is on, all students at this stage factor in their grade point average and conduct a cost-benefit analysis to determine whether the heavy demands of time and relative benefits of continuing studying are worthwhile compared to their interest in the subject matter and eventual qualification. The cost-benefit analysis process, Kember explains, continues to happen as students progress through their course, and decisions to remain or drop out of the course will be influenced by changes in the social and academic variables in the model. For instance, intrinsic interest changes from module to module and motivation to remain is strengthened toward the end as completion approaches. These changes, according to Kember, affect the nature of the cost-benefit decision.

In a similar attempt, Rovai (2003) proposed a composite persistence model for distance online programs based primarily on Tinto's (1975) and Bean's and Metzner's (1985) models. While Rovai believes that a synthesis of both models is a better predictor of the persistence of nontraditional students than either model by itself, he acknowledges that neither model considers the special needs and skills required of online learners. Thus, Rovai incorporates elements that address the needs and skills required in online learning as well as the requirement to harmonize learning and teaching style to explain student persistence in online programs. This model consists of four factors, two of which exist prior to students' admission to an online program including student characteristics (e.g. age, gender, ethnicity, and prior academic performance and preparation) and skills (e.g. computer and information literacy and time management), and two that affect students' persistence once they are enrolled including external (e.g. hours of employment, opportunities to transfer, and finances) and internal factors (e.g. self-esteem, study habits, satisfaction, and interpersonal relationships).

The models reviewed up to this point have been mostly influenced by sociological theories (Bean & Eaton, 2000, 2001). Bean and Eaton argue that while these models identify the factors associated with persistence, they do not explain the mechanism by which these factors lead to reduced attrition. According to them, leaving college is behavior and behavior is psychologically motivated. Thus, they proposed a psychological model of college student retention that accounts for the role of psychological theories in traditional student persistence theories. These theories, they suggest, help explain some important links in sociological persistence models. Four psychological models form the basis of their model: attitude-behavior theory, coping behavioral theory, self-efficacy theory, and attribution theory.

According to Bean and Eaton, students enter college with a set of past experiences and abilities that interact with external, academic, and social variables at the institution. Based on these interactions, students engage in a series of self-assessments that can be explained by psychological processes and help students connect their past experiences with their feelings about college. Hence, interaction with college variables alone does not lead to academic and social integration at college, but it is rather these psychological self-assessment episodes that result in emotional reactions and in turn motivate students to engage in adaptive strategies.

Bean and Eaton (2000, 2001) use the attitude-behavior theory to represent the overall flow of their model. According to this theory, a student's attitude toward college, that is their favorable or unfavorable assessment of the institution, influences their intention to persist which leads to actual persistence. One of the psychological attributes that influence a student's decision to persist is self-efficacy. Bean and Eaton use Bandura's (1986, 1997) model of self-efficacy and define it as an individual's perception of their ability to reach a certain outcome. This psychological attribute is context specific and is based on observation and past experiences. Accordingly, students who are more confident in their ability to survive and adapt will show higher levels of persistence and achievement. Linking their model to traditional persistence models such as that of Tinto (1975), they argue that higher levels of academic and social self-efficacy lead to higher levels of social and academic integration. In addition to self-efficacy, Bean and Eaten consider coping behavior and locus of control in their model of student retention. Locus of control refers to individual's ability to provide internal or external causes of their past success and failures. According to this theory, individuals with an internal locus of control recognize that they are instrumental in their success or failure, while individuals with an external locus of control attribute their success and failure to external sources such as chance or fate. In this model, students with an internal locus of control are more likely persist because they believe they are in control and thus are more motivated to produce the effort to succeed. Finally, coping behavioral theory suggests that through the process of assessment of one's self and the environment, individuals are able to adjust to the new environment by using different coping strategies. According to Bean and Eaton, the social and academic integration factors presented in traditional student persistence models can be viewed as a result of coping behaviors individuals perform within the institutional environment.

This review of persistence models and theories suggest the complex web of factors that influence persistence. This complexity is evident by changes in factors influencing persistence as a result of changes in learning medium and learners' demographics (Bean & Metzner, 1985; Kember, 1995). Further, a learner's decision to persist or dropout is not only influenced by internal (i.e. motivation and skills) or institutional (i.e. academic support) factors, but also by external factors that cannot be controlled (i.e. work and family commitment). Finally, these models suggest that the act of persistence is psychologically motivated (Bean & Eaton, 2000, 2001). These sources of influence range from motivational factors, self-efficacy beliefs, the value learners assign to learning tasks, and goals. However, neither intention nor desire alone is sufficient in supporting learners' persistence if they lack the ability to exercise control over their own motivation and behavior (Bandura, 1986; Gollwitzer & Sheeran, 2006), thus highlighting the need to examine the issue of persistence as a result of the interaction between behavior and motivational factors. Given the differences between learning in MOOCs and formal online courses as well as differences between MOOC learners and residential students, it is safe to argue for the need to reexamine the issue of persistence in MOOCs and how motivational and behavioral factors operate within this new context. In the following section, a review of studies on persistence in online and MOOC settings will be provided.

Persistence research in online learning. The issue of low completion rates has also been a challenge in online programs and courses. Using archival data for students enrolled at a regional public university located in the Southwestern United States, Atchley, Wingenbach, and Akers (2013) compared completion rates of students enrolled in online courses and students enrolled in traditional courses. The sample included 5,778 students enrolled in courses taught in both an online and traditional lecture format by the same professor during the same semester and year. Chi square analysis revealed statistically significant difference in course completion between students enrolled in online courses and students enrolled in traditional courses with the lowest course completion rates at 93.3% for online courses compared to traditional courses at 95.6% (χ^2 (2, N = 5,778) = 14.132, $p < .05$). Similar findings have been found for community college students. Xu and Jaggars (2011) analyzed a data set containing nearly 24,000 students who initially enrolled during the summer or fall of 2004 and were tracked until the summer of 2008 in 23 community colleges in Virginia. The researchers found a trend of increasing attrition rates over the 4 years, with a consistent advantage of the traditional format over the online format in terms of course persistence as well as end of course grade. Building on their study, Xu and Jaggars (2013) used a large administrative dataset from Washington State's community and technical college system. This dataset included 125,218 course enrollments by18,567 students who initially enrolled in one of Washington State's 34 two-year public community or technical colleges during the fall term of 2004 through the summer of 2009. The researchers found that the online format had a significant negative impact on both course persistence and course grade.

Specifically, they concluded that if a student enrolls in an online class, their likelihood of persisting to the end of the course decreases by 7 percentage points. For those students who do persist through their online courses, their final grade would decrease by more than 0.3 points.

As a result of the higher dropout rate witnessed in online courses compared to traditional classes, a significant number of studies have been conducted to identify factors related to successful completion of online programs. In his review of the literature, Park (2007) reviewed dropout research in distance learning in an attempt to identify major factors that can explain dropout of nontraditional adult distance learners. Park used the keywords persistence, dropout, attrition, stopout, and retention as well as distance learning, e-learning, and online learning to identify relevant studies in three major databases: ERIC, EBSCO, and PsychINFO, published from 1987 to 2006. Out of the 93 studies initially located, 18 unique studies focused on identifying factors related to persistence of nontraditional online learners. These studies were reviewed based on Rovai's persistence model (2003) and the factors identified from the literature were categorized into student characteristics prior to class, student prior skills, external factors, and internal factors.

Studies investigating students' characteristics found mixed results. While some studies found variables such as age, ethnicity, gender, employment status, and socioeconomic status to be significant predictors of learners' decisions to persist or dropout, other studies concluded that such a decision is more complex and these variables only indirectly have an impact on dropout through social and academic variables.

Students' prior skills such as prior online class experience, literacy, academic profile, study skills, and time management skills have also been examined in these studies. However, Park concludes that there is little empirical support in previous studies for the significance of these factors on student persistence and further investigation of these factors is needed. External factors such as time conflict, family issue, financial problem, employment status, and managerial support have been identified and investigated. These factors have been deemed most important in terms of factors influencing nontraditional students' persistence, with time conflict being the most frequently cited factor. Finally, internal factors such as course design issues and learners' motivation have been identified by previous research as factors influencing learners' persistence in online programs. In terms of course design, factors such as course workload, technical difficulties, lack of interaction with instructors, and peers have been found to play an important role in the decisions of dropout. Motivational factors have also been deemed critical. These factors include learners' satisfaction, high task value, and interest.

Lee and Choi (2011) reviewed the existing empirical studies in peer-reviewed journals on online course dropouts in postsecondary education that were published between 1999 and 2009. A total of 35 empirical studies were selected for inclusion in this review. These studies were found in Education Research Complete, ERIC, and PsycINFO using several keywords such as dropout, retention, persistence, attrition, withdrawal, and online. Studies that were excluded were those pertaining to online K-12 classes, nonempirical papers, studies that were not peer reviewed, or studies that investigated demographic characteristics, such as age, gender, or marital status because of the incompatibility of the findings in many studies regarding the relationship between these variables and persistence online. Ultimately, 44 factors were identified and grouped into nine factors using the constant comparative method: (a) academic background, (b) relevant experiences, (c) skills, (d) psychological attributes, (e) course design, (f) institutional support, (g) interactions, (h) work commitment, and (i) supportive environment. These nine categories were then grouped into three main sections: (a) student factors, (b) course/program factors, and (c) environmental factors.

Student factors included those related to academic background, relevant experiences, relevant skills, and psychological attributes. For the academic background factor, studies reviewed showed a significant negative correlation between academic performance and dropout rates. Academic performance in these studies was measured either by high school GPAs and math SAT scores, number of courses completed, and previous GPAs. Further, previous relevant experiences, whether it be experience with online courses or the content of the course, has been shown to be a significant predictor of learner persistence in online courses. Students' management and computer skills were also identified as critical factors in learners' decisions to drop out. The specific variables investigated in these studies included the ability to estimate the time and effort required for a task, to manage time effectively, to balance multiple roles, and to cope with difficulties during courses, Internet searching, file management, and Internet applications. Finally, students' psychological attributes were the most frequently examined category of student factors and included variables such as locus of control, motivation, self-efficacy, satisfaction with courses and instruction, and confidence—all of which have been found to be significant factors related to learners' persistence in online courses.

As for the program/course factors, three subcategories were identified: course design, institutional support, and interactions. Course design variables that were found to be significant predictors of students' persistence included interactivity, overall quality, and relevance to students' needs and learning style. Institutional support (e.g. online tutorials, web-based orientation sessions, and online advisor counseling) has also been found to influence learners' decision to drop out in online courses. Further, learners' interactions with peers, faculty, and content have also been examined in relation to persistence in online courses. While peer interaction in the studies reviewed did not indicate a significant relationship with course completion, learners' interaction with faculty (e.g. immediate feedback, support for struggling learners, and participation in social class activities) as well as frequency and duration of interaction with course content did. The last category of factors, environmental factors, included two subcategories: work commitments and supportive study environments. Review of the studies indicates that full-time employee or changes in student's work responsibilities seemed to negatively influence their chances of completing a course. In addition, students who receive support from family, friends, and employees as well as have comfortable circumstances in which to study were more likely to persist and complete an online course.

Persistence research in MOOCs. The relatively low completion rate of MOOC participants has been a central criticism in the popular discourse (Balakrishnan &

Coetzee, 2013; Jordan, 2013, 2015; Reich, 2014), with completion rates often falling below 10% (Breslow et al., 2013; Hollands & Tirthali, 2014). Even though recent reports on MOOC participants indicate that course completion is not one of the main goals for registering for a MOOC, that does not necessarily mean that all those who do drop out do so because they have achieved their individual goals. Rather, there is a consistent pattern of dropout behavior throughout MOOCs, which indicates that some participants are losing the will and motivation for reasons that might be internal to the learner or the course itself (Balakrishnan & Coetzee, 2013). Furthermore, current studies show that even though participants who indicate an intent to complete a course are more likely to do so, the majority of them still drop out before completing the course or earning a certificate (Gütl, Rizzardini, Chang, & Morales, 2014; Riech, 2014). Studies that have been conducted to examine the high dropout rates in MOOCs suggest that initial participant motivation and online design features that support SRL processes may matter for persistence and retention in MOOCs (Cisel, 2014; Kop & Fornier, 2010; Kop et al., 2011; Nawrot & Doucet, 2014; Wang & Baker, 2015). Some preliminary results from current research on factors related to low persistence rates and some strategies that can be gleaned from the literature to help mitigate this problem are presented.

One of the extensive studies that have been conducted in this area includes the work of Adamopoulos (2013). In order to identify important factors that impact completion rate in a MOOC and estimate their relative effect, the author employed Grounded Theory Method (GTM) on quantitative data that integrates econometric, text mining, opinion mining, and predictive modeling techniques toward a more complete analysis of the information captured by user-generated content. In this study, the author collected qualitative and quantitative data on 133 MOOCs offered by 30 universities and 6 providers including Canvas Network, Codecademy, Coursera, edX, Udacity, and Venture Lab. Furthermore, 1,163 textual reviews submitted online to CourseTalk.org by 842 students who participated in at least 1 course were collected and analyzed. Lastly, additional data related to students, the platform where the course is hosted, the university which offers the course (i.e. the ranking for the academic discipline of each course offered), and the course itself (i.e. estimated workload, duration, assessment, certification) were included in the analysis. The dependent variable was self-reported progress of each student in each course and was coded as follows: Course Not Completed (i.e. dropped), Course Partially Completed (e.g. complete 70% of the course or complete the course without submitting the assignments), and Course Successfully Completed. These data were collected in order to identify important features that determine students' satisfaction and completion in MOOCs.

Using data and opinion mining and natural language processing techniques, the researcher mined MOOC features that students have commented on in their review of the course, identified opinion sentences and words in each review, and estimated the corresponding sentiment score for each feature by assigning a negative or a positive to each opinion sentence. Following the GTM and the triangulation of data, the following categories emerged as being related to students' satisfaction and retention in MOOCs: student course evaluation (e.g. evaluation of professor and course material), course characteristics (e.g. difficulty, discipline), university characteristics (e.g. ranking), platform characteristics (e.g. usability), and student characteristics (e.g. gender). In order to examine the importance of each factor in student retention in MOOCs, explanatory econometric analysis using an ordered choice model was employed. The analysis revealed that the variable Professor had the largest significant effect (0.39, $p < 0.1$) on the probability of students completing the MOOC successfully. Furthermore, the more satisfied the students are with the course material and assignments the more probable that they will complete the course successfully. On the other hand, course difficulty, course workload, and duration in weeks all had negative effect on student retention. Furthermore, the analysis revealed that self-paced MOOCs compared to courses that have specific timetables and deadlines had a negative effect, while peer assessment had a positive effect compared to automated feedback. Finally, the results suggest that the likelihood of dropping a MOOC also depends on the academic discipline and team project but not on student demographics.

In another attempt to understand completion and persistence in MOOCs, Balakrishnan and Coetzee (2013) examined factors that affect participants' dropout rates along the way in order to motivate the development of interventions to increase engagement and improve retention. In this study, the researchers focused on student behavior in an edX MOOC that was offered in the fall of 2012 and examined their actions in the course from week to week in order to predict drop out behavior using the Hidden Marvok Models (HMM). This course was edX's offering of UC Berkeley's CS169.1x - Software as a Service course with 29,882 participants.

To build this predictive model, the researchers identified several independent MOOC features and assigned each student a score every week for each of these features. Features included student "in/out" state, percentage of lecture videos watched, number of forum threads viewed, number of forum threads posted, and the number of times the course progress page was checked. The data analyzed in this study included clickstream data, assignment grades, and forum threads and comments. The researchers found that learners who checked their progress four or more times a week were far less likely to drop out of the course compared to those who rarely or stopped checking their progress.

Another study that explored the problem of high dropout rates in MOOCs was conducted by Nawrot and Doucet (2014). In order to investigate MOOC participants' withdrawal reasons and the rate of occurrence of each reason, an online survey was distributed to 508 participants who were recruited via a crowdsourcing platform. The online survey solicited information about demographics, MOOC experience, and the reason for MOOC dropout. Although participants were provided with 12 sample reasons adapted from other studies (i.e. Adamopoulos, 2013), they were encouraged to provide other reasons for their decision to withdraw from the MOOC. The analysis revealed that the main reason for the high MOOC withdrawal rate is lack of time management, which was indicated by as much as 68.9% of the survey participants. Other significant factors influencing participants' MOOC dropout decisions were mainly related to the difficulty, attractiveness, and suitability of the course.

Nawrot and Doucet (2014) argue that a high level of self-discipline, including time management skills, is necessary for successful completion of a MOOC because learners are expected to become managers of their own learning in such environments. Based on the results of this study, the authors suggest that in order to optimize the learning process, increase learner engagement, and decrease dropout rates, MOOCs must be designed in a way that supports time management and metacognitive skills. Some MOOC design recommendations provided by the authors include the need to account for different levels of time management by permitting the gradual development and modification of schedules, priorities, and goals. Furthermore, MOOC platforms should personalize action plans by identifying the necessary activities and subprocesses, with an assigned time budget for each task, based on users' profiles and specific goals. Moreover, the authors assert that MOOC platforms should particularly account for the analysis of students' life cycles and for the support of probabilistic queries by computing and visualizing the probability of meeting deadlines and the impact of different what-if scenarios such as adjusting the schedule if 1 day was lost due to external circumstance. Finally, MOOC platforms could provide users with tips on effective learning environment organization and offer support for personal knowledge management.

Similarly, Gütl et al. (2014) used an online survey soliciting information about dropout reasons in a 4-week MOOC focusing on the topic of e-learning. In order to uncover learners' motivation for enrolling in the MOOC, the reasons for leaving the MOOC, and how students organized (when and where) to work on the MOOC, MOOC participants were asked to fill out two surveys, a precourse survey to gather demographic information and learning preferences, and a postcourse survey. There were two versions of the postcourse survey, one sent out to participants who had completed the MOOC to evaluate their overall experience and another one sent out to the group of students who did not complete the MOOC to investigate personal, academic, help, and support reasons for dropping out. For both groups, the following instruments were used: Computer Emotions Scale (CES) (Kay & Loverock, 2008), Intrinsic Motivations Measure (IMM) (Tseng & Tsai, 2010), and the System Usability Scale (SUS) (Brooke, 1996). Out of the 1,680 participants who enrolled in this MOOC, only 8.5% completed it, all of whom responded to the postcourse survey.

As for 91.5% who did not finish the course, only 134 responded to the postcourse survey focusing on dropout aspects. Out of those 134 participants, 51.49% were male and 48.51% were female with ages ranging from 17 to 63 years. Only 37% of those participants reported having previous MOOC experiences. The majority (33.58%) indicated the reason to enroll in the MOOC was to experience MOOCs, which is not surprising given that over 60% of respondents had never participated in MOOCs prior to this one. This was followed by an intention to complete the course (22.39%), to take a sneak preview into the topic (17.92%), a desire to learn without formally completing the course (8.96%), and interest in the content (3.73%). A number of users also indicated "other" reasons for participating such as learning about methodology and for professional reasons.

Personal reasons for not completing the MOOC included issues related to job changes, health problems, and family responsibility. Further, 13.43% indicated that the MOOC did not meet their expectations. In terms of academic reasons for not completing the MOOC, the majority (70.15%) indicated that it was difficult to work and study at the same time followed by their lack of technical preparation for the MOOC (14.93%). Other reasons included “academic program too difficult/demanding,” “program was not challenging,” “classes were poorly taught,” “course was poorly created,” and finally “not academically prepared for this program.” Support and help reasons for dropping out of the MOOC included the lack of encouragement/support to continue from family or employer (35.82) followed by poor feedback on assignments and tests (32.09%), lack of training to use the technologies required in the MOOC (22.39%), and the lack of support from the MOOC technical staff (17.91%). Finally, the learning environment reasons for dropping out included issues such as little interaction with other students (28.36%), little interaction with the instructors (24.63%), and the lack of personalization (14.93%). However, the most selected category was “Other” (32.84%) and included responses such as “too many forums which caused confusion” and “lengthy and boring videos.”

Participants who dropped out were also asked to specify the time they allocated to work on the MOOC. Almost half of the participants did not allocate more than 1 to 2 hours and only 11.19% spent 5 hours or more studying the course each week. When asked about where they worked on MOOC content, 50.75% of participants indicated “at home after work,” 11.19% worked on the course “during lunch time,” and 10.45% allocated time “at work.” Other locations provided by participants included “at work and home,” “at night,” or “did not have time.” Finally, in an open-ended section of the survey, participants mentioned the lack of monitoring and feedback from tutors, participation in forums, and the effort required to master activities as some of the issues they did not like about the MOOC. They also indicated their need to improve their overall effort to be able to succeed in the MOOC as evident in their comments regarding the need for "discipline," "focus," "time management and planning," and "active communication" in order to complete a MOOC.

To examine differences between completers and noncompleters, survey data examining perception of learning activities and intrinsic motivation were analyzed and compared. The perception of learning activities items included items regarding participants' ability to plan the learning activities, whether they had fun doing the learning activities, whether the time spent was appropriate given their progress, and if they think they needed more information to complete the learning activities. The perception on all items was better for the group who completed the MOOC than it was for the group that did not. To measure intrinsic motivation, data regarding participants' motivational attitude about learning a new set of tools, utilizing the tools to finish the learning tasks, and reflecting on knowledge gained from completing the learning activities using different tools was collected. The findings reveal no difference between groups as they both showed high intrinsic motivation except for the item about learning to use new tools in which the dropout group showed less motivation.

In a more recent study by Loya, Gopal, Shukla, Jermann, and Tormey (2015), the researchers examined how 27,993 students who participated in the Introduction to Programming in SCALA course offered on the Coursera platform in 2012 managed the flexibility of learning in MOOCs by assessing the relationship between conscientious behavior and MOOC completion rates. Conscientiousness is used in the literature to describe people's dispositions to act in different aspects of their life (not just in learning) and is regarded as being relatively stable over time (Maltby, Day, & Macaskill, 2007) and includes features like organization, self-discipline, metacognition, thoroughness, and reliability. In this study, the authors examined whether conscientiousness or metacognition, as measured through observations of learning practices that show evidence of planning, organization, self-discipline and reliability, was associated with dropout rates in the MOOC. Participants in this MOOC were considered “completers” if they had submitted all required assignments (the total number of assignments required was seven) or submitted assignments for at least the first 5 weeks and had also watched at least 6 weeks of lecture videos. Conscientiousness (i.e. showing evidence of planning, organization, self-discipline, and reliability) was measured by calculating a regularity index. Participants who typically watched or downloaded a video on the same day every week had a regularity index of 1 while those who watched videos on a range of different days scored 0 on the regularity index.

Using Coursera course data, Loya et al. (2015) found that only 9.1% of those who did not have a regular day for first watching the videos (regularity score of 0) completed the course compared to over 90% of those with a regularity score of .57 or higher. This shows clear association between regularity score and completion, indicating that those who are more regular in their study habits are more likely to complete the course than those who are less regular. The authors argue that this finding challenges the notion that MOOCs are more suited to participants who are flexible in their approach to learning as it shows clear evidence that those participants who have a learning plan and stick to it are more likely to complete a MOOC. Based on the results of this study, the authors suggest that MOOCs might be an appropriate platform to not just help people learn, but also help them learn how to learn by providing opportunities for learners to plan for learning, reflect on their plan, and review performance at the end.

Wang and Baker (2015) argue that factors influencing MOOC completion cannot be fully understood by analyzing interaction data without investigating the motivation that underlies their decisions to persist or dropout of a MOOC. Consequently, the researchers examined the relationship between a number of motivational measures and MOOC completion in the Big Data in Education MOOC delivered on the Coursera platform. Completion in this study was measured according to the pace and expectations set by the instructor, which was earning a final grade average of 70% or higher. This grade was calculated by averaging the 6 highest grades extracted out of a total of 8 weekly assignments. To examine learners' motivation, participants were asked to fill out a precourse survey that measured three motivational constructs, MOOC-specific items, and two subscales from the Patterns of Adaptive Learning Survey (PALS) measuring mastery-goal orientation and academic efficacy (Midgley et al., 2000). In addition, an item measuring confidence in completing the MOOC was included. The MOOC-specific items asked participants to rate their reasons for enrollment and included items related to the MOOC content (e.g. extending current knowledge of the topic) and features of MOOC as a new platform (e.g. curious to take an online course). A total of 2,792 out of 48,000 MOOC participants responded to the precourse survey. Over half of the respondents were male (62%) among which 9% were between 18 to 24 years old, 38%

were between 25 to 34, 26% were between 35 to 44, 17% were between 45 to 54, 8% were between 55 to 64, and 1% were 65 or older.

Using two-sample independent *t* tests, Wang and Baker (2015) found that students who were motivated by the opportunities of online courses and/or MOOCs as opposed to MOOC content were less likely to complete this MOOC. The two PALS subscales measuring mastery-goal orientation and academic efficacy were tested at scale-level averages and individual items. No significant difference in both motivational constructs was found between completers and noncompleters at the scale level. However, when examined at the item level, only one item, "I'm certain I can master the skills taught in class this year," had a statistically significant difference between groups. Lastly, using a single-item measure, learners were asked to self-rate their confidence in completing the MOOC according to the pace set by the instructor. Analysis of this item revealed that respondents who completed the course self-rated higher than those who did not complete the course. The researchers hypothesize that the absence of significant differences between completers and noncompleters in terms of mastery-goal orientation and academic efficacy could be attributed to several reasons. Given the lack of formal credit in MOOCs, the researchers suggest that the concept of course completion as defined in this study might have a different meaning in a MOOC context. The lack of tangible rewards also suggests that most students come to the MOOC with mastery goals. As for the finding for academic efficacy, the researchers propose that the items used to measure this construct were too general to capture domain-specific differences.

The studies reviewed up to this point reveal one common problem among MOOCs: their low completion rates. However, it is important to note that these studies examine retention and persistence in terms of MOOC completion. Some researchers argue that measuring persistence and retention in the traditional sense (i.e. the fraction of total number of MOOC registrants who earned a certificate or completed a course) is misleading, as it does not take into account participants' intention and goals for registering for a MOOC. They suggest that using retention-based metrics with those learners whose explicit goal is to complete the MOOC, or by defining persistence in relation to individual goals for participating in a MOOC, might provide a more accurate picture for which the problem of attrition in MOOCs could be examined (DeBoer et al., 2014; Ho et al., 2014; Koller et al., 2013, Reich, 2014; Wang & Baker, 2015). MOOC participants share this perspective as well. Liyanagunawardena et al. (2014) explored MOOC participants' views on what dropout means to them in the context of a MOOC. Six participants between the ages of 36 and 55 were interviewed using a semistructured interview protocol. In total, the 6 participants have registered in 27 MOOCs (ranging between 1 to 7) and have participated in 21 MOOCs (ranging between 1 to 6). Participants challenged the traditional definition of dropout, arguing that given the voluntary nature of participating in MOOCs, it is more about failing to achieve their personal goals. For instance, two participants explained that if a participant is still engaging with the content or plans on returning to the resources at a more convenient time they should not be considered dropouts regardless of quiz and assignment deadlines. Another participant argued that some people join MOOCs to learn a specific topic or skill and are not necessarily interested in the whole offering. According to this participant, the timing of last interaction with the MOOC is irrelevant if a person was able to learn something and reach their personal goals. This is consistent with what was found in the qualitative study reported previously by Zheng et al. (2015). Zheng et al. (2015) found that participants were not in agreement as to what counts as completing a MOOC. While some were disappointed that they did not complete all activities, others were satisfied with their learning once their specific learning goals were reached even when they did not complete the MOOC. Based on their analysis, the researchers concluded that meaningful learning is not defined by time in the course or completion, but rather by each participant's learning goals. However, the extent to which they are able to achieve those goals is influenced by retention-related factors such as lack of time, high workload, and challenging course content.

In an effort to examine course completion rates in a contextualized manner that takes into account the variation in participants' goals and patterns of behavioral engagement, a group of edX researchers (Ho et al., 2015) analyzed data from nine HarvardX courses in an attempt to answer the following questions: (a) across multiple courses, what are the completion rates of students who intend to complete a course compared with other students? And, (b) what are patterns of attrition among students who intend to complete a course compared with other students?

EdX courses utilize a common precourse survey that probes students in four dimensions including intention (how much of the course they intended to complete), motivation (reasons for enrolling in the MOOC), preparedness (familiarity with the course content and with online learning in general), and finally demographic characteristics (year of birth, gender, educational level, English fluency, and country of residence). The measures included in this study were students' self-report intentions for registering for the MOOC, student demographics, and course completion computed from course event log. The precourse survey item asking students about their intention was "People register for HarvardX courses for different reasons, which of the following best describes you?" and they were given 4 choices: (a) here to browse the materials, but not planning on completing any course activities, coded as Browse; (b) planning on completing some course activities, but not planning on earning a certificate, coded as Audit; (c) planning on completing enough course activities to earn a certificate, coded as Complete; and (d) have not decided whether I will complete any course activities, coded as Unsure. A total of 290,606 registrants and 79,525 survey responses were included in the final analysis. Based on students' responses to the presurvey, 56% indicated an intention to complete the course, 26% indicated an intention to audit the course, 3% indicated an intent to browse the course, and 15% were unsure.

Using logistic regression, Ho et al. (2015) found that a student's stated intention is a stronger predictor of course completion than any demographic predictors. In addition, the researchers found that even though certification rates among those who intended to complete the course were higher than for students with other intentions and higher than the rate for all students in the course, the majority of them were still not successful in doing so. In numerical terms, while a student who intends to earn a certificate is 4.5 times more likely to do so than a student who intends to browse a course and 3.5 times more likely to do so than a student who intends to audit a course, only 22% of those who intended to complete went on to earn a certificate. Another major and interesting finding of this study is the number of survey respondents who did not intend to complete a course but went on to complete it. In this sample and on average across courses, 6% of intended-browsers, 7.5% of intended-auditors, and 10% of students with unsure commitments to the course earned a certificate. The authors suggest that this finding adds to our understanding about the relationship between intention and MOOC completion as it might be an indication that participants who express any intention at all and put in the effort to complete a voluntary precourse survey are more likely to complete a MOOC than those who do not even attempt to complete the precourse survey. In terms of completion differences among the four groups, the researchers found that completion patterns among students with different levels of stated intention held across all stated intention groups, as attrition was very high early in courses, and soon levels out at a relatively low level. Finally, learners who expressed any intention at all regardless of whether they intended to complete the course or not were more likely to complete the MOOC than those who do not complete a precourse survey. Across all nine MOOCs, the average completion rate for all participants was 6% compared to 16.5% for survey respondents regardless of their stated intention. This finding highlights the importance of goal setting and its potential in illuminating our understanding of persistence in MOOCs.

Ho et al.'s (2015) study has major implications for MOOC research, especially in terms of understanding completion rates and how instructional designers can use that information to improve MOOC design and support learners' persistence in MOOCs. The researchers argue that the finding that students who enroll in a MOOC with the goal of completing it do so at much higher rates than students who do not can serve as a useful benchmark to examine a MOOC's success. However, while students who intended to complete a MOOC were more likely to do so, there were many students with other stated intentions who went on to complete the course. In addition, attrition rates were highest during the early days of the course among all intention groups. Based on these findings, the authors caution instructional designers when developing adaptive or personalized approaches based on students' initial intentions as these intentions might change, but rather focus their efforts on building community and supporting learners' engagement in the early days of a MOOC when attrition is highest. Finally, the researchers emphasize the need to delineate the different reasons for why learners drop out of MOOCs because different reasons require different instructional approaches. For instance, for those learners who opt to drop out because of other life commitments, design intervention or support for specific learning skills is not necessary or useful.

In a similar attempt, Woodgate, Macleod, Scott, and Haywood (2015) sought to investigate persistence as it relates to MOOC participants' personal goals. Specifically, they investigated whether learners who indicated an intent to achieve a Statement of Accomplishment (SoA) were able to do so, and whether learners who did persist in the MOOCs and gained SoAs exhibited different behaviors in terms of their use of the online features and tools of the MOOC platform. The data used were obtained from the first six of the University of Edinburgh MOOCs that were offered on the Coursera platform and covered different subjects such as Education and Digital Culture, Equine Nutrition, and

Introduction to Philosophy. Two sources of data were used in this study including a precourse survey that solicited information regarding learners' demographics and intentions to earn a SoA as well as interaction data with the MOOC platform such as watching lectures, reading and posting to forums, taking quizzes, and engaging in peer-assessment activities.

The researchers found evidence of age-related difference between intent to earn a SoA and outcome. Learners who were 24 years old and younger had the highest intention to gain an SoA but less than half of them actually reached that goal. In contrast, for participants 55 years old and older, the number of participants who earned an SoA was higher than the number who indicated an intent to earn one. The researchers also explored the differences in behaviors between those who achieved an SoA and those who did not. They found SoA achievers to be active autonomous learners who were motivated to take advantage of all educational opportunities presented to them in the MOOC, while learners who did not achieve SoAs were more passive in their interactions with the content. For instance, those who did not achieve an SoA watched videos and did some quizzes, but their engagement with the forums or peer assessment activities was minimal. When it comes to engagement with forums, over 70% of non-SoA achievers never read a single forum post compared to 85% of SoA achievers who did so. However, when it came to posting to the forum, less than half of the SoA achievers posted at least once to the forum. This, according to the researchers, might be indicative of participants' preferred learning style as they would rather engage in individual rather than social activities.

Alraimi, Zo, and Ciganek (2015) conducted a survey study with 316 users of 3 major US-based MOOC platforms (Coursera, edX, and Udacity) to identify factors that enhance an individual's intention to continue using MOOCs using the Expectation-Confirmation Theory (ECT) (Oliver, 1980) that had originally been used in the marketing literature to explain consumer satisfaction and purchase behavior. According to this theory, postpurchase satisfaction is influenced by expectations and perceived performance, which can lead to confirmation (i.e. product or service meets consumer expectations), negative disconfirmation (i.e. product or service does not meet expectations), or positive disconfirmation (i.e. product or service exceeds expectations). Seven constructs were examined in this study: MOOC continuance intention, motivation as measured by perceived usefulness (extrinsic motivation) and perceived enjoyment and satisfaction (intrinsic motivation), perceived reputation, perceived openness, and confirmation. Perceived openness of the MOOC and reputation of the MOOC instructors and universities have been added to the model because they are inherent features of MOOCs that have either been implied or overlooked by MOOC research according to the authors. A total of 316 responses from users of three main MOOC platforms (Coursera, edX, and Udacity) were included in the final analysis of the model proposed using Partial Least Squares (PLS). The research model explained 64.4% of the variance for the intention to continue using MOOCs and was significantly influenced by perceived reputation, perceived openness, perceived usefulness, perceived enjoyment, and user satisfaction.

It is important to note that the outcome variable used in the study conducted by Alraimi et al. (2015) is intention to use MOOCs rather than actual completion of MOOCs, which was considered to be a limitation by Hone and El Said (2016). Consequently, Hone and El Said tested a model that affected learners' retention in MOOCs rather than intention to continue using MOOCs; however, their model included factors pertaining to learners' perception of MOOC features and how they influence their experiences including experiences with MOOC instructors, other students, and MOOC design and content. Different scales were adapted to measure instructor, colearners, and MOOC design and implementation perceptions. Instructor effects in this study included instructor-learner interaction, instructor support, and instructor feedback. Colearner effects included learner-learner interaction. MOOC design and implementation effects included course content, course structure, and information delivery technology. For the outcome variable, a self-report measure of learner retention using three items asking about when they dropped out, how much of the assignments/assessments they completed, and how many content/video they watched was created and used alongside a categorical measure of whether the MOOC had been completed to earn a credential.

The sample for this study was drawn from a student population at two higher education institutions in Cairo, Egypt. Those students were invited to participate in MOOCs as an optional self-learning element in their formal studies. Those participants who agreed to participate in this study engaged with MOOCs offered on different platforms such as edX and FutureLearn. A total of 376 out of the 486 who initially agreed to participate were retained in the final sample. Based on the exploratory factor analysis of the different constructs included, only three were significant and thus retained in the final model: course content, instructor-learner interaction, and perceived effectiveness. This revised model overall explained 79% of the variance in learner retention. In this study, no effects were found for the type of MOOC platform or participants' demographics on retention. Finally, participants' responses to open-ended questions revealed several themes. For instance, participants who completed the MOOC provided positive comments regarding the content of the course such as its practicality and relevance while noncompleters discussed negative issues related to the content such as it being too complex or boring. Interaction in the MOOC was also a theme that emerged among noncompleters as they discussed feeling isolated with poor communication and interaction with instructors and peers.

The purpose of this section was to provide an overview of current state of research on persistence and retention in MOOCs. While none of these studies employed SRL as a framework to examine persistence in MOOCs, they do highlight the importance of participants' positive motivational beliefs and ability to self-manage and regulate their own learning and behaviors in order to succeed and persist in MOOCs, which is not surprising given the nature and scalability of these courses. These factors include learners' level of self-discipline and skills related to self-regulated learning such as time management (Balakrishnan & Coetzee, 2013; Gütl et al., 2014; Loya et al., 2015; Nawrot & Doucet, 2014), peer learning and interaction (Adamopoulos, 2013; Alraimi et al., 2015; Gütl et al., 2014; Woodgate et al., 2015), effort regulation (Gütl et al., 2014; Hone & El Said, 2016), and help seeking (Gütl et al., 2014). Further, in terms of motivational beliefs, these studies have consistently found that the perceived value of MOOC learning tasks related to participants' persistence (Alraimi et al., 2015; Hone & El Said, 2016). However, the findings regarding goal orientation and self-efficacy were not as expected and could be attributed to several reasons. First, the outcome variable used in these studies was not based on participants' goals for joining the MOOC but was rather operationalized by the authors, bringing into question the validity of these findings. Another issue could be related to the instruments used. For instance, Wang and Baker (2015) attribute the lack of difference in self-efficacy to the instrument used as it may have been too general to detect differences between completers and noncompleters. Finally, earlier studies utilizing the social-cognitive framework of SRL in traditional learning contexts show the mediational role that motivational beliefs such as self-efficacy play in motivating persistence and academic achievement (Multon et al., 1991). Consequently, examining the relationship between motivational beliefs and SRL behavior and skills in this new context might bring forward some insights regarding the relationship between such beliefs and persistence in MOOCs. In the following section, a review of the social-cognitive model of SRL that acknowledges the cyclical nature of SRL where motivational beliefs influence learners' adoption of SRL strategies and cognitive and metacognitive processes during different phases of learning tasks is presented (Cleary et al., 2012; Pintrich, 2000a; Schunk, 2005; Zimmerman, 2011).

Self-Regulated Learning (SRL): Models

The role of Self-Regulated Learning (SRL) to promote student engagement and academic achievement has been well researched. As a result, different definitions and frameworks of SRL processes and design strategies have been proposed by researchers reflecting different theoretical orientations (Cho, 2004; Efklides, 2011; Kitsantas & Dabbagh, 2010; Pintrich, 1995; Puustinen & Pulkkinen, 2001; Zimmerman, 1990, 2008). SRL is viewed as a proactive process that a learner engages in either personally (e.g., setting goals and selecting learning strategies), or socially (e.g., seeking help from peers and/or experts) to progress and acquire academic skills (Zimmerman, 2008). From a behavioral science perspective, SRL involves setting up one's own stimuli and the consequences of their response, and the research focus from that perspective is on the behavioral responses of learners to environmental stimuli such as self-reinforcement (Schunk, 1996). For cognitive researchers however, SRL involves more than overt responses, it involves internal mental activities such as rehearsal and learning strategies. These activities are a result of different cognitive processes such as motivation, self-efficacy, and choice. Choice is particularly important because the less choice a learner has, the more likely that the learning is externally regulated as opposed to self-regulated (Schunk, 1996; Zimmerman, 1990). These views of SRL had their limitations. For instance, learners who were taught the use of SRL strategies rarely transferred what they had learned to new tasks (Pressley & McCormick, 1995). This suggests that mere awareness of the effectiveness of these strategies is not sufficient but rather other motivational aspects (e.g. lack of enjoyment and poor tradeoff between gains and effort) should be considered in learners' decision to apply these strategies (Zimmerman & Schunk, 2011). More recently, a different conceptualization of how SRL is attained and utilized was developed within the social-cognitive theory framework. This perspective not only views SRL as being internally and behaviorally derived, but also considers other sources of motivation (i.e. self-efficacy) and emphasizes the simultaneous influence and interactions of social and contextual factors (i.e. help seeking and feedback) on learners' adoption of SRL processes (Kitsantas & Dabbagh, 2010; Pintrich, 2000a, 2004; Schunk, 2005; Zimmerman & Schunk, 2011). The social-cognitive perspective of SRL has been defined as, "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features of the environment" (Pintrich, 2000a, p. 453). Under this view, SRL is a multidimensional process rather than an aptitude or a personality trait and thus varies depending on environmental characteristics and demands, learning tasks, and contexts in which individuals learn (Cleary et al., 2012; Pintrich, 2000a). Furthermore, this contextualized model integrates SRL processes and key motivational beliefs in a single model in which skills and will become integrated and interdependent processes of SRL that cannot be fully understood apart from each other (Pintrich, 2000a; Pintrich & De Groot, 1990; Schunk, 2005; Zimmerman, 1990, 2000a). Hence, using this model as a framework for exploring participants' learning experiences in MOOCs can provide valuable insights about the beliefs and attributions that drive motivation and influence behavior and persistence in this new learning context.

The social-cognitive model of SRL. A number of closely related models that are based on this view have been developed such as Zimmerman's (2000a) and Pintrich's (2000a, 2004) models. Both models acknowledge the cyclical nature of SRL where motivational beliefs and contextual factors influence learners' behaviors and adoption of cognitive and metacognitive processes during different phases of the learning task and across tasks. According to Zimmerman's (2000a) three-phase cyclical model, self-regulated learning is defined as self-generated thoughts, feelings, and behaviors that are planned and cyclically adapted based on performance feedback in order to attain self-set goals. Under this view, all learners exhibit SRL skills in varying degrees, however, what distinguishes highly self-regulated learners is that they are consciously aware of the relations between the different SRL processes and learning goals and they are motivated to apply those processes in order to achieve these goals (Zimmerman & Schunk, 2007). For example, learners who possess a high degree of SRL skills are able to transform their mental abilities (e.g. verbal aptitude) into an academic performance skill (e.g. writing) (Zimmerman, 2008). Zimmerman's three-phase self-regulated learning model represents the cyclical nature of SRL and consists of three distinct phases in which the different processes are applied. The contextualized cyclical process of SRL involves three sequential phases: forethought phase (i.e. processes and motivational beliefs that proceed efforts to learn), performance phase (i.e. processes that occur during the learning task), and self-reflection phase (i.e. processes and motivational beliefs that occur after completing the learning task). Within each of these phases, different metacognitive processes, motivational beliefs and feelings, and learner behavior are represented. During the forethought phase, the learner sets the stage for the task by setting personal goals and strategic plans to accomplish those goals. During the performance phase, learners implement the plans set in the forethought phase and keep track of their learning progress by employing different observation and control strategies such as attention focusing, task strategies, help seeking, metacognitive monitoring, and self-recording. The final phase of the model, self-reflection, occurs after the learning task has been completed. During this phase, learners self-evaluate their performance relative to self-set standards, reflect on the reason for this level of performance, and decide whether there is a need to modify their learning strategies during the following learning attempt to improve learning. Within each of these phases, different motivational beliefs/feelings interact with each other as well as with other metacognitive processes within this integrative model. These sources of motivation include goal orientation, self-efficacy, task value and interest, satisfaction, and causal attribution. These motivational constructs not only play a vital role in initiating and sustaining learners' efforts to self-regulate their learning, but also increase learners' attention, effort, and persistence on time-consuming and difficult learning tasks (Cleary et al., 2012; Cleary et al., 2014; Wang, Shannon, & Ross, 2013).

Pintrich (2000a, 2004) adopts a four-phase model. These phases include: the forethought, planning, and activation phase (i.e. planning, goal setting, and activation of perceptions and knowledge of the task, context, and self in relation to the task); monitoring phase (i.e. metacognitive awareness of different aspects of the self, task, and context); control phase (i.e. efforts to control and regulate different aspects of the self, task, and context); and reaction and reflection phase (i.e. reactions and reflections on the self, task, and context). According to Pintrich, the regulation processes in each of these four phases can be applied to four domains: cognition, motivation and affect, behavior, and context. For instance, during the forethought, planning, and activation phase, learners set goals (regulation of cognition), adopt specific goal orientation (regulation of motivation), engage in time and effort planning in preparation for task (i.e. regulation of behavior), and form specific perceptions of task and context (i.e. context regulation). During the monitoring phase, learners evaluate cognitive progress in relation to goals (regulation of cognition), are aware of any decrease/increase in their self-efficacy or the presence of negative effects such as anxiety (regulation of motivation), monitor their effort and need for help (regulation of behavior), and monitor the need to change task conditions (regulation of context). In the control phase, learners engage in the selection of appropriate learning strategies such as elaboration and organizational strategies (regulation of cognition), control their motivation through the use of coping strategies such as self-talk (regulation of motivation), change effort or engage in help-seeking behavior in order to do well and reach goals (regulation of behavior), and change or leave tasks based on outcome in relation to goals (regulation of context). Finally, learners in the reflection phase engage in various SRL processes such as make judgments about the effectiveness of the learning strategies employed (regulation of cognition), reflect on the reasons for the outcome (regulation of motivation), and evaluate and reflect on the task (regulation of context).

Based on this model, the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich et al., 1993), an instrument designed to assess college students' motivational orientations and their use of different learning and behavioral strategies for college courses, was developed. The MSLQ consists of two sections: a motivation section and a learning strategies section. The motivation section consists of 31 items that assess 6 subscales: intrinsic goal orientation, extrinsic goal orientation, task value, control of learning beliefs, self-efficacy for learning and performance, and test anxiety. The learning strategies section includes 50 questions that measure learners' use of cognitive and metacognitive strategies as well as learning resources management strategies. A total of 31 items are related to students' use of different cognitive and metacognitive strategies and divided into 5 subscales: rehearsal, elaboration, organization, critical thinking, and metacognitive self-regulation. The learning resources management subscales contain a total of 19 items and measures time and study environment, effort regulation, peer learning, and help seeking. Scores are derived from the mean of the items comprising the various subscales. There are a total of 81 items scored on a 7-point likert scale, from 1 (*not at all true of me*) to 7 (*very true of me*). The 15 distinct subscales in the MSLQ are designed to be used together or individually.

Clearly, there is an overlap between Zimmerman's (2000a) and Pintrich's (2000a, 2004) SRL models with each adopting slightly different vocabulary (Puustinen & Pulkkinen, 2001). The forethought, planning, and activation as well as the reaction and reflection phases of Pintrich's model align with Zimmerman's forethought and reflection phases. However, Pintrich distinguishes between the monitoring and control processes, which mirror the performance phase processes in Zimmerman's model. Despite these differences, these social-cognitive models of SRL assume a correlation between SRL processes and motivational variables within each of the phases of the model as well as potentially causal influences across the phases. Thus the processes utilized in the forethought phase influence the performance phase, which in turn influences the self-reflection phase. The SRL cycle is completed when self-reflection processes impact forethought processes of future learning tasks. Researchers argue that these models possess several key qualities over other SRL models. First, because these models are context-specific and integrate contextual and motivational aspects of self-regulation, they provide a better framework for understanding not just how SRL happens (i.e. metacognitive and behavioral aspects), but also where (i.e. task and performance context) and why (i.e. self-motivational aspect). Examining self-motivational aspects in relation to SRL processes and skills is particularly important in the context of MOOCs since participants join MOOCs with varying motivations and goals. Furthermore, research presented earlier in this paper has shown that motivational factors such as task value, self-confidence, and motivation play a role in learners' persistence in MOOCs (Milligan et al., 2013). Finally, the temporal sequence of these models reflects the temporal dimension of most learning tasks. Thus, these models can be applied, extended, and customized to virtually any task or performance to understand learner regulation (Cleary et al., 2012).

SRL is thought to be particularly important during personally directed activities such as independent study and self-select reading (Zimmerman, 2008) or in student-centered classrooms where students are expected to have more control over the learning process such as communities of learners classrooms and project-based instruction (Pintrich, 2000a). More recently, this assertion is extended to the context of online learning given the high autonomy needed for effective learning as well as the ability to manage and organize a large volume of information delivered from multiple sources, which can be overwhelming to even the most experienced of learners (Artino, 2009; Dabbagh & Kitsantas, 2004; Schunk & Ushr, 2011). Dabbagh and Kitsantas (2004) contend,

> in a Web-based learning environment, students must exercise a high degree of self- regulatory competence to accomplish their learning goals, whereas in traditional face-to-face classroom settings, the instructor exercises significant control over the learning process and is able to monitor student attention and progress closely. (p. 40)

Accordingly, this study examines the relationship between two components of the social-cognitive model of SRL across different phases of this model: motivational beliefs (goal orientation, online learning self-efficacy, and online learning task value) and behaviors (use of resource management strategies) as well as the relationship between these different SRL processes and one academic outcome (persistence). An overview of constructs specific to this study is provided next.

Motivational beliefs specific to this study. The social-cognitive perspective of SRL acknowledges the role that motivational beliefs play in enacting the behavioral skills needed to self-manage and regulate one's learning (Cleary & Zimmerman, 2012; Pintrich, 2000a; Zimmerman, 2000a, 2000b). This view differs from behavioral views that emphasize a singular trait or ability as well as metacognitive views that focus on knowledge states in that it acknowledges the role that one's beliefs and motives play in enacting SRL behaviors and covert processes as well as the quality of these actions. This perspective of SRL does not view motivational beliefs as a separate area of SRL, but rather different motivational beliefs are infused across different phases and interact with behavioral, contextual, and cognitive factors to affect SRL (Pintrich, 2000a, 2000b; Schunk, 2005; Zimmerman, 2000a, 2000b, 2011). Positive motivational beliefs (i.e. setting mastery goals, holding positive self-efficacy beliefs, and valuing the potential of learning task outcome) increase learners' attention to the learning process and outcome, increase learners' effort to master difficult tasks, as well as increase their persistence on time-consuming tasks such as mastering complex skills (Bandura, 1986, 1997; Wigfield, Klauda, & Cambria, 2011; Zimmerman, 2000b, 2011). There are different sources of enhanced motivation within the social-cognitive view of SRL. Based on the literature reviewed so far, the specific forethought motivational beliefs that will be examined in this study include goal orientation, online learning self-efficacy, and online learning task value.

Goal orientation. Goal orientation refers to the purpose or reason for learner achievement (Pintrich, 2000a; Zimmerman, 2011). According to Pintrich, goal orientation

> represent[s] the idea that achievement goals are not just simple target goals or more general goals, but represent a general orientation to the task that includes a number of related beliefs about purposes, competence, success, ability, effort, errors, and standards. (2000b, p. 94)

For instance, while an individual might state they want to score at least 80% on a given assignment, goal orientation would explain why individuals set that goal, thus reflecting different levels of analysis (Pintrich 2000a, 2000b; Schunk, 2005). In that sense, goal orientation is different from target goals in that it reflects a general reason for why learners set specific achievement tasks as well as the standards and criteria for evaluating their performance and success on the task (Pintrich, 2000b).

Generally, two types of goal orientation have been examined in relation to different outcomes such as self-efficacy, use of SRL strategies, and persistence: performance and learning goals. Performance goal orientation refers to one's judgment of self, ability, and competence relevant to others, while learning goal orientation, also known as mastery goal orientation, refers to goals that focus on the learning task in terms of increasing one's competence and mastery of the task (Pintrich 2000a, 2000b; Zimmerman, 2011). Goal orientation is important due to its motivational influences because it serves as a standard against which learners approach a task and self-evaluate their learning and performance. For instance, individuals exhibiting learning or mastery goal orientation orient their monitoring and evaluation processes to evidence that indicates learning and employ cognitive strategies that help them progress toward their learning goals. On the other hand, individuals with performance goal orientation are more likely to focus on others' progress in terms of grades or scores and regulate their monitoring and cognitive processes to demonstrate their superiority over others. Studies examining the relationship between these goal orientations and different outcome measures (e.g. self-efficacy, interest, self-regulation, effort, and persistence) have shown that learning or mastery goal orientation is more advantageous and predicts a generally adaptive pattern of outcomes and is positively related to their time, effort, and adaptive help seeking compared to performance goal orientation (Pintrich, 2000a, 2000b; Schunk, 2005; Zimmerman, 2011). More recently, researchers have found evidence of a tridimensional nature of goal orientation and further divided the performance approach into two distinct factors: performance approach orientation and performance avoidance orientation. While both variables share the same outcome goal of meeting normative standards in comparison to others, the performance approach is characterized by the desire to show superiority and gain favorable judgments from others while performance avoidance is characterized by a desire to avoid unfavorable judgment from others. Research using a tridimensional model of goal orientation shows evidence indicating that not all of them are less adaptive or in opposition to mastery or learning goal orientation as predicted by bidimensional goal orientation models (Elliot & Harackiewicz, 1996; Zweig & Webster, 2004). For instance, performance approach has been found to be positively and significantly related to a number of adaptive outcomes such as self-efficacy (Zweig & Webster, 2004). Following this logic of separating performance orientation into approach and avoidance orientations, other researchers proposed a similar distinction between mastery approach and mastery avoidance orientations. Mastery approach is characterized by a desire to learn and master a task, while mastery avoidance is characterized by a desire to avoid failure in learning and misunderstanding (Elliot, 1999; Pintrich, 2000b). However, this distinction between mastery approach and avoidance orientations has not been widely embraced and the mastery avoidance construct is not as well defined theoretically and operationally as the other goal orientation constructs (Pintrich, 2000b; Senko, 2016). Consequently, a tridimensional dispositional goal orientation measure with three subscales of performance-orientation approach, performance-orientation avoidance, and learning orientation will be used in this study (Zweig & Webster, 2004).

Online learning self-efficacy. Self-efficacy has been identified as a central construct in motivational models as well as the forethought phase of the social-cognitive model of SRL (Zimmerman, 2000b). Self-reported self-efficacy has been found to have a positive influence on learning outcomes such as task persistence, task choice, skill acquisition, use of SRL strategies, and academic achievement and performance (Hodges, 2008; Multon et al., 1991; Pajares, 2008; Pintrich & De Groot, 1990; Zimmerman, 2000a, 2000b). Perceived self-efficacy was formally defined by Bandura (1997) as one's personal beliefs about their capabilities to organize and execute courses of action to attain designated goals. Thus, self-efficacy beliefs do not concern an individual's actual skills and abilities but rather their judgment about the skills and abilities they possess. It is hypothesized that those with higher levels of self-efficacy will expend more effort and persist longer in the face of difficulties than those who are unsure of their capabilities (Bandura, 1997; Multon et al., 1991). Self-efficacy is not a single disposition but is rather domain specific which varies from situation to situation. Thus, beliefs about one's performance ability on a math test differ from one's judgment about ability to perform on a history test. Further, self-efficacy is sensitive to variation in performance context. Hodges posits, "Changes in the mode of education and training, for example from face-to-face to online, may affect learner self-efficacy beliefs" (2008, p. 7). Further, Pajares (1996) cautions, "because judgments of self-efficacy are task and domain specific, global or inappropriately defined self-efficacy assessments weaken effects" (p. 547). Given the sensitivity of self-efficacy beliefs to changes in domain and context, a number of self-efficacy measures have been developed to measure individuals' self-efficacy beliefs about performance in different domains and context.

There are generally three types of self-efficacy when extended to the domain of online learning. These three types of self-efficacy encompass self-efficacy for online learning, computer self-efficacy, and Internet self-efficacy. While computer and Internet self-efficacy measures examine one's belief about using computers (i.e. computer self-efficacy) (Brown et al., 2003) and the ability to organize and execute Internet actions required to produce given attainments (i.e. internet self-efficacy) (Eastin & LaRose, 2000), they do not measure one's perception of capabilities to use such technologies within the context of learning-specific content using them (i.e. self-efficacy for online learning). Yet, most self-efficacy research in online learning environments has focused on either computer self-efficacy or Internet self-efficacy, so less is known about the role that self-efficacy for online learning plays in relation to different outcome measures such as achievement and persistence (Artino & McCoach, 2008; Hodges, 2008). One proposed explanation for the gap in research in that area is the dearth of validated scales that aim specifically at measuring efficacy for learning in online learning environments. As a result, researchers began to develop and validate original scales sensitive to its nature and domain of functioning (Artino & McCoach, 2008). Consequently, this study aims at examining efficacy in terms of the extent to which individuals feel confident they can learn effectively using self-paced, online courses as it most closely reflects the domain of functioning and task demands of learning in MOOCs.

Online learning task value. The concept of task value has its root in the expectancy-value theory perspective on motivation (Wigfield & Eccles, 2000). According to Wigfield and Eccles (2000) and Eccles and Wigfield (2002), there are four components of task value that can influence achievement, namely: attainment value, intrinsic value, utility value, and cost. Wigfield and Eccles (1992) defined attainment value as the personal importance of doing well on a task. Intrinsic value is defined as the subjective interest or enjoinment the individual gets from the activity and the content of the task. Utility value is defined as how useful the task is in facilitating important current and future goals even if the individual is not interested in the task for its own sake, such as career goals. Finally, the cost components of task value are conceptualized as the negative aspects of engaging in a particular task, such as fear and anxiety, as well as the effort needed to succeed in such tasks. However, while proponents of this expectancy-value theory argue that an individual's choice, effort, persistence, and performance in an activity can be explained and directly influenced by the extent to which they attach different types of values to the activity, it is not sufficient to motivate individuals if they do not have strong expectancy that they will do well on that activity (Wigfield & Eccles, 1992, 2000)

Within the social-cognitive framework of SRL, task value is a central motivational belief within the forethought phase and is especially relevant in an informal learning context such as MOOCs (Littlejohn et al., 2016). Task value refers to the perceived worth of a particular task (Zimmerman, 2011) and is defined as one's judgment of how interesting, important, and useful a learning task is to them (Artino, 2009; Artino

& McCoach, 2008). Like self-efficacy, task value has been found to be positively related to motivation, performance, and persistence, especially in online learning contexts (Alraimi et al., 2015; Hone & El Said, 2016). Further, in some studies, task value has been shown to be the strongest individual predictor of academic outcomes such as satisfaction as well as continued motivation and the use of SRL strategies in online learning contexts (Artino, 2009). Given the absence of external or formal accreditation of learning within MOOCs, it is safe to hypothesize that only those who deem the learning tasks to be worthy of their time and effort because it is useful and important to them will persist longer. In this study, a six-item task value subscale designed to assess students' judgments of how interesting, useful, and important the MOOC is to them will be used to measure participants' task value beliefs (Artino & McCoach, 2008).

SRL strategies specific to this study. What distinguishes the social-cognitive perspective of SRL is that it considers behavioral, motivational, cognitive, and contextual factors in understanding and explaining SRL. The self-regulation of behavior involves the active control or use of various resources that the individuals have available to them, such as time, environment, peers and instructors, and effort (Pintrich, 2000a, 2000b). According to Pintrich (2000a), persistence is a common indicator of motivation and therefore motivational beliefs have direct implications for the behavior of effort and persistence. Holding strong goal intentions for learning does not necessarily lead to goal achievement if learners are unable to self-regulate during goal striving (Gollwitzer & Sheeran, 2006). For instance, some studies found that goal orientation indirectly affected achievement through effort regulation in online learning (Cho & Shen, 2013). Further, all learners require assistance from time to time, whether it to be to understand material and concepts or when confused about how to approach a task or navigate an online system. However, substantial individual differences occur in learners' help-seeking behavior, which suggests a complex interplay between social and motivational factors (Schunk, 2005). One possible explanation for the wide variation in individuals' help seeking behavior has been attributed to goal orientation (Ryan, Pintrich, & Midgley; 2001). Individuals who hold a mastery goal orientation are more likely to seek help from others compared to those with a performance goal orientation, because the latter are more concerned about how others evaluate and judge them. While motivational factors such as self-efficacy explain why some learners engage in a task and put in the effort to persist in the task, it does not account for the specific strategies and behaviors that learners employ to optimize learning (Puzziferro, 2008). In order to understand the relationship between learners' use of SRL strategies and persistence, it is important to examine the interplay between motivational and behavioral constructs within and across the difference phases of the social-cognitive perspective of SRL. The novelty and flexibility of learning within MOOCs has shown to be overwhelming for some learners, especially for those who lack MOOC experience or the skills to manage their learning and effectively utilize the different resources available to them (Daradoumis et al., 2013; Gütl et al., 2014; Kop & Fournier, 2010). Hence, the resource management strategies constructs of time and study environment, effort regulation, peer learning, and help seeking from the MSLQ (Pintrich et al., 1993) were chosen for this study given their relevance and importance for successful learning in an informal, flexible, and distributed learning environment such as MOOCs.

SRL skills become even more crucial for learners' success in online learning environments where learning management and control relies heavily on learners' skills and commitment (Artino, 2007, 2009; Hsu, Ching, Mathews, & Carr-Chellman, 2009; Hu & Driscoll, 2013; Kitsantas & Dabbagh, 2010; Tsai et al., 2013). In the following section, a review of the literature on SRL in online learning in general and MOOCs specifically is presented.

SRL and online learning. SRL has attracted researchers for decades and has been extensively researched in the context of traditional classroom settings. These early investigations have consistently found moderate to strong correlation between SRL strategies and course performance. In these investigations, SRL processes were able to predict students' grades and mediate the effects of the student verbal ability measure on their writing outcome (Pintrich & De Groot, 1990; Zimmerman & Bandura, 1994; Zimmerman & Kitsantas, 1999). In addition, motivation and the use of self-regulated strategies have been positively associated with students' performance in and satisfaction with online courses (Artino, 2009; Artino & McCoach, 2008). With the rapid growth of online learning opportunities, these skills become even more relevant and essential for learners' success as the responsibility for completing learning tasks and course requirements shift from the instructor to the learner (Artino, 2009; Hsu et al., 2009; Hu & Driscoll, 2013; Kitsantas & Dabbagh, 2010; Tsai et al., 2013).

Puzziferro (2008) hypothesized that online learners' final letter grades and satisfaction would differ based on their technology self-efficacy scores as well as their use of SRL strategies of rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment, effort regulation, peer learning, and help seeking as measured by the MSLQ (Pintrich, et al., 1993). To test this hypothesis, all students enrolled in selected online classes offered by a southeastern community college were invited to participate in the study. There were three surveys: Questionnaire A measuring online technology self-efficacy (Miltiadou & Yu, 2000), the MSLQ, and experiential and demographic factors at the beginning of the course; Questionnaire B measuring satisfaction, instructor, and course variables at the end of the course; and a modified end-of-course questionnaire, C, was administered to students who withdrew from the course. The response rate for the first survey was 43% ($N = 815$) and the response rate for the second questionnaire (B or C) was 78%.

Puzziferro (2008) found no significant difference in the online technology self-efficacy scores by final grade or satisfaction. However, ANOVA analysis revealed that significant differences in mean scores by final grade existed for time and study environment and effort regulation. Post hoc analysis suggests that students who received higher grades (A or B) in the online course were more likely to manage their study time and environment to suit their learning needs and styles than those who withdrew or received lower grades. Similar patterns were observed for effort regulation; however, significant differences were also observed between those who withdrew and those who received a grade of C, indicating that those who withdrew demonstrated a lower ability to regulate and manage effort. Using satisfaction as an outcome variable, significant differences were found for rehearsal, elaboration, metacognitive self-regulation, and time and study environment only.

Using structural equation modeling with maximum likelihood estimation, Wang et al. (2013) tested a model for the relationship among students' characteristics (i.e. gender, education level, and number of online courses taken previously), technology self-efficacy (Miltiadou & Yu, 2000), self-regulated learning (i.e. task value, self-efficacy, test anxiety, elaboration, critical thinking, metacognitive self-regulation, and time/study environmental management as measured by a modified version of the MSLQ to fit an online context), and course outcomes (achievement and course satisfaction). Over 2,000 graduate and undergraduate students who were identified as taking online classes during the Fall 2008, Spring 2009, Summer 2009, and Fall 2009 at a southeastern university were invited to participate in this study. However, only 256 completed the survey. Out of those, 47.30% were males and 53.10% were females, 37.11% were graduate students and 62.89% undergraduates, with most of the responding students being enrolled in the College of Business, Education, and Engineering.

Some of the findings from this study were consistent with the findings from the study conducted by Puzziferro (2008) and some were not. The study by Puzziferro (2008) found that self-regulated learning is a predictor of course satisfaction and performance. Similarly, this study indicated that by using more effective learning strategies, one increases their levels of motivation, and the increased levels of motivation toward online courses lead to higher levels of course satisfaction and levels of technology self-efficacy, which lead to higher final grades. However, the finding regarding the effect of technology self-efficacy was not consistent. Unlike the previous study, this study found that students with higher levels of technology self-efficacy tend to perform better and receive better grades. The authors note, however, that the instrument used in this study measured two distinct self-efficacy domains: general computer self-efficacy and online learning platform-related self-efficacy. In addition, the only student characteristic that seemed to affect learning strategies directly was the number of previous online courses taken. Thus, the number of previous online courses taken influenced effectiveness of learning strategies directly, which affected the levels of motivation through the effectiveness of learning strategies.

In another attempt to determine the role of SRL strategies in online learning achievement, Cho and Shen (2013) conducted a path analysis using multiple SRL constructs with a total of 64 survey responses from students enrolled in Introduction to Gerontology delivered fully online via Blackboard. The SRL constructs included in this model were goal orientations, academic self-efficacy, metacognitive regulation, effort regulation (as measured by MSLQ), and interaction regulation (writing, responding, and reflection strategies), as well as total time spent on the course website. The researchers found that while intrinsic and extrinsic goal orientations significantly correlated with academic self-efficacy, extrinsic goal orientation was not associated with any types of regulation nor did it influence students' academic achievement as measured by final total points. However, intrinsic goal orientation was found to directly influence metacognitive regulation, which had an indirect effect on achievement, mediated by effort regulation.

Further, academic self-efficacy directly influenced interaction regulation; and both academic self-efficacy and intrinsic goal orientation indirectly influenced effort regulation and interaction regulation through metacognitive regulation. Both total amount of login time in Blackboard and effort regulation influenced students' achievement directly, and all the other variables (excluding extrinsic goal orientation) influenced achievement indirectly. Based on the results of this study, the researchers assert that student interaction is a critical aspect of online SRL and argue for the need to examine its role more thoroughly. Further, they recommend that online instructors enhance intrinsic goal orientation by incorporating authentic problems for learners to engage in, promote academic self-efficacy by enhancing instructor presence, and scaffold students to regulate their learning by guiding and promoting student-to-student interaction.

In a review of the literature, Artino (2007) examined studies conducted on SRL within the social-cognitive framework in online and distance learning from 1995 through 2006. Three major themes emerged from this review: studies that aimed at identifying effective motivational, cognitive, and behavioral strategies used by online learners and how they relate to each other and to other measures of learning outcome; studies that looked at how design strategies and the learning environment interact with learners' varying abilities and aptitudes; and studies that investigated the effective integration of technology tools to support SRL and the extent to which different SRL processes might be supported by these tools.

Artino concludes that although many studies reviewed are more descriptive in nature and may suffer from methodological limitations, they are consistent with the research in SRL in traditional classrooms. He argues that these studies support the relationship between motivation and learning strategies, and students' performance in online learning environments. Artino also asserts that the studies examining SRL support in online courses, especially for learners with less-developed SRL skills, indicate that consideration for SRL in course design can be an effective instructional strategy and recommends that scaffolding SRL should be integral to online course design.

In a more recent review of the literature, Broadbent and Poon (2015) conducted a meta-analysis on empirical studies from the last decade to identify which SRL strategies are associated with academic outcomes in online higher education environments. Only studies between the years 2004 and 2014 that examine the application of SRL strategies by higher education students who enrolled in fully online or web-based courses were included. Additional inclusion criteria were that the outcome variable achievement was measured by numerical grade or grade point average (GPA) in an online assignment, exam, subject, or degree; and that the SRL strategies examined have been clearly identified within the SRL literature. Based on the inclusion criteria, only 12 studies were included in this systematic review. Effect sizes were extracted from each paper and converted to r values in this study. The researchers found that the MSLQ was the most popular instrument used to assess SRL strategy ($N = 9$). The SRL strategies identified from the literature review included metacognition, time management, effort regulation, peer learning, elaboration, rehearsal, organization, critical thinking, and help seeking. Meta-analysis of all 12 studies combined showed that SRL strategies were significantly associated with online academic achievement. In terms of individual SRL strategies, 6 studies explored the role of time/study management in online academic success and 5 studies found a significant positive relationship with academic achievement. Meta-analysis of these 6 studies combined showed significant but weak association with academic achievement. Effort regulation was examined in 5 studies. Four of these studies found a significant positive relationship. Aggregating across all studies, effort regulation was significantly but weakly associated with online academic achievement. All of the 4 studies examining the effect of peer learning on academic achievement found a significant positive relationship, however, meta-analysis of these studies showed that peer learning was nonsignificantly but moderately associated with online academic achievement. Help seeking was only examined in 1 study and was found to be weakly but significantly associated with achievement. Finally meta-analysis of studies examining elaboration, rehearsal, and organization were found to be nonsignificantly associated with online achievement. Based on their review of the literature, the researchers concluded that the SRL strategies deemed crucial in the traditional classroom do not necessarily fit the needs of online learners (i.e. rehearsal, elaboration, organization). Further, they argue for the need to prioritize peer learning in the context of online learning and that more research is needed in this area. Finally, they call for the need to explore the mediating effect of additional factors such as motivation on SRL strategies if we are to improve our understanding of the influence of learners' SRL strategies on online achievement and success.

SRL continues to be a main area of investigation to this day in the field of online learning. More interestingly, research in the area of online SRL has rapidly increased in the past five years (Tsai et al., 2013). A review of various studies has indicated that learners' motivational beliefs and support for SRL strategies in an online learning environment can assist with learners' achievement, satisfaction, and persistence (Artino, 2009; Cho & Shen, 2013; Hu & Driscoll, 2013; Puzziferro, 2008; Tseng et al., 2014; Wang et al., 2013), increase the effectiveness of ePortfolio activities (Cheng & Chau, 2013), predict leaners' online information searching strategies (Tseng et al., 2014), and enhance learner-to-learner interaction (Cho & Kim, 2013). The importance of learners' motivational beliefs and SRL skills in supporting learners' success and persistence in online courses has led a number of researchers to examine the implications of SRL on course development and technology integration and provide some guidelines for the design of online learning environments that promote SRL skills including the work of Cho (2004) and Kitsantas and Dabbagh (2010). Cho (2004) groups online course design strategies into cognitive, metacognitive, resource management, and affective SRL domains and provides practical design advice and examples of how each domain can be effectively promoted through online course development. Furthermore, researchers suggest that aligning instructional or design interventions with the pedagogical categories of Integrative Learning Technologies (ILT) in the design and development of online learning can support and promote SRL and motivation, particularly with college students (Dabbagh & Kitsantas, 2005, 2009; Kitsantas & Dabbagh, 2010). Kitsantas and Dabbagh (2010) define ILT as

> a dynamic collection or aggregation of web tools, software applications, and mobile technologies that integrate technological and pedagogical features and

> affordances of the Internet and the World Wide Web to facilitate the design, development, delivery, and management of online and distributed learning. (p. 21)

The researchers map the five ILT pedagogical categories of collaborative and communication tools, content creation and delivery tools, administrative tools, learning tools, and assessment tools to the different SRL processes and provide some practical examples of different technology tools that can be incorporated into the learning environment to promote and support these processes. A number of studies were conducted to examine the role of utilizing technology tools from the different categories of the ILT in supporting different SRL processes. For instance, Dabbagh and Kitsantas (2005) sought to examine whether different categories of ILT support different SRL processes as well as to understand learners' perception of the usefulness of the different technology tools in supporting the completion of assignments in three college-level hybrid courses. A total of 65 students between the ages of 22 and 45 participated in this study. A Web Supported Self-Regulation Questionnaire (WSSRQ) was used to assess the degree to which 4 categories of the ILT (i.e. content creation and delivery tools, collaborative and communication tools, administrative tools, and assessment tools) supported 6 SRL processes of goal setting, use of task strategies, self-monitoring, self-evaluating, time planning and management, and help seeking for 12 different tools used in these courses. Analysis revealed that different ILT supported different SRL processes. For instance, it was found that time planning and management was supported primarily via administrative and communication and collaborative tools, while administrative tools, collaborative and communication tools, and content creation and delivery tools were most effective in supporting learners' help seeking. In addition to the quantitative data gathered in this study, learners from two of the three courses (*N* = 46) were asked to respond to open-ended questions pertaining to their perception of the usefulness of the different technology tools used in these blended courses in supporting the completion of five course assignments involving specific learning tasks. Qualitative analysis of learners' responses indicated that ILT features supported different SRL processes while completing these tasks. For instance, content creation and delivery tools were most useful in scaffolding the SRL processes of help seeking, task strategies, self-evaluation, and goal setting while completing exploratory learning tasks, while collaborative and communication tools were useful in supporting the application of time planning and management and help-seeking processes while completing group assignments. This study indicates the potential that different technologies have as teaching and learning tools in supporting learners' application of different SRL processes. However, this study clearly indicates that different tools scaffold the use of different SRL processes, thus highlighting the need to identify the critical SRL processes and skills learners need to complete and persist given the context (e.g. formal vs. informal learning contexts) and learning demands of specific learning tasks (e.g. exploratory vs. collaborative learning tasks) (Broadbent & Poon, 2015; Dabbagh & Kitsantas, 2005, 2009; Fontana et al., 2015; Greene, 2014). Hence, in the following section, a review of studies on SRL in MOOCs is provided.

SRL and MOOCs. Different approaches to researching individual SRL processes and how these relate to learning in MOOCs have been used including surveys (Beaven et al., 2014), interviews (Milligan et al., 2013), design-based research (Gutierrez-Rojas, Alario-Hoyos, Perez-Sanagustin, Leony, & Delgado-Kloos, 2014), logfile data (Fournier, Kop, & Durand, 2014), discourse analysis (Guàrdia, Maina, & Sangrà, 2013), and autoethnography (Bentley et al., 2014; Kop & Fournier, 2010). A sample of these studies is presented next.

Kop and Fournier (2010) conducted a study to investigate issues related to autonomy and self-directed learning in a MOOC. Specifically, the researchers examined whether the four dimensions of autonomous learning identified by Bouchard (2009) match the experiences and perceptions of PLENK10 MOOC participants and if additional dimensions can be justified based on those experiences. These include psychological dimensions such as motivation and confidence, pedagogical dimensions such as goal setting and self-evaluation, delivery model of resources such as learners' ability to navigate and locate information, and finally how learners perceive the value of their learning. Quantitative measures such as surveys and Moodle data mining functionality, as well as qualitative method in the form of virtual ethnography, were used. Different analysis tools and methods were used including Social Network Analysis (SNA) to examine activities and relationships in the course, an aggregator statistic functionality to gather data on course-related use of blogs and micro-blogs, and the SNA tool SNAPP to deliver real-time visualization of Moodle discussions.

The researchers found that psychological factors such as motivation and confidence influenced the level of participation in the MOOC. For instance, novices indicated their lack of confidence in actively participating alongside high-profile contributors and experienced MOOCers while others indicated that those contributors served as a source of motivation to participation in the course. Furthermore, time management and goal setting were mentioned as important factors influencing participation especially at the start of the course when the amount of resources and communication that need to be managed and organized is overwhelming. Finally, additional factors emerged as influencing participants' engagement and participation in this course including critical literacy and technical skills needed to manage learning in a chaotic and distributed environment.

In order to generate a list of critical MOOC design elements from learners' perspectives, an exploratory study was carried out by Guàrdia et al. (2013). The researchers mined participants' comments and blog posts about popular educational technology-related MOOCs using MOOC hashtags such as #edcmooc, #etmooc, #CCK12. A total of 82 blog posts were identified as quality blog posts (i.e. presenting deep reflection, founded critique, and relevant improvement suggestions of MOOCs) and were included in the discourse analysis. The qualitative analysis revealed that support for SRL processes and skills is critical in increasing learners' empowerment and behavioral engagement in MOOCs. For instance, the researchers recommend including digital planning tools that provide a suggested pace for learning, description of the tasks and estimated times for completion, as well as tips for coping with some of the challenges faced in MOOCs by encouraging peer assistance and revision of goals and agenda. Furthermore, providing suggestions for effective learning strategies as well as detailed criteria for assessment can support learners' self- and peer-assessment efforts.

Using a design-based research methodology, Gutierrez-Rojas et al. (2014) designed and developed an app called MyLearningMentor with the purpose of supporting less-experienced MOOC learners navigating their way through a MOOC environment by supporting effective study habits. An initial attempt to validate the existence of the problem (i.e. the need to support less-experienced learners in MOOCs) was through the distribution of a 5-point Likert scale survey to 41 second-year higher education students who had considerable experience in traditional and blended learning but little experience in online learning. The results of the survey corroborated the initial hypothetical problem as they indicated that those learners lacked the time management, organization, and study skills needed to complete an online course successfully.

Based on the results obtained from this survey, a feature requirement list for the app was generated: (a) distributed as a mobile app; (b) customizable to different learners' profiles with different schedules, aims for participation, and study preferences; (c) an adaptive daily planner to help with task organization; (d) crowdsourced information about the different tasks required to complete a MOOC and their level of difficulty; (e) tips and hints about effective time management, social learning, and work habits; and (f) serve as a meeting point for MOOC learners and volunteer mentors. This app is still in the mockup phase and more research is needed to confirm the effectiveness of such an app to support SRL in MOOCs. However, it does confirm the existence of the problem and the need to support less-experienced MOOC users in developing SRL skills.

In a more recent study, Hood et al. (2015) investigated the differences between self-reported SRL behavior between learners who were working as data professionals or those studying toward a higher education degree and other learners during an eight-week Introduction to Data Science MOOC offered on the Coursera platform. In this study, a modified version of a survey that is based on Zimmerman's (2000a) three phases of self-regulated learning and designed to measure self-regulated learning in adult learners in informal learning contexts (Fontana et al., 2015) was distributed to MOOC participants during the second week of the MOOC. Out of the 788 respondents, 141 were studying for a higher education qualification, 59 were both currently employed as a data professional and studying for a higher education qualification, and 285 were neither employed as a data professional nor studying for a higher education qualification.

Factor analysis of the survey instrument uncovered an eight-factor structure of goal-setting, self-efficacy, task strategies, learning strategies, help seeking, self-satisfaction and evaluation, task interest, and learning challenge. The researchers found significant differences in perceived ability to self-regulate (measured through overall SRL scores) between learners who were employed as data professionals or working toward a higher education degree and those who were not. This difference was not only evident in the overall SRL score as the data also indicated that participants' background and context was a significant predictor of how a participant will employ SRL subprocesses as well. When it comes to the differences in SRL subprocesses between participants who were employed as data professionals and those who were working toward a degree in higher education, the data indicated there were significant differences in self-efficacy, task interest, and learning challenge. While data professionals scored higher on the self-efficacy subprocesses, participants who were working on a higher education qualification scored higher on task interest and learning challenge. Both groups scored significantly higher on task strategy, self-satisfaction, and self-evaluation compared to those participants who were neither employed as data professionals nor working toward a degree in that field. Based on these findings, the authors argue that the relationship between learners' context and role and their ability to self-regulate their learning must be considered in the design and structure of MOOCs. The flexible nature of learning in a MOOC coupled with the varying levels of SRL skills and experience in MOOC participants requires instructional designers to pay close attention to ways to support the development of the SRL subprocesses that are most important for effective participation and learning in a MOOC if MOOCs are to fulfill their potential of providing freely accessible, high-quality learning opportunities.

In a follow-up study, 32 participants from 16 different countries who identified in the previous study as data professional were invited to participate in semistructured interviews (Littlejohn et al., 2016). The purpose of these interviews was to examine in more detail the SRL strategies they apply in a MOOC and explore how SRL strategies vary between high and low self-regulatory learners. Based on participants' responses to the survey, an SRL profile was created for each participant. These profiles included their overall SRL score as well as a separate score for the eight SRL processes uncovered in the previous study. Interviews were transcribed and analyzed independently by two different researchers using the eight SRL processes as a coding framework to identify themes relating to learners' behaviors for each of the SRL subprocesses. Another round of analysis was conducted in relation to participants' SRL scores to uncover differences between those with high and low SRL profile scores. The analysis of interviews indicated strong differences in the following SRL subprocess: motivation and goal setting, self-efficacy, task strategies, task interest and value, self-satisfaction, and evaluation.

Motivation and goal setting in this study refers to learners' reasons for taking the course and the learning and performance outcomes they set for themselves at the start of the MOOC. The researchers found marked differences between the two groups of participants. Unlike learners with low SRL scores who indicated passing assignments and earning a certificate of completion as their goals, the majority of learners who had a high SRL score were intrinsically motivated and driven to participate in the MOOC to develop specific knowledge and skills related to their work context. This difference in motivations and goals shaped how they applied the different SRL subprocesses examined and their perception of the learning experience. For instance, when asked about how valuable the MOOC and different activities were to them, the majority of learners with high SRL scores evaluated their engagement with MOOC content and activities in relation to their applicability to their workplace context and practice while low SRL score participants measured the value of the tasks extrinsically and discussed earning a certificate as being a symbol of learning. These differences were also reflected in their task strategies as high SRL score participants were more autonomous and flexible in their learning approach, determining the activities they need to engage with based on their own needs. On the other hand, low SRL score participants who were aiming to gain a certificate were more structured and linear in their approach. Low SRL learners also dedicated specific and greater amounts of time to engage with the MOOC. When asked about how they evaluated their learning, both groups indicated that they used activities and assignments as a benchmark. However, learners with high SRL scores saw these activities as being a source of formative self-assessment with the knowledge and skills development being the measure of their learning rather than achievement on the assignments. Further, this group also compared their progress in relation to other MOOC participants in order to improve their own approach rather than measuring their performance against others. Those who had high SRL scores were also highly satisfied with their performance and progression toward their goals. Even though learners with low SRL scores indicated that they used the assignments to evaluate their progress, they perceived these learning tasks and assignments as being summative and functioning as the end point of their learning. Those learners tended to be less satisfied and more likely to express disappointment in their performance. Finally, there were no differences between high and low SRL score groups in term of self-efficacy as both groups expressed confidence in their ability to engage with and complete all MOOC activities. However, those who scored the highest and lowest on the self-efficacy subscale showed consistent themes. For those who scored the highest, two factors emerged: (a) They were familiar with the content knowledge and concepts being discussed in the MOOC, and (b) they had previous experience engaging with MOOCs. On the other hand, learners with low self-efficacy scores were not as confident in their existing content knowledge, however, they did show confidence in their ability to learn in general.

Expanding on this study, Milligan, Littlejohn, and Hood (2016) compared the findings from this study to another MOOC entitled the Fundamentals of Clinical Trials

(FCT) aimed at health professionals and those studying for a health professional role which attracted 22,000 registrants from 168 countries. Similar to the previous two studies, a survey was administered to participants to generate SRL profiles compromised of an overall SRL score, as well as scores for each of eight SRL subprocesses. A total of 350 responded to the survey of which 126 identified as health professionals (Milligan & Littlejohn, 2016). A total of 35 Out of the 126 participants who identified as health professionals were interviewed using a semistructured interview protocol and analyzed using a similar method (Littlejohn et al., 2016). Similarities and difference between the findings from the Introduction to Data Science and FCT MOOCs were identified across three SRL processes: goal setting, self-efficacy, and learning and task strategies.

Those who had high overall SRL scores in both studies exhibited mastery goal orientation as they set specific goals related to their career and professional practice and structured their learning around specific content knowledge and expertise. On the other hand, those with low overall SRL scores described their goals in more general terms such as love of learning and curiosity. However, unlike high self-regulators in the Introduction to Data Science MOOC, FCT participants exhibited performance goal orientation (i.e. earn a certificate) in tandem with more specific professional goals. The researchers attribute this difference to two major differences between the MOOCs. First, the FCP MOOC was offered by Harvard Medical School and thus a certificate of completion carries greater value that the one offered by the Introduction to Data Science MOOC. Second, the FCT course was more rigidly structured and encouraged all participants, regardless of SRL skills, to focus on the course content and objectives. Thus, high self-regulators on the FCT course were more likely to articulate goals that mirrored the course objectives than participants in the other MOOC. Regardless of whether high self-regulators intended to complete the course or not, high self-regulators in both MOOCs focused on extending their expertise and skills to benefit their current or future roles.

The findings regarding self-efficacy were similar to those in the previous study as both groups in the FCT MOOC showed high levels of self-efficacy and the factor that seemed to influence level of self-efficacy was experience with learning within MOOCs. As such, the researchers suggest that providing some initial orientation training to ensure that learners are familiar with the MOOC and how they may interact effectively with it might lead to higher levels of self-efficacy. Finally, there were markedly strong differences in terms of learning and task strategies between high self-regulators in the Introduction to Data Science and FCT MOOCs. Whereas participants in the former MOOC showed more flexibility and customization in their approach to learning to fit their needs, those in the FCT were more structured and followed the same approach in completing all MOOC requirements such as watching videos, reading, and simple note taking. This difference, the researchers argue again, could be related to the difference in course structure and design between the two MOOCs highlighting the contextual influence on the application of SRL in MOOCs.

Research on the role of SRL in MOOC learning is gaining traction. While the studies reviewed in this section do not examine the direct relationship between SRL and MOOC persistence, the SRL processes that emerged in these studies are consistent with the factors that were deemed necessary for learners' persistence online and in MOOCs.

These factors include time management (Balakrishnan & Coetzee, 2013; Gütl et al., 2014; Lee & Choi, 2011; Loya et al., 2015; Nawrot & Doucet, 2014; Park, 2007), peer learning and interaction (Adamopoulos, 2013; Alraimi et al., 2015; Gütl et al., 2014; Lee & Choi, 2011; Park, 2007; Woodgate et al., 2015), effort regulation (Gütl et al., 2014; Hone & El Said, 2016; Lee & Choi, 2011), and help seeking (Gütl et al., 2014; Lee & Choi). Further, the studies indicate the role that motivational beliefs such as self-efficacy for learning within a MOOC and goal orientation play in shaping how they apply different SRL processes to support their learning and reach their goals (Broadbent & Poon, 2015; Littlejohn et al., 2016; Milligan et al., 2016; Multon et al., 1991). Thus, using the social-cognitive framework of SRL to examine the role of motivational beliefs and SRL strategies in learners' persistence in MOOCs might uncover some relations that did not emerge in previous studies that focused on either motivational factors or SRL strategies and behaviors separately (Broadbent & Poon, 2015; Wang & Baker, 2015). Accordingly, the following section reviews some studies conducted at the intersection of the social-cognitive model of SRL and persistence in online learning in general and in MOOCs specifically.

SRL and Persistence in Online learning and MOOCs

Artino and Vermillion (2007) sought to examine the relationship between students' motivational beliefs (i.e. goal orientation and self-efficacy), use of SRL strategies (i.e. elaboration, critical thinking, and metacognitive strategies), and their motivational engagement (i.e. effort, persistence, and procrastination) in fully online courses offered by a large public university in northeastern United States through

WebCT. Specifically, the research questions that were addressed were: (a) are students' achievement goal orientation and academic self-efficacy associated with their use of SRL strategies in online courses? And (b) are students' achievement goal orientations and academic self-efficacy related to their motivational engagement (i.e. effort, persistence, and procrastination) within those online courses? A convenience sample of 107 undergraduate and graduate students responded to a 66-item survey measuring the different constructs in this study. Achievement goal orientation was measured using the Patterns of Adaptive Learning Survey (Midgley et al., 2000) and included 3 subscales: a 5-item mastery orientation scale, a 5-item performance approach orientation scale, and a 2-item performance avoidance orientation scale. Further, 4 subscales were adapted from the MSLQ (Pintrich et al., 1993) including a 7-item self-efficacy for learning and performance scale, a 5-item elaboration scale, a 5-item critical thinking scale, and a 10-item metacognitive self-regulation scale. Finally, motivational engagement was measured using a 3-item effort scale, a 4-item persistence scale, and a 5-item procrastination scale adapted from Wolters (2004).

Correlational analysis indicated a significant positive correlation between mastery orientation and self-efficacy. Further, results showed a positive significant correlation between mastery orientation and self-efficacy and the use of SRL strategies. However, no significant relationship was found between performance-approach and performance-avoidance goals and students' reported use of any of the three SRL strategies. In terms of motivational engagement, mastery orientation was found to be significantly and positively related to both effort and persistence and negatively related to procrastination, while self-efficacy was only positively and significantly related to persistence and performance-approach was only positively and significantly related to procrastination. Performance-avoidance, on the other hand, was unrelated to any of the motivational engagement variables.

Further, multivariate regression was conducted to determine if the achievement goal orientations and self-efficacy could be used to predict the three motivational engagement variables. Results of the regression analysis indicate a statistically significant relationship between motivational beliefs variables (i.e. mastery orientation, performance-approach orientation, performance-avoidance orientation, and self-efficacy) and the three motivational engagement variables of effort, persistence, and procrastination. More specifically, the four predictor variables accounted for 12% of the variance in self-reported effort and 16% of self-reported level of persistence. When controlling for the other predictors, however, only mastery orientation was a significant positive predictor of effort and persistence.

Using the social-cognitive model of SRL as a framework, Artino (2009) examined the relationship between online learners' motivational beliefs as measured by their online technology self-efficacy (i.e. their confidence in their ability to learn the material presented in an online self-paced course) and task value (i.e. their judgment of how interesting, useful, and important the online course was to them) as well as negative achievement emotions as measured by boredom and frustration and four outcome measures: the use of SRL strategies as measured by elaboration, metacognition, satisfaction, and continuing motivation to enroll in future online courses. The sample included 481 undergraduates from a U.S. service academy who participated in a self-paced online training program developed by the U.S. Navy. The survey instrument included several subscales adapted from other instruments: the online technology self-efficacy and task value subscales from Artino and McCoach (2008), the elaboration and metacognition strategies from the MSLQ (Pintrich et al., 1993), and the satisfaction subscale from Artino (2008). Continuing motivation to learn was measured with a single self-report item: Considering your experience with this online course, would you choose to enroll in another self-paced online Navy course in the future? The response scale ranged from 1 (definitely will not enroll) to 6 (definitely will enroll).

Correlation analysis revealed that both self-efficacy and task value were significantly and positively related to their use of elaboration, metacognition, satisfaction, and continuing motivation. To explore the unique variance in the outcome measures that can be explained by learners' motivational beliefs, multiple regression analyses were conducted. In these analyses, elaboration, metacognition, satisfaction, and continuing motivation served as the dependent variables and self-efficacy, task value, boredom, and frustration as the independent variables while controlling for age, gender, online technology experience, online learning experience, and prior knowledge. Analysis revealed that task value was the strongest individual predictor of all outcome measures. Beta coefficients for the different measures were $\beta = .51$ for elaboration, $\beta = .57$ for metacognition, $\beta = .46$ for satisfaction, and $\beta = .17$ for continuing motivation. As for self-efficacy, even though correlation analysis revealed that self-efficacy for learning online significantly and positively correlated with elaboration and metacognition, it did not add unique information to the prediction of either outcome measure in the regression analysis. However, self-efficacy was a positive predictor of satisfaction (β = 20) and continuing motivation (β = .17). All findings were significant at the $p < .001$ level.

Based on the findings from this study, Artino argues that mere knowledge of effective learning strategies does not mean that learners will utilize these strategies if they are not motivated to do so. Accordingly, learners' beliefs about the usefulness and importance of learning tasks are vital to sustain engagement in a highly autonomous online learning environment where there is minimal instructor involvement. Further, consistent with the cyclical social-cognitive view of SRL, positive beliefs about the usefulness of the learning tasks as well as learners' confidence in their ability to perform the actions necessary to attain their goals were found to be critical factors contributing to higher levels of satisfaction and motivation to continue to participate in future online learning tasks.

In an experimental study, Hu and Driscoll (2013) examined whether a web-based SRL strategy training positively influenced learners' achievement motivation, self-reported use of SRL strategies, and persistence in a community college web-enhanced College Success course. The participants in this study were 21 (8 treatment vs. 13 control) undergraduate students. Five participants in the treatment and 7 in the control condition were required to take the course because of deficiency on the College Placement Test. The intervention study consisted of 4 stages lasting 14 weeks. In the first stage, which started during the second week of the course, all participants filled out a survey in which they provided demographic information (i.e. year in school, age, gender, and GPA) and completed an assessment on their initial motivation indicators and use of SRL strategies adapted from the MSLQ (Pintrich et al., 1993). During the second stage, which occurred a week later and lasted for four weeks, participants in the treatment group were provided with SRL strategy training that included two parts: an online tutorial on SRL strategies (five chapters) and web-based interactive strategy application practices. The chapters in this tutorial contained information about different SRL processes such as metacognitive, motivational and cognitive strategies, and examples of the strategies and when and how to use them. It also contained exercises or case studies for participants to become familiar with SRL. After the four-week of SRL strategy training, participants in the treatment group entered the third stage in which they had to complete an online study plan, and then a self-evaluation for two learning periods with each learning period lasting four weeks. At the beginning of each learning period, participants completed an online study plan in which they set goals and selected learning strategies for completing the learning tasks followed by a self-evaluation at the end of the four-week learning period to reflect on their progress and effectiveness of strategies. In the final stage, both groups completed final questionnaires. In this stage, learners' motivation indicators and reported use of strategies were measured again. Open-ended questions about participants' use of learning strategies were also included.

Given the small sample size in this study, quantitative data were analyzed using nonparametric statistical procedures. In terms of learning achievement, significant differences were found between the treatment and control participants on overall achievement and final exam scores. Further, while all of the treatment participants completed all course assignments, four of the control participants did not complete some of the final assignments (project and paper). In terms of learners' motivation, significant difference was found between the treatment and control group on self-satisfaction. Further, self-satisfaction was significantly and positively correlated with final cumulative score. This finding was also supported by qualitative data analysis as students who received higher final grades made 20 out of the 29 references to self-satisfaction. Surprisingly, no significant differences were found between the treatment and control students in terms of task value, self-efficacy, and goal orientation. Further, within-group comparison indicated that experimental participants reported significantly lower task value and extrinsic goal orientation at the end than at the beginning of the study. While there was an increase in reference to task value in the open-ended questions between the beginning and the end of the experiment, these references were negative such as referring to the course as being too easy. Based on this finding, the researchers argue that task value seemed to be influenced by other variables such as challenging course content.

In terms of reported use of SRL strategies, no significant differences were found between groups. However, a positive correlation was found between self-satisfaction and use of cognitive, metacognitive, resource management, and total strategies after the intervention. Further, within-group comparisons showed significantly higher use of rehearsal strategies and significantly lower use of resource management strategies at the end than at the beginning of the study for the treatment group. The researchers offer two possible explanations for the significant decrease in use of resource management strategies. First, there was a significant positive correlation between task value and use of resource management strategies after the intervention. According to the social-cognitive model of SRL, the use of SRL strategies is influenced by motivational beliefs. Thus, when taking into consideration the significant decrease in task value for the treatment group, it is reasonable that they stopped using or reduced the frequency of using some of the strategies as the easiness of the course did not offer opportunities for participants to utilize these strategies. Another explanation is that the frequency of use of strategies does not necessarily indicate effective use of strategies. Thus, significant decrease in strategies could indicate intentional and effective adjustment to task difficulty. Finally, persistence in this study was measured using five indicators: first-term credit hour completion, first-term GPA, continuing enrollment until the second term, second-term credit hour completion, and second-term GPA. The treatment learners achieved significantly higher than the control learners on second-term GPA. Further, during the study there were no dropouts from the treatment group compared to one from the control group. Finally, while the dropout rate increased during the second semester, the treatment condition still had a much lower incompletion rate compared to the control group (12.5% and 29% respectively). The researchers suggest that the treatment group's better performance on persistence might be attributed to their satisfaction and overall achievement as significant positive correlations were found between cumulative course score and four of the measures for persistence as well as satisfaction and three of the persistence measures. Putting all these findings together, it appears that with the treatment group achieving significantly better than the control students, they might be more likely to feel satisfied with the learning experience and be more persistent when facing difficulties.

Surprisingly, despite the consensus regarding the importance of SRL skills in online learning and MOOCs, very few studies have examined its relationship to learners' persistence in MOOCs. One of the few studies that employs SRL framework as a lens to examine learner persistence in MOOCs is that by Poellhuber, Roy, Bouchoucha, and Anderson (2014). The researchers used the social-cognitive model of SRL to examine the multiple relationships between motivation and engagement in a French language economics MOOC offered in 2012. Specifically, the authors sought to answer three research questions: (a) What are the ongoing relationships between participants' motivations, learning goals, types of engagement with course materials, quiz scores, resource management strategies and motivation regulation strategies?; (b) How well does a self-regulation model explain these relationships?; and (c) What factors and variables predict engagement with the course materials, persistence, and results? In this study, persistence was defined and measured as having at least one activity in at least four different course weeks and/or having completed the final exam.

Two questionnaires were used in this study. The first one was distributed a few days before the course began and measured learners' motivation and reasons for joining the MOOC. Motivation was measured using the MSLQ task value subscale (Pintrich et al., 1993) and a distance study self-efficacy scale. Further, goals were measured using the intrinsic-extrinsic goals subscales of the MSLQ as well as the percent of activities participants intend to complete. The first questionnaire received a total of 563 answers. A second questionnaire was sent out after week 1 of the MOOC and included questions regarding participants' SRL strategies. Specifically, three subscales from the resource management strategies section of the MSLQ were used: time and study environment, help seeking, and peer learning subscales. Only 105 answered the second questionnaire and consequently these variables were dropped from the final model. However, time and study environment was significant in some of the preliminary analysis. Additionally, cluster analysis of trace data was used to develop behavioral engagement types using data such as video consultation, readings and PowerPoint downloads, and discussion forum contributions. This led to the emergence of five types of behavioral engagement: the absent, the assessor, the curious leader, the independent activist, and the social activist. Further, a weekly composite behavioral engagement score was calculated based on three variables: number of connections, number of different days connected, and variety of resources used.

Results of the study confirmed the relationships predicted by the SRL model. For instance, significant relationship was found between initial motivation as measured by task value and self-efficacy and the three variables related to participants' goals (i.e. intrinsic goals, extrinsic goals, and percent of activities participants intend to do). In terms of persistence, a logistic regression model was iteratively built by gradually integrating all variables that were significant in the preliminary analysis. In this study, persistence was defined as having at least one activity in at least four different weeks of the course and/or having completed the final assignment. This model predicted persistence for 90% of participants from the behavioral engagement measures (i.e. engagement score and profiles) and the intrinsic-extrinsic goal orientation from the

MSLQ with intrinsic goal orientation being associated with higher persistence and extrinsic goal orientation being associated with lower persistence.

In addition, Kizilcec et al. (2016) used the social-cognitive model of SRL to examine the issue of persistence in MOOCs. In their study, the sample was selected based on successful completion of a MOOC on the topic of education offered by Pontificia Universidad Católica de Chile offered on the Coursera platform. In addition to Coursera's certificate, Chilean nationals were offered a chance to earn a certification recognized by the Chilean government by passing an in-person exam at the university. The researchers surveyed 17 learners who passed the official exam. Out of those 17 learners, 11 were females, between the ages of 25 and 50 or older, and all were full-time employees who held a degree in education or a related field. The survey included items related to the metacognitive and resource management SRL strategies they used during the course such as time management, self-study, and help-seeking strategies. Participants were also asked an open-ended question to provide recommendations for other learners to help them succeed in the course. A total of 35 recommendations were provided by learners and coded independently by 2 researchers based on Pintrich's metacognitive and resource management categories, which resulted in a set of 7 SRL strategies including goal setting/planning, time management, study environment, effort regulation, help seeking, self-monitoring, and self-evaluation. The most commonly reported recommendations were time management (10 out of 35) and effort regulation (8 out of 35).

Using these strategies reported by successful learners, the authors sought to test the hypothesis that prompting learners with SRL strategies improves persistence and achievement in a self-paced MOOC. In order to do so, learners who signed up for the same MOOC several weeks later were randomly assigned to either a control or SRL group. The experiment was embedded in the MOOC survey and was made available for two weeks. A total of 741 reached the stage in the survey at which they were randomly assigned to conditions, and 653 unique participants were retained in the final sample: 322 assigned to the control group and 331 assigned to the SRL group. The average age was 40, 61% were women, and 89% had a bachelor's or higher degree with most participants located in Mexico, Chile, and Colombia. However, 13% were excluded later from further analysis because they had already watched over 90% of the lectures and the experiment was intended to support learners at an earlier stage of their learning resulting in a final sample of 569.

Once participants were assigned to either group in the course survey, they were presented with different information. The SRL group was presented with a list of the seven strategies identified above such as review your goals constantly, take notes and summarize the course content to better understand it, find fellow students, and choose a good study environment, followed by quotations provided by learners who completed the MOOC successfully. Further, participants were asked to rate how helpful they thought the strategies will be for them (from 1 to 5) and write a brief message addressed to new learners about the strategies. The control group was presented with the official course description topics and were asked to rate how useful they thought the MOOC will be for their career (from 1 to 5). Additionally, they were asked to write a message to the MOOC designers about the topics they found the most and least interesting and why.

Two main outcome measures were used in this study: persistence and achievement. Persistence in this study was measured in terms of the percentage of lectures watched, and achievement as the percentage of assessments completed with a passing grade. Two additional behavioral outcomes were used: how many days learners were active in the course after taking the survey (posttreatment), and how many unique lectures they watched (posttreatment). Although most respondents rated the SRL tips very helpful, no significant benefit from providing SRL study tips over the control task was found for several course outcomes. Persistence, achievement, number of active days, and viewed lectures following the intervention were similar. Based on these findings, the researchers argue that simple SRL prompts at the beginning of a MOOC are insufficient to support the application of these strategies and should rather be integrated with the rest of the MOOC such as embedding technological aids that adaptively support SRL throughout the MOOC.

Finally, in order to generate a list of design guidelines for learning analytics that could help to facilitate SRL strategies to support learners persistence in MOOCs, Park et al. (2016) reviewed studies about SRL and analyzed the learning analytics capabilities of existing typical MOOCs platforms such as edX, Coursera, and FutureLearn. Based on this review, design guidelines that could be applied to the design and development of a MOOC platform to support SRL were derived. These guidelines were then validated and evaluated through two empirical studies: expert Delphi questionnaires and in-depth interviews with MOOC learners.

The first draft of design list recommendation contained 8 dimensions of SRL strategies (e.g. seeking social help, self-evaluation, goal setting and planning, seeking information) and 16 corresponding design principles. A panel of 17 experts in 2 rounds then validated the draft using a 5-point Likert-type scale with 1 indicating "highly invalid" and 5 indicating "highly valid." In addition, comments and feedbacks on each item of the design guidelines were requested. Those experts were selected based on two criteria: (a) they had a Ph.D. in Educational Technology, or (b) they were Ph.D. candidates experienced in research in MOOCs or e-learning designs for more than 7 years. Based on the feedback from the first round, 4 items were eliminated and a second round of expert panel review was conducted.

In addition to the panel review, in-depth interviews with 12 MOOC learners were conducted to understand the difficulties they face as they learn in MOOCs as well as helpful factors for SRL in MOOC learning environments. All of the interviewees mentioned their difficulties in learning in MOOCs with self-regulation strategies and over half of them felt that factors to help them engage in self-regulatory learning activities were insufficient in MOOC platforms. Interestingly, even interviewees who had earned some certificates described the difficulties they had to overcome to persist in MOOCs. Some of the comments they mentioned included: low intrinsic/extrinsic motivation, time management, and lack of personal contact or interactions. In addition, interviewees provided some recommendations and suggestions to improve the design of MOOCs to support SRL. While some of the suggestions they provided were already included in the design guideline, they also provided additional recommendations such as providing more detailed feedback on assignments (quantitative and qualitative) and personalization based on their level, preference, and learning styles or patterns.

Based on the results of both expert reviews and learners' opinions and experiences, the design guidelines were revised and the final version of the SRL strategies and the corresponding design guidelines of learning analytics to facilitate these SRL strategies in MOOCs included the following (Kizilcec et al., 2016, p. 142):

- Self-evaluation:
  - Content analysis of learner's reflections.
  - Learning history compared to others (achievements, progress, activities, e-portfolio, etc.).
- Organizing and transforming:
  - Learner's preferred contents types (video clips, texts, images, voices, etc.).
  - Student's participant activity records to upload and author contents.
- Goal-setting and planning:
  - Setting learning objectives and plans for effective time management.
  - Monitoring learner's plans, styles, and patterns.
- Keeping records and monitoring:
  - Records of student's learning activities such as note-taking, searching, downloading, and printing.
- Rehearsing and memorizing:
  - Details about participation in the exercise, discussion, homework, etc.
- Reviewing Records:

    - Quantitative and qualitative analysis of learning exercise such as quiz, discussions and exams for reviewing.
- Seeking information:
    - References and links referred by learners and others.
- Seeking social assistance:
    - Q&A to overcome problems or solve the problems.
- Self-consequences:
    - History of certificates or credits with invested time and earned achievement scores.
    - Enrolled and completed rates of courses monthly or annually.
- Structuring personalized learning environments:
    - Recommending courses for each learner's level or interest.
    - Feedback on learning success and failure appropriate for individual learning styles or patterns.

In conclusion, these studies indicate that motivational beliefs such as goal orientation, task value, and academic and online learning self-efficacy significantly predict effort, persistence, the use of SRL strategies, satisfaction, and continuing motivation to learn (Artino, 2009; Artino & Vermillion, 2007; Poellhuber et al., 2014). Further, while the studies on the role of SRL skills in learners' persistence in MOOCs are limited, the few studies reviewed have consistently identified time management, effort regulation, peer interaction, and help seeking as important factors in contributing to learners' persistence, albeit the varying definitions of persistence used, and success in

MOOCs (Kizilcec et al., 2016; Park et al., 2016). However, MOOC platforms in their current state do not support learners' use of SRL strategies (Park et al., 2016), highlighting the need to understand the role that motivational beliefs and SRL strategies play in supporting learners' experience in MOOCs. This line of investigation can help identify critical SRL factors associated with learners' persistence in this new learning context and form the basis for the design of interventions that can enhance the learning experience and support learners' persistence in MOOCs.

Chapter Summary

Student learning persistence is one of the most widely studied areas in higher education and now spans more than five decades. Despite this long history and extensive literature, an initial review of the literature clearly shows that different terms such as persistence, retention, dropout, and attrition are being used interchangeably in these discussions. This adds to the difficulty of studying and measuring this outcome of interest (Bean & Metzner, 1985; Lee & Choi, 2011; Reason, 2009). In this study, I use the term *persistence to goals* to denote the outcome of interest for two reasons. First, as mentioned previously, retention is an institutional phenomenon while persistence is an individual phenomenon. That is, institutions retain students to graduation, while students persist to goals (Reason, 2009). Retention rates are important indicators of institutional effectiveness and are usually reported to government agencies, which affects the ranking of the institution and in some cases the level of funding received (Kember, 1995). However, this is not the case in MOOCs. In MOOCs, where educational access and lifelong learning are primary goals, completion or retention rates should not matter as much as learners' achievement of goals. I argue that participants' achievement of goals is a better indicator of MOOC success and effectiveness. Second, if we agree with this line of reasoning, it makes no sense to use the term *retention* in these discussions because the educational goal of MOOCs becomes one of supporting MOOC learners as they *persist*, or in other words continue action despite the presence of obstacles (Rovai, 2003), to achieve their personal goals.

Because this study looks at persistence to goals rather than certificate attainment or MOOC completion, this literature review began with a review of studies examining participants' goals for joining MOOCs and their relation to the ways they impact behavioral engagement in these learning environments. Findings from these studies show that learners do in fact join MOOCs for varied reasons such as to satisfy curiosity or understand specific concepts (Zheng et al., 2015), lifelong learning (Yousef et al., 2015), and for professional development purposes (Milligan et al., 2013). While these studies indicate that goals do shape the ways in which participants decide to engage with a MOOC, they also highlight some factors that mediate such behavioral engagement such as motivation, confidence in learning in MOOCs, and prior experience in these online learning settings (Broadbent & Poon, 2015; Milligan et al., 2013). The complexity of learning behavioral engagement and persistence is supported by the long history of persistence research and different models proposed to explain such behavior and choice. These models indicate the significant role that motivational beliefs and the value they assign to the learning tasks play in learners' decisions to persist or drop out (Bean & Eaton, 2000, 2001; Kember, 1995; Tinto, 1975). While these factors have also been identified as significantly related to learners' online and MOOC persistence (Alraimi et al., 2015; Lee & Choi, 2011; Park, 2007), they are not sufficient if learners are not proactive in behavior and utilize a variety of learning and resource management strategies to accomplish their goals (Artino, 2009; Gollwitzer & Sheeran, 2006; Multon et al., 1991). These strategies include time management (Balakrishnan & Coetzee, 2013; Gütl et al., 2014; Kizilcec et al., 2016; Lee & Choi, 2011; Loya et al., 2015; Nawrot & Doucet, 2014; Park, 2007), peer learning and interaction (Adamopoulos, 2013; Alraimi et al., 2015; Gütl et al., 2014; Lee & Choi, 2011; Park, 2007; Woodgate et al., 2015), effort regulation (Gütl et al., 2014; Hone & El Said, 2016; Kizilcec et al., 2016; Lee & Choi, 2011), and help seeking (Gütl et al., 2014; Kizilcec et al., 2016; Lee & Choi, 2011; Park et al., 2016). One framework that allows us to examine the meditational role motivational beliefs play in utilizing such strategies and help understand factors influencing learners' persistence in MOOCs is the social-cognitive model of SRL (Multon et al., 1991; Pintrich, 2000a; Ryan et al., 2001; Zimmerman, 2000a, 2011).

The role of self-efficacy and goal orientation on learners' persistence in MOOCs has also shown mixed results. A number of reasons could be used to explain these findings. In terms of goal orientation, qualitative research suggests that performance orientation does not necessarily lead to maladaptive behaviors and outcomes (Hood et al., 2015). This is consistent with recent findings that point to evidence of a tridimensional nature of goal orientation that further divides performance orientation into performance approach and performance avoidance orientations (Elliot & Harackiewicz, 1996; Zweig & Webster, 2004). However, all studies reviewed used a bidimensional measure of goal orientation (Poellhuber et al., 2014; Wang & Baker, 2015). Consequently, a tridimensional measure is used that might be more sensitive to the differences in goal orientation. As for self-efficacy, the instruments used in these studies were too general and measured general technology or academic self-efficacy (Puzziferro, 2008; Wang & Baker, 2015). However, self-efficacy is task and domain specific, thus general self-efficacy measures might not be able to detect effects (Bandura, 1997; Pajares, 1996). Further, studies suggest that experience with learning within a MOOC influences the level of self-efficacy (Hood et al., 2015; Milligan et al., 2016). Hence, this study utilizes a self-efficacy measure that more closely reflects the nature of learning in MOOCs and examines efficacy in terms of the extent to which individuals feel confident they can learn effectively using MOOCs (Artino & McCoach, 2008). Finally, MOOC studies reviewed either focused on motivational factors (Wang & Baker, 2015) or SRL behavior and strategies but not the relationship between them. However, qualitative evidence suggests that these motivational beliefs shape how people engage in a MOOC (Milligan et al., 2016), highlighting the probability that motivational factors such as online learning self-efficacy, task value, and goal orientation could have an indirect effect on persistence through the utilization of these strategies. This is consistent with research on the role of motivational beliefs and SRL in online learning (Cho & Shen, 2013; Ryan et al., 2001). Consequently, this study utilizes the social-cognitive framework of SRL and examines these different relationships within a MOOC.

Although limited in number and of varying quality, research on the role of SRL in MOOCs suggests that positive motivational beliefs and adaptive SRL behaviors are critical for learners' success and persistence. The current study builds on these findings and adds some needed research at the intersection of the role of motivational beliefs on the use of SRL strategies and how these relationships can help us understand the issue of learners' persistence in MOOCs. Specifically, two research questions are examined:

- Is there a relationship between MOOC participants' motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value), use of SRL strategies (i.e. time and study environment, effort regulation, peer learning, and help seeking), and their self-reported persistence to goals in MOOCs?
- After controlling for MOOC experience, do motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value) and use of SRL strategies (i.e. time and study environment, effort regulation, peer learning, and help seeking) predict self-reported persistence to goals in MOOCs?

Chapter 3: Method

This section describes the methods used to explore the relations between MOOC learners' motivational beliefs, use of SRL strategies, and self-reported persistence to goals in a MOOC. In addition, this study examines whether participants' motivational beliefs and use of SRL strategies can predict self-reported persistence to goals in MOOCs. Given the varying and shifting goals of MOOC participants as indicated in the literature, persistence in this study is defined as the self-reported percentage of self-set goals that participants were able to achieve in a MOOC instead of the traditional benchmark of course completion or other behavioral and course interaction measures (i.e. percent of videos watched or assignments submitted). The specific SRL constructs that were examined are in line with the processes that have been deemed in the literature as relevant to participants' success and persistence in MOOCs (Balakrishnan & Coetzee, 2013; Gütl et al., 2014; Hone & El Said, 2016; Kop & Fournier, 2010; Loya et al., 2015; Milligan et al., 2013; Nawrot & Doucet, 2014). These include online learning self-efficacy, online learning task value, goal orientation, and resource management strategies (i.e. time and study environment, effort regulation, peer learning, help seeking).

The overarching research questions that guided the design of this study are:

- Is there a relationship between MOOC participants' motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value), use of SRL strategies (i.e. time and study environment, effort regulation, peer learning, and help seeking), and their self-reported persistence to goals in MOOCs?

- After controlling for MOOC experience, do motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value) and use of SRL strategies (i.e. time and study environment, effort regulation, peer learning, and help seeking) predict self-reported persistence to goals in MOOCs?

This chapter begins with a description of the setting in which the study was conducted and the participants of this study, followed by details about the research design, measures that were used to answer the research questions, study procedures, and finally statistical analysis by research question.

Setting

The MOOC Humanizing Online Instruction (HumanMOOC) is designed to be a professional development experience for those who wish to improve their online teaching practices by introducing them to the Community of Inquiry (CoI) framework (Garrison, Anderson, & Archer, 1999). The first week of the MOOC is designed to orient participants to the MOOC, provide a schedule of activities, and explain how to effectively participate in the MOOC using social media. The following three weeks are divided into three weekly modules with each focusing on one of the three presences of the CoI framework, namely, instructor, social, and cognitive presence. Within each weekly module, learning objectives, to-do-lists, articles and annotations, and assignments are provided. Further, a live Google hangout session with an expert in the field was streamed and recorded each week. For the instructor presence week, participants were asked to complete two assignments: create a course introduction video that they can use in their own courses and to use Flipgrid, a video discussion tool, to reflect on the pros and cons of using instructor videos. For the social presence week, participants were asked to engage in discussion on the use of multimedia and social media tools to enhance social presence in their courses, submit a short list of three to five personal goals for building social presence in their courses and the tools they might use via Flipgrid, and finally share some resources related to social presence to YellowDig, a social learning platform that allows instructors and students to share articles and videos. For the final week of the MOOC, the cognitive presence week, participants were asked to complete two assignments. The first assignment was to design a peer review assignment that they can use in their own online courses, and the second was to reflect on a triggering event that went viral on social media and how they can use that to engage their students in their courses. Each week of the MOOC is designed as a stand-alone module in which participants can earn individual badges for completing the assignments assigned for each week or elect to complete all assignments and earn a completion badge.

The design intent of the HumanMOOC was to create a community space to explore and share ideas and thoughts regarding online learning and teaching rather than knowledge dissemination. However, the designers of the HumanMOOC understood that not all participants are comfortable sharing their learning process and thoughts openly on the web using social media. As such, a dual-layer design was used to accommodate the needs and preferences of HumanMOOC participants while still supporting the development of an active community of learners (Kilgore & Al-Freih, 2016). The first layer, called the "embedded layer," was contained within the MOOC's Canvas Management System space and served as a private "members-only" sharing and learning space for those who were not as comfortable having their thoughts and comments out on the open Web. The learning design within this private space was based on the principles of social constructivism where participants collaborate, share, discuss, and learn by engaging in authentic activities. Further, learning activities and technologies were used within this private space to evoke and nurture the development of a community of practitioners among HumanMOOC participants. The second layer of the course was built around the principles of connectivism and is called the "exoskeletal layer." In this portion of the MOOC, participants were encouraged to share their learning process and progress openly on the Web using blogs, Twitter, and other tools they wanted to explore. Further, learning was more rhizomatic in nature as the community and connections established extend beyond and after the course (Cormier, 2008). Participants in both layers engaged in the same weekly activities and assignments, however, the way that learning occurred and how assignments were created and shared were different.

Participants

Participants in this study were a single population of adults, 18 and older, registered the HumanMOOC that was being offered on the Canvas Open Network in the fall of 2016. All participants who registered for the HumanMOOC were invited to participate. Thus, this study utilized a convenience sampling procedure by collecting results from all participants who self-selected to participate rather than random sampling procedures. The HumanMOOC has been offered on the same platform three times so far, in the fall of 2013, the spring of 2015 (N = 638), and the winter of 2015 (N = 862). Based on demographic data collected from the first two offerings of the MOOC, it was expected that the majority of participants would be 30 and older and have a master's or doctoral degree (Kilgore, Bartoletti, & Al-Freih, 2015). In terms of sample size, a desired sample size was determined as a function of effect size, alpha level, and power (Cohen, 1988). A priori power analysis for a multiple regression with 10 predictors (i.e. MOOC experience, motivational beliefs, and SRL strategies variables) was conducted in G*Power to determine a sufficient sample size using an alpha of 0.05 and a power of 0.80 (Faul, Erdfelder, Buchner, & Lang, 2009). For the effect size, Cohen (1988, 1992) provides effect size indexes for different tests and their values for small, medium, and large effects (see Table 1). Accordingly, a medium effect size for multiple regression was selected (f^2 = 0.15). Based on these assumptions, the desired sample size was 118.

Table 1

Effect Size Indexes and Values for Small, Medium, and Large Effects

Test	Effect Size Symbol	Small Effect Size	Medium Effect Size	Large Effect Size
t-test for means	d	.20	.50	.80
Correlation	r	.10	.30	.50
ANOVA	f	.10	.25	.40
Multiple Regression	f^2	.02	.15	.35

For this study, a total of 515 registered in the fourth offering of the HumanMOOC, however, only 334 accessed the course at least once. Out of the 334 participants who were invited to participate in the study, a total of 111 responded to the survey resulting in a 33.23% response rate, which was sufficient to detect a moderate effect size of .16. In terms of course activity, only 75 posted at least one discussion post or assignment, 21 earned the Instructor Presence badge, 21 earned the Social Presence badge, 14 earned the Cognitive Presence badge, and 13 earned the CoI badge.

The sample (N = 111) included 67.6% females and 32.4% males. Consistent with previous offerings of the HumanMOOC, the majority of respondents were 30 and older and have a master's or doctoral degree. Specifically, 30.6% were 50 years or older, 17.1% were between the ages of 45 and 49, 15.3% were between the ages of 40 and 44, 15.3% were between the ages of 35 and 39, 17.1% were between the ages of 30 and 34, 3.6% between the ages of 25 and 29, and only .9% between the ages of 20 and 24. In terms of educational attainment, 24.3% hold a doctoral degree, 51.4% have a master's degree, 19.8% have a bachelor's degree, 2.7% have an associate's degree, and 1.8% have a G.E.D. or a high school degree.

The ethnic background of participants was as follows: 77.5% White/Caucasian, 4.5% African American, 3.6% Hispanic/Latino, 3.6% East Asian, 2.7% African, 2.7% Middle Eastern, 1.8% Caribbean, .9% Asian, and 2.7% Mixed. Respondents were also asked about their place of residence, which is as follows: 73% in North America, 9.9% in Europe, 4.5% in Australia, 3.6% in Africa, 2.7% in South America, 2.7% in the Middle East, 1.8% in Central America, and 1.8% in Russia. Participants were also asked about whether they have enrolled in and completed some or all of a different MOOC in the past, with 62.2% indicating previous experiences with MOOCs.

Research Design

Using a quantitative survey methodology, this single-group, cross-sectional study employs a posttest-only correlational design resulting in a nonexperimental study (Warner, 2013). While no cause-effect relationships can be established using correlational designs, such designs serve a number of purposes. For instance, correlational studies are an efficient strategy (in terms of cost and time) to identify related variables that can be used in future casual-comparative and experimental studies (Warner, 2013). Given the short history of research on SRL in MOOCs and the novelty of MOOCs as a learning environment, this methodology helps highlight the important SRL factors that can be used in future experimental or design-based research studies in order to increase learners' persistence in achieving their personal goals for joining MOOCs.

Measures

A number of measures were adapted to measure various aspects of participants' demographics and MOOC experience, motivational beliefs (goal orientation, online learning self-efficacy, and online learning task value), use of SRL strategies (time and study environment, effort regulation, peer learning, and help seeking), and persistence to goals in the Human MOOC. The independent variables used to answer both research questions include a tridimensional dispositional goal orientation measure (Zweig & Webster, 2004), the Online Learning Value and Self-Efficacy Scale (OLVSES) (Artino & McCoach, 2008), and the resource management strategies subscales of the MSLQ

(Pintrich et al., 1993). These variables were included in future analysis by computing the mean score for the items associated with each subscale. The outcome variable in this study was a self-report single item measure of persistence to goals. The reliability and validity evidence of the scales used in this study is summarized in Table 2. A description of each of the measures used and the data analytic techniques used to investigate their validity and reliability evidence as well as exploratory factor analysis conducted to examine the unidimensionality and internal reliability of the subscales using the study data are described in the following sections.

Table 2

Reliability and Validity Evidence of the Scales Used in this Study

Authors	SRL Processes	Scale/Subscale	Number of Items	Level of Measurement	α	Validity
Zweig and Webster (2004)	Goal orientation	Performance Orientation (Approach) subscale of the Dispositional Goal Orientation Scale	7	7-point Likert scale	.82	Convergent and predictive validity established
		Performance Orientation (Avoidance) subscale of the Dispositional Goal Orientation Scale	7	7-point Likert scale	.69	
		Learning Orientation subscale of the Dispositional Goal Orientation Scale	7	7-point Likert scale	.85	
Artino and McCoach (2008)	Online learning self-efficacy	Self-efficacy for learning with self-paced online training subscale of the OLVSES	5	7-point Likert scale	.87	Predictive validity established
Artino and McCoach (2008)	Online learning task value	Task value subscale of the OLVSES	6	7-point Likert scale	.85	Predictive validity established
Pintrich et al. (1993)	Time management and study environment	Time and study environment subscale of the MSLQ	8	7-point Likert scale	.76	Predictive validity established
Pintrich et al. (1993)	Effort regulation	Effort Regulation subscale of the MSLQ	4	7-point Likert scale	.69	Predictive validity established
Pintrich et al. (1993)	Peer learning	Peer learning subscale of the MSLQ	3	7-point Likert scale	.76	Predictive validity established
Pintrich et al. (1993)	Help seeking	Help seeking subscale of the MSLQ	4	7-point Likert scale	.52	Predictive validity established

Note. OLVSES = Online Learning Value and Self-Efficacy Scale. MSLQ = Motivated Strategies for Learning Questionnaire.

Demographics and MOOC experience. The demographics and MOOC experience variables included in this study were gender, age, educational attainment, ethnicity, place of residence, and whether they have previously participated in MOOCs. MOOC experience was described to participants as those who had previously signed up for a different MOOC and had completed some or all of the assignments. Further, an open-ended question about the primary goals they had for joining the HumanMOOC was included. Variable items and level of measurement are provided in Table 3.

Table 3

Demographic and MOOC Experience Variables

Variable	Items Included	Level of Measurement
Gender	• Male • Female	Dichotomous nominal
Age	• 18 to 19 years • 20 to 24 years • 25 to 29 years • 30 to 34 years • 35 to 39 years • 40 to 44 years • 45 to 49 years • 50 years and over	Categorical nominal
Educational attainment	• Primary/Elementary School • Secondary/Middle School • High School or G.E.D. • Associate's Degree • Bachelor's Degree • Master's Degree • Ph.D./Doctorate	Categorical nominal
Ethnicity	• White/Caucasian • African American • African • Hispanic/Latino • Middle Eastern • Caribbean • South Asian • East Asian • Mixed • Other: ________	Categorical nominal
Place of residence	• North America • Central America • South America • Europe • Africa • Middle East • Asia • Russia • Australia • Other: ________	Categorical nominal
MOOC experience	• Yes • No	Dichotomous nominal
Primary goal(s) for participation	• What was your primary goal(s) for enrolling in the HumanMOOC?	Open-ended question

Motivational beliefs. The motivational beliefs variables used in this study were examined within the social-cognitive framework of SRL. These variables include goal orientation (Zweig & Webster, 2004), online learning self-efficacy (Artino & McCoach, 2008), and task value (Artino & McCoach, 2008). Permission to use these scales was requested from, and granted by, scale developers via email. Description of each subscale, and the results of the exploratory factor analysis to examine the factor structure and internal reliability of each scale using the current data ($N = 111$), are provided next.

Goal orientation. The scale used to measure participants' goal orientation is the tridimensional dispositional goal orientation measure created by Zweig and Webster (2004). A total of 32 items measuring 3 goal orientation subscales of performance-orientation approach, performance-orientation avoidance, and learning were included in the initial measure. These items were drawn from 2 established goal orientation scales as well as newly created items. Specifically, 20 items were drawn from the learning and performance orientation items of the general goal orientation scale created by Button, Mathieu, and Zajac's (1996), two items from the performance avoidance orientation items of the goal orientation scale created by Elliot and Church (1997), and 10 new items created by the authors. Further, two versions of the scale were created: a general measure and a situation-specific measure. The general version included the instructions: "For each of the statements below, please circle the number that indicates your degree of agreement or disagreement using the following scale." The situation-specific version included the same items except for the general instructions that read, "Please think about your general attitude toward, and goals for this class. Using the following scale, please circle the number that indicates your degree of agreement or disagreement with the statements with respect to this course."

A series of studies were conducted with over 900 participants to examine the reliability and validity of the new general scale using different analysis techniques such as exploratory and confirmatory factor analysis, internal consistency reliability analysis, test-retest reliability, and convergent and predictive validity. Content validity was established by having a panel of Ph.D. students review the initial items. The factor structure of the scale was pilot tested with the first sample (n = 194) and included university students enrolled in Management Sciences and Industrial Psychology courses. Based on the results of the reliability and exploratory factor analysis, a number of revisions were made to the items to improve the reliability of the subscales and the factor loading of some items. Eventually, 21 items were retained and exploratory factor analysis was conducted again on the revised measure with a second sample of university students enrolled in an Introductory Psychology course (n = 285). Further, internal consistency reliability analysis as well as confirmatory factor analysis was conducted on this sample to test the fit of the measurement and structural models. The resulting measure comprised 21 items measuring 3 subscales, with each subscale containing 7 items. Internal consistency reliabilities for the 3 subscales scales were: learning orientation (α = .85), performance-orientation approach (α = .82), and performance-orientation avoidance (α = .69). Further, to establish the distinctiveness of the goal orientation subscales and self-efficacy constructs, chi-square analysis (i.e. chi-square degrees of freedom ratio, the goodness-of-fit, the adjusted goodness-of-fit, the comparative fit index, and the root mean square error of approximation) were conducted to test four different models. The first model tested the assumption that goal orientation and computer self-efficacy are a unitary construct. The second model tested the assumption that goal orientation is a unitary concept distinct from computer self-efficacy. The third model tested the assumption that computer self-efficacy and learning orientation are indistinct but different from performance approach and performance avoidance orientations. Finally, the fourth model tested the assumption that goal orientation comprises three distinct but correlated factors and that computer self-efficacy is distinct and correlated with goal orientation. The results indicated that the last model fit the data very well and provided a significantly better fit to the data than the one-, two-, or three-factor models.

A third sample was used to assess the internal consistency, test-retest reliability (over a three-month period), and convergent validity of the measure. Those included university students enrolled in a Management Sciences course (n = 196 for Time 1, n = 62 for Time 2). The test-retest reliability coefficients for the goal orientation scale at Time 1 and Time 2 were: learning orientation (r = .73), performance-orientation approach (r = .84), and performance-orientation avoidance (r = .78). Further, convergent validity was examined by testing the statistical relationship between the goal orientation measure and the VandeWalle's Work Domain Goal Orientation scale (1997). All the corresponding subscales on each of the measures showed a strong, positive relationship. Finally, a fourth sample (n = 261) was used to assess the predictive validity of specific (n = 131) versus general (n = 130) measures of goal orientation on course grades. Only the situation-specific measure was able to predict a significant amount of variance in final grades.

The final situation-specific measure of goal orientation was used in the current study. This measure contains a total of 21 items measured on a 7-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree, with each subscale being measured by 7 items. An example of a performance-orientation approach subscale statement is, “I value what others think of my performance.” An example of a performance-orientation avoidance subscale statement is, “Typically, I like to be sure that I can successfully perform a task before I attempt it.” Finally, an example statement from the learning orientation subscale is, “I prefer to work on tasks that force me to learn new things.” Tables 4, 5, and 6 provide a list of the 21 items contained in the goal orientation subscales.

Table 4

Performance Orientation Approach (POA) Subscale Items

	Original Items
POA1	I value what others think of my performance.
POA2	It’s important for me to impress others by doing a good job.
POA3	I don’t care what others think of my performance (reverse coded).
POA4	I’m not interested in impressing others with my performance (reverse coded).
POA5	I like to meet others’ expectations of me.
POA6	The opinions others have about how well I can do certain things are important to me.
POA7	It’s better to stick with what works than risk failing at a task.

Table 5

Performance Orientation Avoidance (POV) Subscale Items

	Original Items
POV1	Typically, I like to be sure that I can successfully perform a task before I attempt it.
POV2	I don't like having my performance compared negatively to others.
POV3	I don't enjoy taking on tasks if I am unsure whether I will complete them successfully.
POV4	I avoid circumstances where my performance will be compared to others.
POV5	Most of the time, I stay away from tasks that I know I won't be able to complete.
POV6	I worry that I won't always be able to meet the standards set by others.
POV7	I avoid tasks that I may not be able to complete.

Table 6

Learning Orientation (LO) Subscale Items

	Original Items
LO1	The opportunity to do challenging work is important to me.
LO2	I prefer to work on tasks that force me to learn new things.
LO3	If I don't succeed on a difficult task, I plan to try harder the next time.
LO4	In learning situations, I tend to set fairly challenging goals for myself.
LO5	I am always challenging myself to learn new concepts.
LO6	The opportunity to extend my range of abilities is important to me.
LO7	The opportunity to learn new things is important to me.

Exploratory factor analysis. To assess the unidimensionality of the seven items making up each of the three goal orientation subscales, three separate EFA analyses using Principle Component Analysis (PCA) were performed for each. For each of the subscales, factorability of the items was examined using several criteria including the determinant and correlation among items, the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO), Bartlett's test of sphericity, the diagonals of the anti-image correlation matrix, and communality values for each item (Tabachnick & Fidell, 2007).

For the performance-approach orientation, the determinant was .013 and all items correlated at least .5 with all other items except for item POA7 "It's better to stick with what works than risk failing at a task," which weakly correlated with only one other item (r = .25). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .8, above the recommended value of .6. Bartlett's test of sphericity was significant (χ^2 (21) = 464.21, p < .001). The diagonals of the anti-image correlation matrix were all over .5 except for item POA7 which was at .42. Finally, the communalities were all above .3, ranging between .62 and .87.

PCA with oblimin rotation was performed on the original seven items making up the performance-orientation approach subscale. The results of the PCA indicated a two-factor structure with eigen values > 1 with the first six items loading on the first factor and explaining 58.34% of the variance, and only one item (POA7) loading on the second factor and explaining 16.26% of the variance.

Given the results of the data screening and initial PCA, item POA7 was removed and PCA was conducted on the remaining six items. The determinant was .015 and items correlated at least at .5 with all other items. KMO was .8 and Bartlett's test of sphericity was significant (χ^2 (15) = 450.18, $p < .001$). The diagonals of the anti-image correlation matrix were all over .5, supporting the inclusion of each item in the factor analysis. Finally, the communalities were all above .3, ranging between .62 and .78. This resulted in a one-factor structure with the initial eigen value explaining 68% of the variance and factor loadings ranging between .79 and .88. Thus, it was decided to remove item POA7 "It's better to stick with what works than risk failing at a task" prior to analysis. The removal of item POA7 slightly improved Cronbach's coefficient alpha from .86 to .90.

The factorability of the performance-orientation avoidance subscale was confirmed using the same criteria. The determinant was .05 and all seven items correlated at least .3 with more than one other item, suggesting reasonable factorability. Secondly, KMO was .8, and Bartlett's test of sphericity was significant (χ^2 (21) = 319.23, $p < .001$). The diagonals of the anti-image correlation matrix were between .73 and .9, supporting the inclusion of each item in the factor analysis. Finally, the communalities were all at or above .3. The PCA resulted in a one-factor solution that explained 51.63% of the variance and factor loadings ranging between .52 and .83. Thus, all items were retained for this subscale. Cronbach's alpha for this subscale in the current study is .84.

For the learning-orientation subscale, the determinant was .009 and all seven items correlated at least .3 with more than one other item, KMO was .84, and Bartlett's test of sphericity was significant (χ^2 (21) = 505.97, $p < .001$). The diagonals of the anti-image correlation matrix were between .75 and .9, and the communalities ranged between .51 and .73. The PCA resulted in a one-factor solution that explained 63.76% of the variance with factor loadings ranging between .72 and .86. Thus, all items were retained for this subscale as well. Cronbach's alpha for this subscale in the current study is .9.

Online learning self-efficacy and task value. Two subscales from Artino and McCoach's (2008) Online Learning Value and Self-Efficacy Scale (OLVSES) were used to assess participants' motivational beliefs: (a) a five-item *self-efficacy* subscale designed to assess students' confidence in their ability to learn the material presented in a self-paced online format; and (b) a six-item *task value* subscale designed to assess students' judgments of how interesting, useful, and important the online course was to them. These subscales were chosen for this study. The initial scale contained three subscales measuring task value components including attainment value/importance, intrinsic interest value, and extrinsic utility value and one subscale measuring self-efficacy for learning with self-paced online training each containing approximately 10 items measured on a 7-point Likert scale ranging from 1= completely disagree to 7=completely agree. This was followed by content validation procedures by 6 content experts and resulted in the reduction of the total items from 41 to 28.

A number of studies were conducted to establish reliability and validity of the newly developed scale. In the first study, a convenience sample of 204 personnel from the U.S. Navy responded to the survey. Based on the results of the exploratory factor analysis conducted on this sample, only 24 items representing 2 (i.e. task value and self-efficacy) out of the 4 factors were retained in the final solution. Reliability analysis of the task value and self-efficacy subscales resulted in the deletion of 2 items from the task value subscale and 1 item from the self-efficacy scale. The Cronbach's alpha for the resulting 14-item task value subscale was .95 and .89 for the 7-item self-efficacy subscale. A second study was conducted to determine whether the hypothesized 2-factor model fits the data. In this study, 646 undergraduates from the U.S. Naval Academy responded to the survey. The results of the confirmatory factor analysis resulted in additional modifications to the scale. The final solution from this analysis resulted in 6 items in the task value subscale (see Table 7) and 5 items in the self-efficacy subscale (see Table 8) with good reliability estimates for both scales (.85 and .87 respectively). Finally, a third study using the 6-item task value and 5-item self-efficacy subscale provided evidence of the subscales' predictive validity. Specifically, students' motivational beliefs as measured by the OLVSES subscales were found to be predictors of students' negative achievement emotions (i.e. boredom and frustration) and use of cognitive and metacognitive learning strategies (Pintrich et al., 1993). An example of a task value subscale statement is, "This course provided a great deal of practical information." An example of a self-efficacy subscale statement is, "I am confident I can learn without the presence of an instructor to assist me."

Table 7

Online Learning Task Value (TV) Subscale Items

	Original Items	Item if Modified
TV1	It was personally important for me to perform well in this course.	It was personally important for me to perform well in this Massive Open Online Course.
TV2	This course provided a great deal of practical information.	This Massive Open Online Course provided a great deal of practical information.
TV3	I was very interested in the content of this course.	I was very interested in the content of this Massive Open Online Course.
TV4	Completing this course moved me closer to attaining my career goals.	Completing this Massive Open Online Course moved me closer to attaining my career goals.
TV5	It was important for me to learn the material in this course.	It was important for me to learn the material in this Massive Open Online Course.
TV6	The knowledge I gained by taking this course can be applied in many different situations.	The knowledge I gained by taking this Massive Open Online Course can be applied in many different situations.

Table 8

Online Learning Self-Efficacy (SE) Subscale Items

	Original Items	Item if Modified
SE1	Even in the face of technical difficulties, I am certain I can learn the material presented in an online course.	Even in the face of technical difficulties, I am certain I can learn the material presented in a Massive Open Online Course.
SE2	I am confident I can learn without the presence of an instructor to assist me.	
SE3	I am confident I can do an outstanding job on the activities in a self-paced, online course.	I am confident I can do an outstanding job on the activities in a Massive Open Online Course.
SE4	I am certain I can understand the most difficult material presented in a self-paced, online course.	I am certain I can understand the most difficult material presented in a Massive Open Online Course.
SE5	Even with distractions, I am confident I can learn material presented online.	

Exploratory factor analysis. To assess the unidimensionality of the task value and self-efficacy subscales, two separate exploratory factor analyses using Principle Component Analysis (PCA) were performed for each. For each of the subscales, factorability of the items was examined using several criteria including the correlation among items, the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO), Bartlett's test of sphericity, the diagonals of the anti-image correlation matrix, and communality values for each item (Tabachnick & Fidell, 2007).

For the task value subscale, the determinant was .04 and all six items correlated at least .34 with all other items, KMO was .81, and Bartlett's test of sphericity was significant (χ^2 (15) = 341.68, p < .001). The diagonals of the anti-image correlation matrix were between .77 and .84, and the communalities ranged between .5 and .73. The PCA resulted in a one-factor solution that explained 61.77% of the variance with factor loadings ranging between .67 and .85. Thus, all items were retained for this subscale. Cronbach's alpha for this subscale in the current study is .87.

For the online learning self-efficacy subscale, the determinant was .103 and all five items correlated at least .5 with all other items, KMO was .87, and Bartlett's test of sphericity was significant (χ^2 (10) = 244.43, p < .001). The diagonals of the anti-image correlation matrix were between .84 and .89, and the communalities ranged between .6 and .7. The PCA resulted in a one-factor solution that explained 65.7% of the variance with factor loadings ranging between .77 and .85. Thus, all items were retained for this subscale as well. Cronbach's alpha for this subscale in the current study is .87.

SRL strategies. Participants' use of SRL strategies was assessed with items derived from the resource management strategies subscales of the MSLQ (Pintrich et al., 1993): (a) an eight-item *time and study environment* subscale designed to assess participants' ability to manage and regulate their time (e.g. scheduling a study time) and study environment (e.g. setting a quiet study space) (see Table 9); (b) a four-item *effort regulation* subscale intended to assess participants' ability to control their effort and attention in the face of distractions or uninteresting tasks (see Table 10); (c) a three-item *peer learning* subscale to assess participants' ability to collaborate with peers to clarify course materials (see Table 11); and (d) a four-item help-seeking subscale intended to assess participants' ability to manage the support of others in the course including peers and instructors when needed (see Table 12). This scale has been widely used in the online learning literature to describe the self-regulatory processes learners engage in in online learning environments (Broadbent & Poon, 2015). The items included in these subscales were similar to the original MSLQ, except that some items were reworded to reflect the online nature of the MOOC. The MSLQ has been under development since the ’80s. The final version of the scale contains a total a total of 81 items measuring various motivation and learning strategies scored on a 7-point Likert scale ranging from 1 = not at all true for me to 7 = very true for me. However, MSLQ is modular so the subscales can be used together or individually, depending on the need of the researcher. For this study, only the 19 items measuring the resource management strategies subscales were used.

Using a sample of 380 Midwestern college students from 37 classrooms and spanning 14 subject domains, the researchers were able to establish the internal consistency, reliability, and predictive validity of the current MSLQ. Confirmatory factor analysis confirmed the underlying theoretical model and the model factors appeared to be the best fitting representation of the data. Internal consistency estimates of reliability were reasonable. The Cronbach coefficient alphas for the resource management strategies ranged between .76 and .52. Finally, the scales’ predictive validity was examined by correlating the subscales with final grade in which they were enrolled when they took the MSLQ. Further, correlations among the subscales of the MSLQ were also examined. Results indicate significant correlations with course grades and use of cognitive learning strategies. Further, all correlations were in the expected direction, adding to the validity of the subscales. Consequently, it can be concluded that the MSLQ is a scale with relatively good reliability in terms of internal consistency, as well as good predictive validity that can be used to assess college students' use of learning strategies. A sample item from the time and study environment subscale is, "I have a regular place set aside for studying." A sample item from the effort regulation subscale is, "Even when course material are dull and uninteresting, I manage to keep working until I finish." A sample item from the peer learning subscale is, "I try to work with other students from this class to complete the course assignments." Finally, a sample item from the help-seeking subscale is, "I try to identify students in this class whom I can ask for help if necessary." Tables 9 through 12 list the 19 items included in the time and study environment, effort regulation, peer learning, and help-seeking subscales.

Table 9

Time and Study Environment (TSE) Subscale Items

	Original Items	Item if Modified
TSE1	I usually study in a place where I can concentrate on my course work.	
TSE2	I make good use of my study time for this course.	I make good use of my study time for this Massive Open Online Course.
TSE3	I find it hard to stick to a study schedule. (Reverse coded)	
TSE4	I have a regular place set aside for studying.	
TSE5	I make sure I keep up with the weekly readings and assignments for this course.	I make sure I keep up with the weekly readings and assignments for this Massive Open Online Course.
TSE6	I attend class regularly.	I participate in the MOOC regularly.
TSE7	I often find that I don't spend much time on this course because of other activities. (Reverse coded)	I often find that I don't spend much time on this Massive Open Online Course because of other activities. (Reverse coded)
TSE8	I rarely find time to review my notes or readings before an exam. (Reverse coded)	I rarely find time to review my notes or readings before an assignment. (Reverse coded)

Table 10

Effort Regulation (ER) Subscale Items

	Original Items	Item if Modified
ER1	I often feel so lazy or bored when I study for this class that I quit before I finish what I planned to do. (Reverse coded)	I often feel so lazy or bored when I study for this Massive Open Online Course that I quit before I finish what I planned to do. (Reverse coded)
ER2	I work hard to do well in this class even if I don't like what we are doing.	
ER3	When course work is difficult, I give up or only study the easy part. (Reverse coded)	
ER4	Even when course materials are dull and uninteresting, I manage to keep working until I finish.	

Table 11

Peer Learning (PL) Subscale Items

	Original Items	Item if Modified
PL1	When studying for this course, I often try to explain the material to a classmate or a friend.	When studying for this Massive Open Online Course, I often try to explain the material to a classmate or a friend.
PL2	I try to work with other students from this class to complete the course assignments.	I try to work with other students from this Massive Open Online Course to complete the course assignments.
PL3	When studying for this course, I often set aside time to discuss the course material with a group of students from the class.	When studying for this Massive Open Online Course, I often set aside time to discuss the course material with a group of students from the class.

Table 12

Help-Seeking (HS) Subscale Items

	Original Items	Item if Modified
HS1	Even if I have trouble learning the material in this class, I try to do the work on my own, without help from anyone. (Reverse coded)	Even if I have trouble learning the material in this Massive Open Online Course, I try to do the work on my own, without help from anyone. (Reverse coded)
HS2	I ask the instructor to clarify concepts I don't understand well.	
HS3	When I can't understand the material in this course, I ask another student in this class for help.	When I can't understand the material in this Massive Open Online Course, I ask another student in this class for help.
HS4	I try to identify students in this class whom I can ask for help if necessary.	I try to identify students in this Massive Open Online Course whom I can ask for help if necessary.

Exploratory factor analysis. To assess the unidimensionality of the task value and self-efficacy subscales, four separate exploratory factor analyses using Principle Component Analysis (PCA) were performed for each. For each of the subscales, factorability of the items was examined using several criteria including the correlation among items, the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO), Bartlett's test of sphericity, the diagonals of the anti-image correlation matrix, and communality values for each item.

For the time and study environment subscale, the determinant was .05 and 18 items correlated at least .3 with at least one other item. KMO was .7, and Bartlett's test of sphericity was significant (χ^2 (28) = 322.40, p < .001). The diagonals of the anti-image correlation matrix were all above .5, and the communalities ranged between .57 and .83. The results of the PCA indicated a three-factor structure with eigen values > 1 with three items loading on the first factor and explaining 39.85 % of the variance, three items loading on the second factor and explaining 19.23% of the variance, and two items loading on the third factor and explaining an additional 13.9% of the variance. Upon closer examination of the items loading on each factor, it was apparent that the items that loaded on the first factor were related to time management (i.e. TSE2, TSE5, and TSE6) with loadings ranging between .8 and .89, items that loaded on factor 2 were the negatively worded time management items (i.e. TSE3, TSE7, and TSE8) with loadings ranging between .72 and .8, and the items that loaded on the last factor were related to study environment (i.e. TSE1 and TSE4) with factor loadings of .83 for both.

Consequently, the negatively worded items were removed and PCA was conducted on the remaining five items, which resulted in a two-factor structure with one factor representing time management (i.e. TSE2, TSE5, TSE6) and the second representing study environment (i.e. TSE1 and TSE4). However, because the original subscale had only two items representing study environment, it was not possible to split the scale to represent two separate factors. Thus, TSE1 "I usually study in a place where I can concentrate on my course work" and TSE4 "I have a regular place set aside for studying" were removed and PCA was conducted again with the remaining three items representing time management.

The determinant was .24 and items correlations ranged between .62 and .74. KMO was .72 and Bartlett's test of sphericity was significant (χ^2 (3) = 153.59, $p < .001$).

The diagonals of the anti-image correlation matrix ranged between .68 and .8. Finally, the communalities were between .73 and .82. This resulted in a one-factor structure with the initial eigen value explaining 78.08% of the variance and factor loadings ranging between .85 and .91. Thus, the final scale contained three items representing time management. For this reason, the variable time and study environment will be referred to as time management from this point on. The items retained for the time management construct were TSE2 "I make good use of my study time for this Massive Open Online Course," TSE5 "I make sure I keep up with the weekly readings and assignments for this Massive Open Online Course," and TSE6 "I participate in the MOOC regularly." The Cronbach's alpha for the final scale improved from .76 to .86.

For the effort regulation subscale, the determinant was .57 and three items correlated at least .3 with at least one other item, KMO was .55, and Bartlett's test of sphericity was significant (χ^2 (6) = 59.81, $p < .001$). The diagonals of the anti-image correlation matrix were between .63 and .76, and the communalities ranged between .5 and .6. The PCA resulted in a two-factor solution with two items loading on the first factor and explaining 45.74% of the variance, and two items loading on the second factor explaining an additional 26.33% of the variance. The items that loaded on the first factor were the negatively worded items ER1 and ER3 with factor loadings of .83 and .9, and the remaining two items ER2 and ER4 loaded separately on the second factor with factor loadings of .82 and .83. Because this subscale has only 4 items, items were removed one at a time in search of a single factor structure. This was achieved by the removal of item ER3 "When course work is difficult, I give up or only study the easy part."

The determinant for the final solution for the effort regulation subscale with three items was .78 and all three items correlated at least .3 with at least one other item. The KMO was .58, and Bartlett's test of sphericity was significant (χ^2 (3) = 26.75, $p < .001$). The diagonals of the anti-image correlation matrix were between .55 and .63, and the communalities ranged between .4 and .65. The PCA resulted in a one-factor solution that explained 52.25% of the variance with factor loadings ranging between .63 and .81. This final solution resulted in a Cronbach's alpha of .54.

For the peer learning subscale, the determinant was .042 and all three items correlated at least .44 with all other items, KMO was .67, and Bartlett's test of sphericity was significant (χ^2 (3) = 93.43, $p < .001$). The diagonals of the anti-image correlation matrix were between .63 and .76, and the communalities ranged between .6 and .77. The PCA resulted in a one-factor solution that explained 68.93% of the variance with factor loadings ranging between .77 and .88. Thus, all items were retained for this subscale. Cronbach's alpha for this subscale in the current study is .76.

For the help-seeking subscale, the determinant was .04 and all four items correlated at least .4 with all other items, except for HS1, which had a significant negative correlation with only one other item. KMO was .63, and Bartlett's test of sphericity was significant (χ^2 (6) = 101.65, $p < .001$). The diagonals of the anti-image correlation matrix were between .57 and .73, and the communalities ranged between .61 and .91. The results of the PCA indicated a two-factor structure with eigen values > 1 with three items loading on the first factor and explaining 52 % of the variance, and only one item (HS1) loading on the second factor and explaining an additional 25.62% of the variance.

Consequently, item HS1 was removed and PCA was conducted on the remaining three items. The determinant was .42 and items correlated at least at .4 with all other items. KMO was .63 and Bartlett's test of sphericity was significant (χ^2 (3) = 94.46, p < .001). The diagonals of the anti-image correlation matrix were all above .6, supporting the inclusion of each item in the factor analysis. Finally, the communalities were all above .53. This resulted in a one-factor structure with the initial eigen value explaining 67.81% of the variance and factor loadings ranging between .73 and .89. Thus, it was decided to remove item HS1, "Even if I have trouble learning the material in this Massive Open Online Course, I try to do the work on my own, without help from anyone" prior to analysis. The removal of item HS1 dramatically increased the scales Cronbach's coefficient alpha from .48 to .75.

Persistence to goals. In order to measure participants' persistence to goals, they were asked to estimate the percent of achieved goals they have set for themselves from zero to 100 percent, making this an interval variable (see Table 13). Such self-report measures of progress have been used previously in MOOC studies (Adamopoulos, 2013; Cross, 2013; Hone & El Said, 2016).

Table 13

Persistence to Goals

Construct Measured		Item
Persistence	Self-report persistence to goals	What percent of your self-set goals for joining this MOOC do you estimate you have achieved? Please slide the marker to the percent of goals achieved |….|….|….|….|….|….|….|….|….|….| 0 50 100

Procedures

After receiving approval from the GMU Institutional Review Board (Appendix A), the week prior to the official launch of the MOOC, a Google hangout session was held to describe to MOOC participants the purpose of the research, research procedures, the consent process, and their rights as subjects in this research. The hangout session was recorded and posted in the Canvas course site for participants to watch later as well as on the recruitment page in Canvas. The outcome variable of interest in this study is the percent of self-set goals achieved for participating in the HumanMOOC regardless of whether participants completed all activity or earned any badges. For this reason, the survey used in this study was called "The HumanMOOC Experience Survey" (see Appendix B) and was available for participants to complete as soon the MOOC officially started on November 14, 2016. Participants were instructed to complete the survey following their last engagement with the MOOC. The survey was created using

SurveyMonkey. A recruitment message (see Appendix C) and a link to the survey were available on the MOOC Canvas site. Further, reminders of the survey as well as a link to the recruitment page on Canvas were included in the weekly MOOC email newsletter sent out to participants. Participants were required to consent by clicking "I Agree" before proceeding to the survey (see Appendix D). No identifiable information was collected to ensure the anonymity and confidentiality of responses. This survey was available until January 1, 2017 to allow participants who were not following the suggested schedule to engage with the MOOC at their own pace. Finally, to entice participation and increase the response rate, all participants who consented by providing their email address at the end of the survey were awarded a $10 e-gift card from either Amazon or Starbucks. This e-gift card was sent to the email address they provided in the survey. This process was explained to participants in the recruitment letter and informed consent.

Statistical Analysis by Research Question

The analysis of data began by screening the data for assumptions and missing values followed by providing descriptive statistics (means and standard deviations) on all variables included in this study. Univariate outliers, normality, linearity, and homoscedasticity were assessed using histograms, residual scatterplots, and significance tests for skewness and kurtosis (Tabachnick & Fidell, 2007). Collinearity statistics such as correlations among predictors, tolerance, and Variance Inflation Factors (VIF) were examined to check for multicollinearity. Multivariate outliers were assessed by calculating Mahalanobis distance and Cook's statistics.

For the first research question: Is there a relationship between MOOC participants' motivational beliefs, use of SRL strategies, and their self-reported persistence to goals in MOOCs? a Pearson product-moment *r* correlation was conducted to assess the relationship between motivational beliefs variables (i.e. goal orientation, online learning self-efficacy, and online learning task value), use of SRL strategies variables (time management, effort regulation, peer learning, and help seeking), and self-reported persistence to goals and to examine any significant relationship between motivational beliefs and SRL strategies variables as well as any significant relationships between motivational beliefs and SRL strategies variables and self-reported persistence to goals. Correlation coefficients (*r*) are reported for each significant relationship and Cohen's (1988, 1992) standard was used to evaluate the strength of the relationship, where 0.10 to 0.29 represents a weak association between the two variables, 0.30 to 0.49 represents a moderate association, and 0.50 or larger represents a strong association (Table 1).

For the second research question: After controlling for MOOC experience, do motivational beliefs and use of SRL strategies predict self-reported persistence to goals in MOOCs? a three-step hierarchical regression was conducted to explore further the relationships between learners' motivational beliefs, use of SRL strategies, and persistence to goals in MOOCs. For this analysis, the predictor variables were grouped into three construct sets. In step 1, MOOC experience was added to the model. This was followed by the forethought motivational beliefs of goal orientation, online learning self-efficacy, and online learning task value in step 2. In step 3, performance SRL strategies of time management, effort regulation, peer learning, and help seeking were entered into the model. Steps 2 and 3 were entered in an order consistent with the social-cognitive view of SRL. This method allows for the examination of significant increase in R^2 for the regression model in each step when the set of predictor variables is added to the model (Warner, 2013). The ΔF test was used to assess whether the addition of the independent variables in each step significantly adds to the prediction of the dependent variable. ΔR^2 was reported for each step and used to determine how much change in variance in the dependent variable can be accounted for by the addition of the set of independent variables. The t test was used to determine the significance of each predictor and beta coefficients β were used to determine the magnitude of prediction for each independent variable.

Finally, responses to the open-ended question, "What was your primary goal(s) for enrolling in the HumanMOOC?" were analyzed using both an inductive data-driven approach as well as a deductive a priori framework or templates of codes (Patton, 2002). For the deductive analysis, three codes were developed based on the achievement goal framework (Elliot & Church, 1997; Zweig &Webster, 2004). These codes were (a) Learning Orientation which was assigned to responses that focused on increasing competence and task mastery, (b) Performance Orientation which was assigned to responses that focused on demonstrating competence by meeting normative standards, and finally (c) No Goals which was assigned to responses that did not indicate any learning goals for joining the MOOC such as "curiosity." For the inductive analysis, initial codes were derived from participants' own responses with no a priori framework or template of codes (Maxwell, 2013) and then grouped together to form themes. Following the initial inductive analysis, a second independent coder used these codes and themes to deductively analyze participants' responses.

Chapter 4: Results

This study explored the relations between MOOC learners' motivational beliefs, use of SRL strategies, and self-reported persistence to goals in a MOOC. In addition, this study examined whether motivational beliefs and use of SRL strategies can predict self-reported persistence to goals in MOOCs. Given the varying and shifting goals of MOOC participants as indicated in the literature, persistence in this study is defined as the self-reported percentage of self-set goals that participants were able to achieve in a MOOC instead of the traditional benchmark of course completion or other behavioral and course interaction measures (i.e. percent of videos watched or assignments submitted). Specifically, this study sought to answer the following research questions:

- Is there a relationship between MOOC participants' motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value), use of SRL strategies (i.e. time management, effort regulation, peer learning, and help seeking), and their self-reported persistence to goals in MOOCs?
- After controlling for MOOC experience, do motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value) and use of SRL strategies (i.e. time management, effort regulation, peer learning, and help seeking) predict self-reported persistence to goals in MOOCs?

In this chapter, the results of the statistical analysis aimed at answering the two research questions are presented. The findings are divided into four main sections: (a) descriptive statistics for all measured variables, (b) correlation analysis results to answer the first research question, (c) hierarchical regression analysis results to answer the second research question, and (d) qualitative analysis results of participants' responses to the open-ended question "What was your primary goal(s) for enrolling in the HumanMOOC?"

Descriptive Statistics

Descriptive statistics for all measured variables are provided in Table 14. Persistence to self-set goals was measured as a percentage, with values ranging between 0 and 100. Persistence had a mean of 51.28 and a standard deviation of 32.56. The remaining 9 variables were measured on a 7-point Likert-type scale. Five out of the 9 variables had a mean above the midpoint of the response scale, while 4 variables had means below the midpoint. Standard deviations for these 9 variables ranged from .84 to 1.65. Visual inspection of the histograms and examination of its corresponding skewness values indicated that 6 variables were negatively skewed, with only online learning self-efficacy having distributions with evidence of significant negative skew (i.e., skewness critical ratio [skewness statistic / standard error] was greater than ±3.29, $p < .05$; Kim, 2013; Tabachnick & Fidell, 2007). The distribution of the remaining 4 variables showed a slight positive skew. Furthermore, all variables were slightly negatively kurtotic, except for online learning self-efficacy, which was slightly positive. Kurtosis critical ratios for all variables were within acceptable limits (Kim, 2013; Tabachnick & Fidell, 2007).

Table 14

Descriptive Statistics for all Variables

Variable	*N*	*M*	*SD*	Skewness Statistic	Skewness *SE*	Skewness Critical Ratio	Kurtosis Statistic	Kurtosis *SE*	Kurtosis Critical Ratio
Persistence	111	51.28	32.56	-.02	.23	-0.09	-1.27	.46	-2.76
Performance-Orientation Approach	111	4.72	1.58	-.61	.23	-2.65	-.25	.46	-0.54
Performance-Orientation Avoidance	111	3.64	1.19	.04	.23	0.17	-.30	.46	-0.65
Learning Orientation	111	6.00	.84	-.71	.23	-3.09	-.19	.46	-0.41
Online Learning Task Value	111	5.07	1.12	-.30	.23	-1.30	-.15	.46	-0.33
Online Learning Self-Efficacy	111	5.63	1.07	-.85	.23	-3.70[a]	.61	.46	1.33
Time Management	111	3.81	1.65	.00	.23	.00	-.99	.46	-2.15
Effort Regulation	111	4.37	1.24	-.13	.23	-0.57	-.02	.46	-0.04
Peer Learning	111	2.60	1.42	.50	.23	2.17	-.67	.46	-1.46
Help Seeking	111	3.18	1.52	.19	.23	0.83	-.74	.46	-1.61

Note. Critical ratio = statistic/SE. All Likert-type variables were measured on a 7-point response scale. Persistence ranged from 0 to 100.

[a]Values were outside the recommended acceptable range of ± 3.29, $p < .001$ (Tabachnick & Fidell, 2007).

It is important to note, however, that the negatively skewed distribution of most of the motivational beliefs and SRL strategies is not unexpected. For instance, it is not surprising to find learners who voluntarily sign up for informal courses with no external incentives to be highly motivated and rate themselves high on SRL behaviors (Milligan et al., 2016; Milligan & Littlejohn, 2016). Further, According to Tabachnick and Fidell (2007), the significance level of skewness and kurtosis is not as important as its actual size and small deviations from normality do not make substantial differences in the analysis. For instance, the effect of positive kurtosis disappears with sample sizes of 100 or more. Thus, while the distribution of online learning self-efficacy scores significantly deviated from normality, this deviation was not extreme (online learning self-efficacy skewness critical ratio = 3.70, cutoff point = ±3.29, $p < .001$). Moreover, the assumptions of normality, linearity, and homoscedasticity in multivariate statistics in ungrouped data apply to the distribution of the residuals, and hence, residual scatterplots can be examined in lieu of individual variable screening (Tabachnick & Fidell, 2007). Finally, in multiple regression, there are no distributional assumptions about individual independent variables besides their relationship with the dependent variable (Tabachnick & Fidell, 2007). Consequently, online learning self-efficacy scores were retained for analysis with no transformation.

Research Question 1: Correlational Analysis

Table 15 presents the results of the correlational analysis conducted to answer the first research question, “Is there a relationship between MOOC participants’ motivational beliefs as measured by goal orientation, online learning self-efficacy, and online learning task value; use of SRL strategies as measured by time management, effort regulation, peer learning, and help seeking; and their self-reported persistence to goals in MOOCs?"

Of the motivational beliefs variables included in this study, only online learning task value was statistically significantly related to persistence ($r = .35$, $p < .001$). However, all SRL strategies variables of time management ($r = .47$, $p < .001$), effort regulation ($r = .30$, $p < .01$), peer learning ($r = .24$, $p < .05$), and help seeking ($r = .21$, $p < .05$) were significantly and positively related to persistence.

For the motivational beliefs variables included in this study, Pearson correlations indicated that performance-orientation approach was statistically significantly related to performance-orientation avoidance ($r = .33$, $p < .01$), online learning task value ($r = .42$, $p < .001$), online learning self-efficacy ($r = .20$, $p < .05$), time management ($r = .31$, $p < .01$), and effort regulation ($r = .43$, $p < .001$). Learning orientation was statistically significantly related to online learning task value ($r = .37$, $p < .001$), online learning self-efficacy ($r = .49$, $p < .001$), and effort regulation ($r = .19$, $p < .05$). Online learning task value and online learning self-efficacy were significantly related to each other ($r = .26$, $p < .01$). Moreover, online learning task value was significantly related to all SRL strategies examined in this study. Specifically, online learning task value was significantly and positively related to time management ($r = .57$, $p < .001$), effort regulation ($r = .58$, $p < .001$), peer learning ($r = .26$, $p < .01$), and help seeking ($r = .29$, $p < .01$). However, online learning self-efficacy was only statistically significantly related to effort regulation ($r = .37$, $p < .001$). Performance-orientation avoidance was not significantly related to any of the variables included this study other than performance-orientation approach.

In terms of the correlations among the SRL strategies examined in this study, time management was statistically significantly related to effort regulation ($r = .44$, $p < .001$), peer learning ($r = .39$, $p < .001$), and help seeking ($r = .44$, $p < .001$). Effort regulation and peer learning were both statistically significantly related to help seeking ($r = .20$, $p < .05$; $r = .65$, $p < .001$).

Table 15

Pearson Correlations for Measured Variables

Variable	1	2	3	4	5	6	7	8	9	10
1. Persistence	1.00									
2. Performance-Orientation Approach	.09	1.00								
3. Performance-Orientation Avoidance	-.15	.33**	1.00							
4. Learning Orientation	-.05	.11	-.12	1.00						
5. Online Learning Task Value	.35***	.42***	.11	.37***	1.00					
6. Online Learning Self-Efficacy	.15	.20*	-.11	.49***	.26**	1.00				
7. Time Management	.47***	.31**	.04	.14	.57***	.17	1.00			
8. Effort Regulation	.30**	.43***	.08	.19*	.58***	.37***	.44***	1.00		
9. Peer Learning	.24*	.17	.07	.00	.26**	-.15	.39***	.10	1.00	
10. Help Seeking	.21*	.15	.04	.07	.29**	-.09	.44***	.20*	.65***	1.00

*$p < .05$. **$p < .01$. ***$p < .001$.

Research Question 2: Hierarchical Regression Analysis

The results of the correlation analysis indicated that the variable performance-orientation avoidance was moderately correlated with only one other predictor, performance-orientation approach (r = .33), and was consequently dropped from the regression model. Prior to regression analysis with the remaining nine predictors, the data was screened for univariate and multivariate outliers, model assumptions (normality, linearity, and homoscedasticity), as was multicollinearity in the predictors. According to Tabachnick and Fidell (2007), examination of residuals' scatterplots (i.e. differences between the obtained and predicted dependent variable scores) provide a simultaneous assessment of the assumptions of normality, linearity, and homoscedasticity between predicted dependent variable scores and errors of prediction. That is, if the residuals are normally distributed across the predicted dependent variable scores (normality), there is a straight line relationship between the residuals and predicted dependent variable scores (linearity), and the variance of the residuals across predicted dependent variable scores is the same for all predicted scores (homoscedasticity), the shape of the scatterplot will be nearly rectangular with concentration of scores along the center. The distribution of the residual scatterplot for the regression model appeared to satisfy these assumptions, as did the histogram of the residuals and normal q-q plots. Multivariate outliers were checked through examination of Mahalanobis distance and Cook's distance. The highest Mahalanobis distance detected in the data was 22.45, less than the critical value of χ^2 = 27.88 for 9 degrees of freedom at α = .001 (Tabachnick, & Fidell, 2007). Further, Cook's distances for all cases were less than 1, with the highest value at 0.09 (Cohen, Cohen, West, & Aiken, 2003). Finally, multicollinearity was assessed through examination of the correlation matrix and collinearity statistics such as tolerance and VIF. All Pearson's correlations among the predictors were less than .80 and ranged between .20 and .65, tolerance values were all greater than .10 with the smallest value being .45, and VIF values were all less than 10 with the highest value being 2.19 (Cohen et al., 2003).

Table 16 presents the results of the three-step hierarchical regression analysis conducted to examine the combined effectiveness of motivational beliefs and SRL strategies variables in predicting learners' persistence to self-set goals in MOOCs. In step 1, MOOC experience was entered as a control variable. Motivational beliefs of performance-orientation approach, learning orientation, online learning task value, and online learning self-efficacy were entered in step 2. In step 3, SRL strategies of time management, effort regulation, peer learning, and help seeking were entered into the model.

Results indicate that the control variable MOOC experience did not play a significant role in learners' persistence to self-set goals. However, when motivational beliefs (performance-orientation approach, learning orientation, task value, and self-efficacy) were entered into the regression model in step 2, a significant change in R^2 was detected, $\Delta R^2 = .22$, ΔF (4, 105) = 7.20, $p < .001$. All motivational beliefs variables entered into the regression model at this step, except for performance-orientation approach, were statistically significant predictors of persistence. The strongest predictor of persistence at this step was online learning task value (ß = .46, t[105] = 4.54, $p <$ .001), followed by learning orientation (ß = -.35, t[105] = -3.28, $p < .05$), and online learning self-efficacy (ß = .25, $t[105] = 2.42$, $p < .05$). Overall, Model 2 accounted for approximately 22% of the variance in learners' persistence, $F(5, 105) = 5.84$, $p < .001$.

In step 3, SRL strategies (time management, effort regulation, peer earning, help seeking) were entered into the regression model and explained an additional 10% of the variance in persistence, $\Delta F(4, 101) = 3.79$, $p < .01$. Of the motivational beliefs variables, only learning orientation (ß = -.29, $t[101] = -2.84$, $p < .01$) and online learning self-efficacy (ß = .21, $t[101] = 2.04$, $p < .05$) remained significant predictors of persistence in this step, although their standardized regression coefficients were slightly reduced. Finally, of the SRL strategies measures, only time management emerged as a significant individual predictor of persistence (ß = .33, $t[101] = 2.94$, $p < .01$).

In sum, the final model for persistence was statistically significant, $F(9,101) = 5.27$, $p < .001$, explaining 32% of the variance in persistence with time management emerging as the strongest positive predictor of persistence (ß = .33, $t[101] = 2.94$, $p < .01$), followed by learning orientation as the strongest negative individual predictor (ß = -.29, $t[101] = -2.84$, $p < .01$), and finally online learning self-efficacy as a positive predictor of persistence (ß = .21, $t[101] = 2.04$, $p < .05$). The effect size for the final regression model with 9 predictors was large (Cohen, 1988, 1992).

Table 16

Model Summaries for the Hierarchical Regression Analysis of Persistence

Variable	R^2	ΔR^2	F	ΔF	Standardized Beta	t
Model 1: MOOC Experience	.003	.003	.30	.30	.05	.55
Model 2: Motivational Beliefs	.22	.22	5.84***	7.20***		
MOOC Experience					.16	1.75
Performance-Orientation Approach					-.09	-.96
Learning Orientation					-.35	-3.28*
Online Learning Task Value					.46	4.54***
Online Learning Self-Efficacy					.25	2.42*
Model 3: SRL Strategies	.32	.10	5.27***	3.80**		
MOOC Experience					.15	1.66
Performance-Orientation Approach					-.15	-1.55
Learning Orientation					-.29	-2.84**
Online Learning Task Value					.20	1.66
Online Learning Self-Efficacy					.21	2.04*
Time Management					.33	2.94**
Effort Regulation					.12	1.05
Peer Learning					.10	.91
Help Seeking					-.03	-.22

Note. MOOC Experience was dummy coded (yes = 1; no = 0).
*p < .05. **p < .01. ***p < .001.

Other Findings

Responses to the open-ended question "What was your primary goal(s) for enrolling in the HumanMOOC?" were analyzed qualitatively using two methods: (a) deductive analysis using an a priori framework or templates of codes based on the achievement goal framework (Elliot & Church, 1997; Patton, 2002; Zweig &Webster, 2004), and (b) an inductive data-driven analysis in which codes and themes are formulated based on participants' responses. For the deductive analysis, the a priori codes and definitions, sample responses that fall under each code, and the number of responses in each category are provided in Table 17. Results indicate that approximately 95.5% of participants' goals fell under the learning orientation goals.

Table 17

A Priori Codes and Sample Responses

Code	Definition	Example Responses	# of Responses
Learning Orientation Goals	Goals that focus on increasing competence and task mastery	"Learn tools and techniques to improve my online college courses" "Think more deeply about how video and other forms of multimedia can enhance online learning"	106 (95.5%)
Performance Orientation Goals	Goals that focus on demonstrating competence by meeting normative standards	"To gain first-hand experience of a cMOOC as primary and personal evidence for my capstone project in my MEd program"	1 (1%)
No Goals	Responses that did not indicate any specific learning goals for joining the MOOC	"Curiosity" "Interest in the topics" "Interesting Topic" "I believe we all need to make our student feel that they are not lost in cyber space. This was a wonderful MOOC"	4 (3.6%)

While the majority of goals fell under the learning orientation code, these goals varied considerably in terms of focus, quality, and specificity. This is evident by the inductive analysis that followed. For the inductive analysis, initial codes were derived from participants' own responses and then grouped together to form themes. Four major themes emerged with most responses falling under more than one theme:

- Theme 1 - Online Teaching: Goals that are related to interest in the content of the HumanMOOC whether for general knowledge and understanding of online learning and teaching or for improving actual teaching practice. Codes or subthemes include:

    - Teaching Practice: goals with explicit reference to improving current or future teaching practices.
    - Knowledge about Online Teaching: goals that indicate an interest in learning about the topics covered in the HumanMOOC with no specific reference to utilization of such knowledge for actual teaching or design practice.

- Theme 2 – Peer Learning and Sharing: Goals under this theme are related to interest in expanding professional networks, learning with and from others, and sharing the knowledge and understanding gained from the MOOC with others. Codes or subthemes include:
    - Peer Learning and Networking: responses under this code refer to goals that are related to expanding one's personal learning network and learning with and from other participants in the HumanMOOC.
    - Sharing with Others: This code refers to goals related to sharing what was learned in the HumanMOOC with other people outside the MOOC, such as people at their institutions.
- Theme 3 – Research and Design: Goals under this theme are those that are not directly related to the act of teaching online but rather for research purposes, instructional design purposes, or for personal exploration of MOOCs and/or the platform used to host the MOOC. Codes or subthemes include:

    - Online Learning and MOOC Research: Responses under this code refer to goals that are related to professional research interests, whether about MOOC design and delivery or online learning in general.
    - Instructional Design: goals under this code refer to participants who join the MOOC to examine the HumanMOOC design and delivery or its content from an instructional design perspective rather than as an online instructor.
    - Exploring MOOCs and/or Canvas: This relates to personal interest in exploring MOOCs and/or Canvas as a hosting platform rather than interest in the content of the HumanMOOC per se.
- Theme 4 – Other: Reponses that did not state a specific learning goal were grouped under this theme such as "curiosity" or "personal interest." Further, some learning goals that did not fall under any of the previous themes but were not reported enough to form their own theme were placed here.

Once these codes and themes were developed, a second independent coder with over 20 years of teaching and research experience in the field of educational technology and instructional system design was asked to use those themes and codes to analyze participants' responses. The inter-rater reliability was calculated as the number of themes for each response the two coders agreed on divided by the total number of responses (N = 111). The percent of agreement between the two coders was 87.4%. Sample responses from which the themes and codes were developed are provided in Table 18.

Table 18

Inductive Themes and Sample Responses

Theme	Codes	Sample Responses
Online Teaching	Teaching Practice	“Finding new resources to improve teaching and learning” “The program I am teaching in is transitioning from a face-to-face to an online format in the next year and I wanted to learn more about strategies for teaching and learning online since it’s not something I have a lot of experience doing” “Learn tools and techniques to improve my online College courses”
	Knowledge about Online Teaching	“Expanding my knowledge and gaining new ideas” “Get updated information on the topic”
Peer Learning and Sharing	Peer Learning and Networking	“Networking and self-improvement” “My goal is to learn more about online learning and to connect with others with the same goal” “Learning, engaging with other learners and expanding my PLE [Personal Learning Environment]”
	Sharing with Others	“Learning new ideas to increase teacher presence in online staff PD [professional development] - and ideas to pass on to Lecturers who are student facing” “As an Instructional Designer, I’m always looking for advice I can give faculty members about improving their course, especially where instructor presence is concerned.”
Research and Design	Online Learning and MOOC Research	“Interested in seeing the course content and ideas about MOOC creation. I am a MOOC researcher and creator” “Research”
	Instructional Design	“To better design and deliver MOOC” “A large part of my job is related to designing online courses. I found this topic relevant and wanted to learn more” “To get resources to help in designing engaging online classes” “I audited the MOOC from a designer’s perspective rather than educator”
	Exploring MOOCs and/or Canvas	“To see how the platform works” “To gain experience with MOOCs” “To learn something new, to explore learning possibilities at canvas”
Other		“Self-development” “Curiosity”

Chapter 5: Discussion

Despite the rise in MOOC enrollments (Shah, 2015), the low completion rates for these courses remain significant (Breslow et al., 2013; Hollands & Tirthali, 2014), which has led some to question the learning effectiveness of these new informal learning environments (Kolowich, 2013). However, some researchers argue that given the open nature of MOOCs and lack of financial consequences for dropping out or not completing all MOOC requirements, completion rates, as a measure of MOOC effectiveness, must be considered in relation to participants' achievement of self-set goals (DeBoer et al., 2014; Ho et al., 2015). Consequently, researchers in the field have been encouraged to explore different ways in which completion and persistence can be examined as a measure of MOOC effectiveness (Ho et al., 2015). While there has been a move toward more contextualized measures of persistence, such as limiting analysis to those who indicate an intention to complete a MOOC (Reich, 2014), the basic traditional assumptions of completion and certification are not being challenged (DeBoer et al., 2014; Heutte et al., 2014). The design of this study is based on the argument that MOOC completion or certification rates should not be of concern in this new and informal learning environment, but rather learners' ability to achieve their self-set goals. Hence, the outcome variable persistence in this study is measured as the percent of self-set goals learners were able to achieve for joining a MOOC. This study aimed at addressing this issue by examining motivational and behavioral factors that can support learners' persistence to their self-set goals. Specifically, this study utilized the social-cognitive model of SRL (Pintrich, 2000a; Zimmerman, 2000a, 2000b) to examine the relations between several motivational belief constructs (goal orientation, online learning task value, and online learning self-efficacy), the use of SRL strategies (time management, effort regulation, peer learning, and help seeking), and learners' persistence to self-set goals in the HumanMOOC, which was offered on the Canvas Open Network in the fall of 2016. These relations were explored using correlation and hierarchical multiple regression analyses on survey data that participants completed at the end of their participation in the HumanMOOC.

The proposed regression model provided a statistically adequate fit for the data obtained, with the motivational beliefs and SRL strategies examined accounting for 32% of the variance in learners' persistence to self-set goals in the HumanMOOC. In this chapter, major findings from this study will be discussed in light of the social-cognitive model of SRL and current SRL research. Also considered in this chapter are the educational implications of the investigation, recommendations for future research directions, and study limitations.

Linking the Major Findings to the Conceptual Framework and SRL Research

For this study, a social-cognitive view of SRL was used as the conceptual framework (Pintrich, 2000a; Zimmerman, 2000a). According to this view, self-regulation is defined as self-generated thoughts, feelings, and behaviors that are planned and cyclically adapted based on performance feedback in order to attain self-set goals. This social-cognitive perspective views self-regulation as a cyclical and multidimensional process rather than an aptitude or a personality trait and thus varies depending on environmental characteristics and demands, learning tasks, and contexts in which learners learn (Cleary et al., 2012). Furthermore, this contextualized view integrates SRL processes and key motivational beliefs in a single model in which skill and will become integrated and interdependent processes of SRL that cannot be fully understood apart from each other (Cleary & Zimmerman, 2012; Pintrich, 2000a, 2004; Zimmerman, 2000a). In other words, this cyclical view of SRL acknowledges the role that motivational beliefs have in influencing learners' adoption of cognitive and metacognitive processes and behaviors during different phases of the learning task and across tasks (Cleary et al., 2012; Cleary & Zimmerman, 2012; Zimmerman, 2011).

Two main SRL models have been developed under the social-cognitive perspective, Zimmerman's three-phase model (2000a) and Pintrich's four-phase model (2000a, 2004). Both models assume correlation between SRL processes and motivational belief variables within each of the phases of the model as well as potentially causal influences across the phases. In these models of SRL, an important distinction is made between motivated behavior such as effort and persistence and motivational beliefs such as self-efficacy, goal orientation, and task value and interest. According to these models, motivational beliefs in one's personal ability and interest in the learning task not only influence their behavioral engagement and persistence on challenging learning tasks, but also their cognitive and metacognitive engagement as well as the intentional enactment of overt behavior such as the use of SRL strategies (Cleary & Zimmerman, 2012).

Guided by this conceptual framework, two research questions were formulated and tested in this study. The specific research questions explored are:

- Is there a relationship between MOOC participants' motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value), use of SRL strategies (i.e. time and study environment, effort regulation, peer learning, and help seeking), and their self-reported persistence to goals in MOOCs?
- After controlling for MOOC experience, do motivational beliefs (i.e. goal orientation, online learning self-efficacy, and online learning task value) and use of SRL strategies (i.e. time and study environment, effort regulation, peer learning, and help seeking) predict self-reported persistence to goals in MOOCs?

Although the MOOC context is different than formal online courses, some of the findings of this study are congruent with prior research and findings in the field of SRL in traditional and formal online learning contexts. That is, positive motivational beliefs were found to be significantly related to each other as well as to the use of SRL strategies in MOOCs (Artino, 2009; Artino & Vermillion, 2007). Further, the SRL strategies examined in this study were found to be significantly related to learners' persistence to self-set goals in MOOCs. However, in terms of the predictive power of the different motivational beliefs and SRL strategies examined in this study, findings were not as consistent. While the findings regarding online learning self-efficacy and time management skills were mostly congruent with general findings in the literature, the findings regarding the significance of goal orientation in the regression model was not as expected. Consequently, discussion of study findings will be provided in light of research on SRL in formal learning and MOOC settings. A detailed explanation of the findings in relation to current literature as well as some possible explanations for some of the unexpected findings is provided in the following sections.

Research question 1: Correlational analysis and findings. The first research question addressed in this study was the relationship between motivational beliefs, use of SRL strategies, and learners' persistence to self-set goals in the HumanMOOC. First, analysis results indicated that positive motivational beliefs were significantly positively associated with the use of SRL strategies examined in this study. In other words, those who scored higher on positive motivational beliefs (i.e. performance-orientation approach, learning orientation, online learning task value, and online learning self-efficacy) reported higher use of SRL strategies during their learning in the HumanMOOC including time management, effort regulation, peer learning, and help seeking. The social-cognitive view of SRL posits that self-regulation involves more than cognitive or behavioral engagement (e.g. resource management and task strategies), but also extends beyond that to consider the sources of such behaviors, which include one's self-efficacy beliefs, task interest and value, and reason for engaging in the task (Cleary & Zimmerman, 2012). These motivational beliefs not only interact with each other but also impact the extent to which students engage in other self-regulatory processes (Cleary & Zimmerman, 2012; Pintrich, 2000a; Zimmerman, 2000a, 2000b). The correlational results of this study confirm the ongoing relationship between motivational beliefs and

SRL strategies predicted by the social-cognitive models of SRL. Qualitative studies in MOOCs support this view and indicate the role that motivational beliefs play in shaping how individuals apply different SRL processes to support their learning and reach their goals in MOOCs (Littlejohn et al., 2016; Milligan et al., 2016). Further, research in formal online learning settings has consistently found motivational beliefs to be significantly and positively associated with the use of a number of SRL processes. For instance, Cho and Shen (2013) found goal orientation and academic self-efficacy to be associated with effort and metacognitive regulation in an Introduction to Gerontology college course delivered fully online via Blackboard. Similarly, Adesope, Zhou, and Nesbit (2015) found motivational beliefs of self-efficacy, task value, and goal orientation to be related to a number of SRL strategies used in an Introduction to Educational Psychology course offered online including time management and effort regulation. Finally, Artino (2009) reached similar correlation patterns and found online learning self-efficacy and task value to be related to a number of adaptive outcomes in an online course such as elaboration, metacognition, satisfaction, and continuing motivation to enroll in future online courses.

The finding regarding the positive relations between performance-orientation approach and use of SRL strategies is worth noting here. Research in MOOCs has relied mainly on a dichotomous conceptualization of goal orientation in which two classes of goals, mastery or learning and performance goal orientations, were used (Güti et al., 2014; Wang & Baker, 2015). However, findings from this study provide support for the trichotomous conceptualization of goal orientation that suggest that performance orientation is not always less adaptive or in opposition to mastery or learning goal orientation (Elliot & Harackiewicz, 1996; Zweig & Webster, 2004). In this study, not only was performance-orientation approach positively associated with online learning task value and online learning self-efficacy, but also with the use of SRL strategies such as time management and effort regulation.

Second, while all positive motivational beliefs in this study were positively associated with the use of SRL strategies, only online learning task value was significantly and positively related to persistence. That is, participants who believed the MOOC to be interesting, important, and useful were also more persistent (i.e. achieved more of their goals) in the MOOC. The construct of task value and interest has been central to a number of validated and widely used persistence models such as that of the nontraditional students persistence model developed by Bean and Metzner (1985), Kember's persistence model for distance and open learning (1995), and Rovai's (2003) composite persistence model for distance online programs. The findings from this study extend current literature on learners' persistence that has identified task value as an important factor in supporting such action in formal learning settings. Park's (2007) review of the literature on factors affecting nontraditional students' persistence in online courses identified task value and interest as one of the most important motivational factors associated with persistence. Similarly, persistence research in MOOCs has found perceived value of learning tasks to be related to participants' persistence in MOOCs in a number of studies (Alraimi et al., 2015; Hone & El Said, 2016). On the other hand, all SRL strategies examined in this study were significantly and positively related to persistence to self-set goals in the HumanMOOC including time management, effort regulation, peer learning, and help seeking. According to the social-cognitive framework of SRL, positive motivational beliefs are not sufficient in influencing positive learning outcomes directly if knowledge and skills are lacking, but rather these beliefs motivate individuals to enact overt behaviors and strategies necessary to improve their competence (Pintrich, 2000a; Schunk, 1995; Zimmerman, 2000a). The pattern of relations between motivational beliefs, use of SRL strategies, and persistence in this study lends support to this theoretical perspective and suggests that SRL strategies and behavior might be more directly related to learners' persistence to goals than motivational variables, but that motivational variables are indirectly related to persistence through the utilization of these strategies (Cleary & Zimmerman, 2012; Neuville, Frenay, & Bourgeois, 2007; Pintrich, 2000a; Zimmerman, 2000a, 2000b). This conclusion parallels empirical findings in formal online learning settings (Adesope et al., 2015; Artino & Vermillion, 2007). For instance, using path analysis, Adesope et al. (2015) found that motivational variables influence the use of SRL strategies (as measured by the MSLQ), which then influence learners' actual behavioral engagement with the online content (e.g. note taking). Further, Cho and Shen (2013) found that the association between goal orientation and academic self-efficacy with students' achievements to be mediated by three types of regulation: effort regulation, metacognitive regulation, and interaction regulation.

Some researchers suggest that the use of SRL processes such as resource management strategies in online learning is critical in online settings because learners lack immediate support and feel socially isolated (Cho, 2004; Cho & Shen, 2013). These challenges become even more prominent in MOOCs where learners are required to decide what, why, and when to learn which can lead to confusion and a sense of isolation, especially for learners who are not autonomous and lack the regulatory skills to persist in such learning environments (Daradoumis et al., 2013; Kop & Fournier, 2010; Mackness et al., 2010). Findings in this study extend empirical support to this notion as it shows that learners who reported more effective time management skills, were able to regulate their effort, engaged in peer learning and collaboration, and sought help when needed also reported higher levels of persistence in the HumanMOOC. Prior research on learners' behavioral engagement and persistence in MOOCs has reached similar conclusions and found factors such as time management (Balakrishnan & Coetzee, 2013; Gütl et al., 2014; Loya et al., 2015; Nawrot & Doucet, 2014), peer learning and interaction (Adamopoulos, 2013; Alraimi et al., 2015; Gütl et al., 2014; Woodgate et al., 2015), effort regulation (Gütl et al., 2014; Hone & El Said, 2016), and help seeking (Gütl et al., 2014) to be important in this new learning environment. These factors have also been associated with better learning outcomes in online learning as well. For instance, both Broadbent (2017) and Puzziferro (2008) found time management and effort regulation to be significantly and positively associated with grade performance in online courses. Additionally, Mahasneh, Sowan, and Nassar (2012) found that the number of help-seeking events nursing students engaged in in a fully online course delivered via Blackboard was significantly and positively related to achievement as measured by their final grades. In terms of online peer interaction, Michinov, Brunot, Le Bohec, Juhel, and Delaval (2011) found that a high level of participation and interaction with others had a positive impact on course performance. Cheng and Chau (2013) have also found peer learning to be positively related to ePortfolio achievement.

The pattern of relations revealed by the correlational analysis highlights the importance of encouraging and supporting positive motivational beliefs during the design and the delivery of MOOCs in order to activate and sustain learners' behavioral engagement and motivation, and ultimately support learners as they persist and achieve their self-set goals in MOOCs. In terms of the relationship between the variables examined in this study and learners' persistence to self-set goals, the strongest correlations (aka effect sizes) were between time management and persistence ($r = .47$, large effect size) and online learning task value and persistence ($r = .35$, moderate effect size) (Cohen, 1988, 1992).

Research question 2: Hierarchical regression analysis and findings. A three-step hierarchical regression was conducted to explore further the relationships between learners' motivational beliefs, use of SRL strategies, and persistence to goals in MOOCs. For this analysis, the predictor variables were grouped into three construct sets. In step 1, MOOC experience was entered into the model. This was followed by the motivational belief variables of goal orientation, online learning self-efficacy, and online learning task value in step 2. In step 3, SRL strategies of time management, effort regulation, peer learning, and help seeking were added to the model. The final regression model for persistence was statistically significant, with time management emerging as the strongest positive predictor of persistence (ß = .33), followed by learning orientation as the strongest negative individual predictor (ß = -.29), and finally online learning self-efficacy as a positive predictor of persistence (ß = .21). However, contrary to other findings in the literature, MOOC experience in this study was neither significantly related to nor did it play a significant role in predicting persistence to goals in the HumanMOOC (Lee & Choi, 2011; Milligan et al., 2013). One possible explanation for this is that the design of the HumanMOOC explicitly addressed the issue of varying levels of social media and MOOC experience of participants by dedicating the first week to orienting participants to the HumanMOOC. Some of the topics covered in the first week included an introduction to the course and its instructors, a Canvas user orientation, strategies and tips for utilizing Twitter and blogs in the MOOC, ways to ask for course or technical help when needed, and a forum for participants to introduce themselves to the community and other participants. Another important issue to consider here is the way in which MOOC experience was measured. MOOC experience in this study was measured as a dichotomous variable (i.e. yes/no). Perhaps measuring this as a continuous variable (e.g. number of MOOCs participants participated in prior to the HumanMOOC) might have yielded different results.

The finding regarding the significant role of time management in predicting learners' persistence in this study comes as no surprise. SRL studies in formal learning settings as well as in MOOCs have consistently found time management to be one of the most important self-regulatory behaviors and related to a number of positive outcomes such as satisfaction, motivation, achievement, and persistence (Balakrishnan & Coetzee, 2013; Guàrdia et al., 2013; Gutierrez-Rojas et al., 2014; Kitsantas, Winsler, & Huie, 2008; Lee & Choi, 2011; Loya et al., 2015; Nawrot & Doucet, 2014; Puzziferro, 2008;

Wang et al., 2013). For instance, in examining the role of motivation and SRL strategy factors in predicting undergraduates' academic college performance during their first and second year of college, Kitsantas et al. (2008) found that only time management remained a significant predictor of students' GPA. Based on this finding, the researchers suggest that instructors and administrators should develop interventions targeting college students' time management skills as a strategy to support struggling students to persist and complete their educational studies. Similarly, Broadbent (2017) found that out of nine different SRL strategies used in a fully online undergraduate courses (i.e. rehearsal, elaboration, organization, critical thinking, metacognition, time management, effort regulation, peer learning, and help seeking), only time management and effort regulation were found to positively influence final grades. Finally, in examining perceptions of factors that support persistence in online courses among community college stakeholders (i.e. administrators, faculty, and students), Stanford-Bowers (2008) found that time management was one of the few factors that all three groups of stakeholders indicated as important in supporting student persistence in online courses.

MOOC researchers argue that a high level of self-discipline, including time management skills, is even more necessary for successful completion of a MOOC because learners are expected to become managers of their own learning in such environments (Nawrot & Doucet, 2014). In analyzing survey data ($N = 508$) collected to examine learners' reasons for withdrawing from a MOOC, Nawrot and Doucet (2014) found the main reason to be participants' lack of time management, which was indicated by as much as 68.9% of the survey participants.

The role of goal orientation in predicting learners' persistence to self-set goals in the HumanMOOC was somewhat surprising, particularly the results pertaining to learning orientation. In this study, a tridimensional dispositional goal orientation measure with three subscales of performance-orientation approach, performance-orientation avoidance, and learning was used (Zweig & Webster, 2004). While learning orientation emerged as significant predictor of persistence in both steps of the hierarchical regression analysis, the association between the two variables, while controlling for other variables in the regression model, was negative. That is, participants who adopted learning goals were less likely to persist and achieve their self-set goals in this current study. Although it is possible that this result found in this study is a statistical anomaly limited to this study, deeper reading within the achievement goal orientation literature points to some alternative explanations that warrant further consideration and discussion.

Despite the long history of research in the area of goal orientation that learners bring to achievement contexts, the findings regarding when and how learning and performance orientations affect learning and achievement are not without inconsistencies (Elliot, Murayama, & Pekrun, 2011; Grant & Dweck, 2003; Ryan, 2012; VandeWalle, Cron, & Slocum, 2001). For instance, Elliot and Church (1997) found that while mastery orientation facilitated intrinsic motivation, it had no reliable effect on graded performance. Further, Ely, Sitzmann, and Falkiewicz (2009) found that inclusion of interaction terms of the three major goal orientation constructs (i.e. mastery, performance approach, and performance avoidance), after controlling for main effects, accounted for an additional 10% of the variance in training time in a web-based educational training program to become electrical technicians. Specifically, they found that trainees with low mastery and low performance avoidance goal orientations completed training quickly, while trainees with low mastery and high performance avoidance goal orientations took considerably longer. These results highlight the complexity of goals individuals bring to learning situations and points to the fact that learners may adopt multiple goal orientations in any given context (Ely et al., 2009; Linnenbrink-Garcia et al., 2012). Not only that, but some research suggests that adopting multiple goal orientations might be even more beneficial in some learning contexts (Neuville et al., 2007). Thus, examining the interaction effects among the different classes of goals might provide a more accurate and comprehensive understanding of their influence on learning processes and outcomes such as persistence to self-set goals. Another possible approach is to move away from the variable-centered approach to researching goal orientation, in which the emphasis is on each goal orientation and how it relates to different predictors and outcomes, to a person-centered approach that allows us to uncover patterns in learners' endorsement of multiple goals simultaneously such as cluster analysis and latent class modeling (Linnenbrink-Garcia et al., 2012).

Furthermore, these mixed results have led some researchers to argue that these inconsistencies in empirical findings could be explained by conceptual disagreements about the definition of these major classes of goal orientations. For instance, some researchers point out that definitions of the major classes of goals are grounded in purpose for engaging in a learning task, which include the reason for why a person engages in a task as well as their desired outcome or aim (Elliot et al., 2011; Ryan, 2012).

According to Elliot et al. (2011), this can be problematic because

> the reason aspect of purpose includes competence but also includes additional content beyond competence (e.g., "demonstrate" in the performance goal construct implicates approval and/or self-presentation, as well as competence per se); the aim aspect of purpose focuses on competence alone. (p. 632)

In other words, while the aim of engaging in a learning task is to develop competence, people's reasons for engaging in these tasks might include additional aspects such as gaining favorable opinions from others. Thus, using the purpose for engaging in a task to define different classes of goals without separating the reason and aim, according to the researchers, lacks precision. Consequently, the researchers separated the reason and aim aspect of goal orientations and defined the different classes of goals in terms of aim (i.e. competence) alone. Under this conceptualization of goals, competence is defined in terms of the standard used in evaluating whether someone is doing well or poorly when engaged in a learning task. Accordingly, different standards used in competence evaluation were identified and used to define different types of goals including task-based competence or self-based competence standards. According to their definition, task-based goals are those that use task requirements as an evaluative standard for competence, whereas self-based goals are those that use one's past or potential future performance as a standard for evaluation. Based on this distinction, the researchers questioned whether these two strands within mastery-based goals are different enough to warrant separate goal constructs. Using confirmatory factor and multiple regression analysis, they found that task-approach goals (i.e. using task requirements to evaluate one's competence) were a positive predictor of intrinsic motivation, learning efficacy, and absorption in class, whereas self-approach goals (i.e. using one's past or potential future performance to evaluate competence) were unrelated to any of these variables. This distinction within mastery or learning orientation might be even more prominent in an informal learning context such as MOOCs where self-based standards as a measure of competence are not only encouraged but also expected.

Similarly, Grant and Dweck (2003) propose that looking into the operational definitions used in different studies on achievement goals orientation might account for the discrepant findings in the literature. For instance, they argue that the separation of performance goals into normative vs. nonnormative performance goals as well as separating learning goals into desire to learn vs. mastering a challenge learning goals might be different and in turn lead to different outcomes. To test this, the researchers conducted a number of studies in which a set of items that tap into the different forms of learning and performance goals commonly used in the literature were developed and tested such as normative outcome goals, normative ability goals, learning goals, and challenge-mastery goals. While both types of learning goals (i.e. desire to learn and develop vs. mastering a challenge) correlated highly to form one construct, the researchers found the effects of learning orientation to be mediated by other factors (i.e. engaging in deeper processing of course material) and the degree of its effect to be influenced by context such as when there is challenge present and the degree to which the learning task is personally important. It is important to note here that the separation of desire to learn and mastering a challenge items of learning orientation measures, while no statistical support for its separation within formal learning contexts was found, might warrant further consideration within a MOOC context. For instance, an exploratory factor analysis of a modified version of an SRL survey that is based on the social-cognitive model was tested in order to identify the SRL subprocesses that are relevant in a MOOC context with learning challenge emerging as a factor in this analysis (Hood et al., 2015). This finding indicates that learning challenge might be an important factor in explaining SRL in informal learning settings such as MOOCs.

To summarize, while the explanations provided above do not provide a direct answer as to why learning orientation emerged as a negative predictor of persistence in the regression model, it does highlight the complexity of relationships between goal orientation and learning outcomes, especially in a novel context such as MOOCs where very little is known about the role of motivational beliefs and how it supports the learning process (Kop, 2011). Thus, examining interaction effects, mediators, or contextual factors that might influence the role of goal orientation in persistence in MOOCs might provide some explanations for this finding in this study (Elliot et al., 2011; Grant & Dweck, 2003; Ryan, 2012, VandeWalle et al., 2001).

Online learning self-efficacy in this study was found to be a significant positive, albeit moderate, predictor of learners' persistence to goals in both step 2 and 3. That is, participants with higher online learning self-efficacy beliefs achieved more of the goals they set for themselves for joining the HumanMOOC than those with lower self-efficacy beliefs. While this is in line with empirical findings in the formal online courses regarding the influence of self-efficacy beliefs on key academic indices such as persistence (Artino & Vermillion, 2007; Multon et al., 1991), it goes in opposition to other quantitative studies that found no significant difference in self-efficacy between MOOC completers and noncompleters (Poellhuber et al., 2014; Wang & Baker, 2015). However, these studies measured different domains of self-efficacy (e.g. PALS academic efficacy subscale and MSLQ self-efficacy scale) and might have been too general to detect effects (Bandura, 1997; Pajares, 1996; Puzziferro, 2008; Wang & Baker, 2015). This explanation is even more plausible when considering qualitative MOOC findings that indicate that efficacy beliefs in one's ability to learn in a MOOC specifically (as opposed to academic or general technology efficacy) is more relevant in this new context (Kop & Fournier, 2010; Littlejohn et al., 2016; Milligan et al., 2016). In the current study, a more context-specific measure of self-efficacy that examined learners' beliefs in the extent to which they feel confident they can learn effectively using self-paced, online courses that more closely reflects the domain of functioning and task demands of learning in MOOCs was used. Given the novelty of MOOCs as an informal learning context, using such measure of self-efficacy that took into account the specific characteristics of the learning tasks might have provided greater predictive power (Bandura, 1997; Pajares, 1996). Another possible reason for the significant result found in this study is the way in which the outcome variable, persistence, was defined and measured. Unlike the previous studies in MOOCs where the outcome variable of persistence or completion was defined by MOOC instructor (Wang & Baker, 2015) or researcher conducting the study (Poellhuber et al., 2014), this study measured persistence in terms of the percentage of goals participants had for joining the MOOC and were able to accomplish by the time they ended their engagement. These differences between studies in terms of measures (e.g. online learning self-efficacy vs. academic self-efficacy) and outcome variables (e.g. persistence to goals vs. certification or completion of MOOC activities) used are important to highlight in this novel environment to help shed some light on factors influencing self-efficacy beliefs and pedagogical and design factors more likely to promote such beliefs in this specific learning context.

Overall, the significant increase in R^2 after the addition of motivational belief variables (step 2) and SRL strategies (step 3) to the regression model in this study lends support for the need to examine motivational beliefs and SRL strategies factors in tandem in order to get a more detailed understanding of learners' persistence in informal online learning settings such as MOOCs.

Other findings: Qualitative analysis of self-set goals for joining the HumanMOOC. One of the challenges facing MOOC researchers and designers is identifying the varying personal goals participants have for joining MOOCs in order to make accurate inferences about completion rates and effective design interventions that can support learners' achievement of those goals (Reich, 2014). In this study, two types of qualitative analysis, deductive and inductive, were performed on participants' responses to the open-ended question, "What was your primary goal(s) for enrolling in the HumanMOOC?" The deductive analysis of participants' goals for joining the HumanMOOC revealed that about 95.5% of them adopted a learning goal orientation. This finding is consistent with other studies about MOOC participants (Wang & Baker, 2015). It should come as no surprise that individuals who sign up for MOOCs come with mastery or learning goals given the informal nature of MOOCs and the lack of tangible rewards or accreditation (Wang & Baker, 2015). However, inductive analysis revealed some deeper issues that might have implications in understanding the results of this study. The inductive qualitative analysis revealed the varying learning goals participants bring to the MOOC, which was different in terms of focus (e.g. content, MOOCs, or Canvas as a hosting platform) and in purpose (e.g. teaching practice, instructional design, research); this is consistent with general findings in the literature on MOOC participants goals for signing up for MOOCs (Gütl et al., 2014; Yousef et al., 2015; Zheng et al., 2015). However, even though most of the goals stated were learning goals, the quality and specificity of the goals varied tremendously. For instance, some respondents were specific in their goals such as this response:

> My primary goal for enrolling in the HumanMOOC is to learn strategies and best practices for promoting interaction for learning by using audio and video to create a sense of "community presence" in online courses. In addition, I want to learn ways to integrate social media as a means to promote social presence and share knowledge horizontally as well as vertically.

However, a sizable number of participants responded with goals that are too general and vague such as "knowledge," "professional development," or "self-development." Based on these observations, two conclusions might be made that can help explain the emergence of learning orientation as a negative predictor of persistence in the regression analysis. First, this finding suggests that other factors, such as goal-setting behavior, might be influencing the direction of this relationship by mediating or moderating the influence of learning orientation on persistence. Research has shown that the beneficial effects of learning orientation are maximized when learners also set specific, proximal, and challenging goals (Locke & Latham, 2006; Seijts, Latham, Tasa, & Latham, 2004). Some researchers have gone as far as to claim that effective goal-setting behavior has greater influence on performance and learning outcomes than goal orientation (Seijts et al., 2004). Research on learners' effective engagement in MOOCs shows the importance of setting clear aims and objectives for their participation (Kop & Fournier, 2010; Little, 2013; Littlejohn et al., 2016; Milligan et al., 2013). The lack of direct instructor support and feedback, structure, or predefined expectations for how to engage or participate means that it is the learners' responsibility to set these goals and work toward them by employing appropriate learning strategies. Second, while research on the role of goal orientation in learners' completion in MOOCs showed no significant difference in mastery-goal orientation (Wang & Baker, 2015), the same study by Wang and Baker (2015) did find that students who were motivated by the opportunities of MOOCs as opposed to MOOC content were less likely to complete the MOOC. These qualitative differences in reported goals in this current study point to other factors that might have had an influence on the role of learning orientation in learners' adoption of SRL strategies, and ultimately, persistence in the HumanMOOC (Kozlowski & Bell, 2006).

Educational Design Implications

The flexible nature of learning in a MOOC coupled with the varying levels of SRL skills and experience in MOOC participants require instructional designers to pay close attention to ways to support the development of the SRL subprocesses that are most important for effective participation and learning in MOOCs. However, simply providing prompts or reminders of effective SRL strategies is not sufficient in promoting the positive effects that SRL has on learners' engagement and persistence in MOOCs. Rather, deliberate design and support for SRL must be integrated and embedded within the online learning environment (Artino, 2007; Dabbagh & Kitsantas, 2009; Kitsantas, 2013; Kizilcec et al., 2016; McLoughlin & Lee, 2010). This is critical because current MOOC platforms do not support learners' use of SRL strategies (Park et al., 2016). While this study is correlational in nature and no strong implications can be made, it does nonetheless provide MOOC instructors and designers with some insight into the role of motivational beliefs and how they might be related to the adoption of SRL strategies and in turn support learners' achievement of self-set goals in MOOCs. Based on the results of this study, a number of recommendations and implications for MOOC instructors and designers are provided. These recommendations are derived from the following study conclusions: (a) the significant relationship between time management, online learning self-efficacy, and online learning task value and learners' persistence to self-set goals in MOOCs; (b) the significant and positive relationship between learners' motivational beliefs and use of SRL strategies, and the use of SRL strategies and learners' persistence to self-set goals in MOOCs which indicates a positive and significant association between positive motivational beliefs and the use of SRL strategies needed to persist and achieve self-set goals in MOOCs; and (c) the possible direct or indirect role that goal-setting behavior has in supporting learners' persistence to self-set goals in MOOCs.

Support for time management. Effective time management has been consistently identified as one of the most important factors related to learners' success in both formal online courses and MOOCs (Balakrishnan & Coetzee, 2013; Dabbagh & Kitsantas, 2009; Guàrdia et al., 2013; Gutierrez-Rojas et al., 2014; Kitsantas et al., 2008; Lee & Choi, 2011; Loya et al., 2015; Nawrot & Doucet, 2014; Puzziferro, 2008; Wang et al., 2013). In this study, time management emerged as the strongest individual predictor of learners' persistence to self-set goals in the HumanMOOC. Some design strategies that can be incorporated in MOOCs to help learners stay on track are to provide learners with a clear and concise list of all activities learners are expected to accomplish for each given objective, along with description of the estimated time for task completion and learning strategy tips that are most appropriate for each given learning task. Another strategy would be to include customizable calendars in which learners have the option to set notification preferences such as how soon and often they are reminded of tasks and goals; set priority levels for each task; and the ability to modify schedules, priorities, and goals (Dabbagh & Kitsantas, 2009; Kitsantas, 2013).

Promote positive task value beliefs. Given the informal nature of MOOCs and the lack of consequences for dropping out, emphasizing the relevance of learning activities and tasks to participants' professional and personal lives becomes even more crucial in sustaining learners' motivation and behavioral engagement in MOOCs. One strategy that has been suggested in the literature to support college students' motivation and positive task value beliefs is the use of social networking tools to create informal networks and personal learning environments that are in line with their individual interests and needs (Dabbagh & Kitsantas, 2013; Kitsantas, 2013). This strategy might be even more beneficial in MOOCs because of the varying goals, needs, and professional backgrounds of MOOC participants. While the use of social networking tools is encouraged in MOOCs, especially cMOOCs, not all participants are comfortable or experienced with using these tools for learning and professional purposes. A number of design strategies can be incorporated into MOOCs to guide participants through this process. For instance, instructional designers can include special modules describing the affordances of different social media tools, such as Facebook and Twitter, and different resources that highlight the learning benefits of each. Additionally, these modules can include step-by-step guides on how to create different accounts and a list of different specialized professional groups that people can join on different platforms.

Another strategy that instructional designers and instructors can use to address course value and relevance is to incorporate authentic problem-centered learning activities (Hew, 2015). Engaging learners with content and learning tasks through the exploration of real-world issues can help learners see the relevance and appreciate the importance of these learning tasks. Further, the design of learning tasks should be flexible enough to allow learners who are engaged with these courses for professional development purposes to use the problems they encounter at the workplace and the tools they use as a way to engage with MOOC content and develop relevant skills.

Support and promote online self-efficacy for learning in MOOCs. This study highlights the supportive role that positive online self-efficacy beliefs in one’s ability to learn in MOOCs have on their persistence and achievement of their self-set goals. A number of design interventions can be incorporated into MOOCs in order to support and promote such beliefs. According to Bandura' theory of self-efficacy (1977), there are a number of sources that can be highlighted in a learning environment to support and promote the development of self-efficacy. Of special relevance to the development of self-efficacy for learning in MOOCs are vicarious experience, or one's observation of a role model performing the task successfully, and verbal persuasion. Hodges (2008) proposes a number of ways in which these sources of self-efficacy can be enhanced and supported in an online learning environment. For instance, Hodges proposes the use of Pedagogical Agents for Learning (PALs) as a way to simulate a learning peer and provide guidance for learners as they engage with different learning tasks. Surprisingly, while the incorporation of virtual agents in MOOCs has the potential of overcoming the challenges of providing direct learner support because of the scalability of these courses, little research has been conducted to examine its utility in MOOCs (Li, Kizilcec, Bailenson, & Ju, 2016). Another way to model effective learning within MOOCs is to invite previous participants who have actively engaged with MOOCs and exemplified proper use of the different resources and tools to share their experiences via live online sessions during the first week of the MOOC (Artino, 2012). In terms of promoting online self-efficacy through verbal persuasion in online learning environments, researchers recommend the use of persuasive and explicit feedback through written or audio communication channels to encourage their continued movement toward goal attainment (Artino, 2012; Hodges, 2008). This feedback should be realistic, as misleading feedback can result in failure and have a negative effect on learners' self-efficacy. Further, feedback should encourage learners to measure their success in terms of self-improvement rather than in terms of comparison to others (Bandura, 1997; Hodges, 2008). Finally, dedicating the first week of the MOOC to orient learners to the MOOC and the different tools they can use to support their learning and interact with the content and other participants has been recommended in MOOC literature to provide guidance for participants with less MOOC experience (Littlejohn et al., 2016; Milligan & Littlejohn, 2016).

Inclusion of varying levels of task challenge. Multiple theories exist that highlight the positive role learning challenge has on learning outcome and motivation such as achievement goal and value-expectancy theories. Based on studies on the relationship between achievement goal orientation and learning outcomes, the positive effects of learning or mastery goals are more evident when the learning tasks are challenging (Grant & Dweck, 2003; Seijts et al., 2004). Further, according to the value-expectancy theory, people are more motivated when they believe their actions will result in positive outcomes and that these outcomes are valuable to them (Wigfield & Eccles, 1992, 2000). However, if a task is too challenging to complete in comparison to its value or too easy to accomplish that it no longer has a value as learning experience, individuals may give up on their goals (Hodges, 2008; Wigfield & Eccles, 1992, 2000). In a MOOC, it is difficult to develop learning tasks with an optimal level of challenge that is appropriate for all MOOC participants because learners join these courses with different, if any, previous experiences and varying skills. Thus, one design strategy that could be implemented in MOOCs is that a number of tasks with varying levels of difficulty and challenge can be designed for each learning objective or skill. For each learning task, the level of difficulty, prerequisite knowledge, and recommended learning strategies that can help learners accomplish these tasks should be stated prior to learners' engagement with the task. This strategy not only has the potential to promote task value beliefs and activate the positive effects of learning orientation (Grant & Dweck, 2003; Wigfield & Eccles, 1992, 2000), but this gradual increase in task difficulty can also support the development of learners' online self-efficacy beliefs (Hodges, 2008).

Goal setting. While this study did not directly investigate goal-setting behavior in MOOCs, the inductive qualitative results combined with previous findings in the literature suggest the possibility that goal-setting behavior in MOOCs might be influencing the relationship between goal orientation and persistence in MOOCs. MOOCs are usually designed with general course-level learning objectives in mind to help structure the content, however, participants are expected to take responsibility for setting their own learning goals according to their personal and professional needs and interests. The variation in specificity and quality of goals stated regardless of their orientation highlights the need to support effective goal-setting behaviors in MOOCs. Research on goal setting and its relation to performance and learning outcomes indicates that short-term or proximal, specific, and challenging goals have more influence on outcomes than does goal orientation (Locke & Latham, 2006; Seijts et al., 2004). With better and more specific goals and aims for participation, MOOC participants are more likely to focus their effort, attention, and time on these goals (Hood et al., 2015; Little, 2013; Littlejohn et al., 2016; Milligan et al., 2013; Sitzmann & Ely, 2011). Kitsantas and Dabbagh (2010) provide a number of practical design suggestions that can be easily integrated into MOOCs to develop and support effective goal-setting behavior such as creating a weekly online goal-setting template of specific MOOC objectives. These templates can be interactive so that each learner can use that as a checklist and break down each MOOC objective into more specific achievable goals. Further, individuals can have the option to set numbers or different colors to each goal to highlight its importance. In that way, learners who start to disengage, whether for factors internal or external to the MOOC, can refocus their attention and effort on those goals that are most important to them instead of giving up on their goals altogether. Giving learners the flexibility and control over their learning goals and tasks in MOOCs has the potential of supporting their achievement of self-set goals in MOOCs by allowing them to set, monitor, and update their goals in a way that is more authentic and relevant to their personal and professional needs.

Putting all these ideas together, one design intervention that combines several recommendations proposed in this section and has the potential of supporting learners' persistence to goals based on the results of this study is the design and implementation of a digital "Weekly Learning Calendar." This calendar is interactive and allows learners to prioritize the weekly MOOC learning objectives based on their individual needs and interest. Further, learners have the opportunity to select and create subgoals based on their individual skill levels and needs. Once goals and subgoals are identified, learners are presented with a list of recommended learning tasks to help them accomplish these goals. Difficulty level, prerequisite skills, and learning strategies are provided for each learning task. Once learners select the tasks that are more relevant to their needs based on the learning goals they prioritized, they get to set specific times during that week to accomplish these learning goals and corresponding tasks as well as customize the reminder setting (e.g. how often and when these reminders be sent). If a participant does not complete the task by the deadline they set, they have the option to select a different time, update their goals, or select a different learning task. Consider the following hypothetical example based on one of the learning objectives of the HumanMOOC:

1. Learners A and B both join the MOOC with special interest in understanding the use of video tools to support "Instructor Presence." However, while learner A is an online instructor interested in creating videos for their own online class, learner B is an instructional designer at a higher education institution and is interested in understanding the different technology options available so they can advise online instructors at their college on the appropriate tools they can use in their courses based on their needs.
2. Thus, both learners go to the "Instructor Presence" week to explore its learning objectives. Both set the objective "Explore tools to create asynchronous video that will enhance instructor presence" as high priority.
3. Based on their selection, a number of short-term subgoals are generated. Learner A selects "Create an introductory video to introduce learners to the course" while learner B selects "Compare and contrast the affordances of different video tools to enhance instructor presence." The learners also have the chance to enter a new goal if their specific goal is not listed. These new goals are added to a database and reviewed by MOOC instructors and

designers so that they can be rephrased in a way that reflects the characteristics of effective learning goals and matched with learning tasks.

4. Once these subgoals are selected, learners A and B are presented with a number of learning tasks that are aligned with their goals. Thus, learner A is directed toward a number of learning tasks, one of which is an "Instructor Introduction Activity." This activity requires learners to script and record a course introduction video that they can use in their online courses. Learner B, on the other hand, is presented with a number of activities including an "Instructor Presence Reflection Activity" in which learners are asked to post a reflection to a discussion board on the pros and cons of instructor videos in online classes as well as a "Compare and Contrast Activity" in which learners are asked to fill out a template with different video tools, the affordance of each, and an example of a learning context in which the use of the tool is most effective.
5. Both learners set a time during that week to complete the tasks and customize the reminder setting. Once the deadlines set by the learners are reached, an email is sent to them to either set the goals and tasks for that week as complete, or make adjustments to the time, goals, or tasks.

Recommendations for Future Research Directions

This is one of few studies that examined the complex relationships between motivational beliefs, use of SRL strategies, and persistence to goals in MOOCs. As mentioned previously, a general consensus is emerging in the field regarding the need to move away from traditional benchmarks of certification and completion as a reflection of MOOC effectiveness, to more contextualized measures that take into account participants' personal goals for joining a MOOC (DeBoer et al., 2014; Heutte et al., 2014; Reich, 2014). While a number of such measures have emerged (Kizilcec et al., 2016; Reich, 2014), this study is unique in that it measured persistence in terms of the percentage of self-set goals achieved as reported by participants themselves. Future research should continue to examine different outcome measures and how such measures relate to the use of different SRL strategies as well as experiment with different ways of measuring learners' persistence to their goals. In addition, this study relied on learners' self-reported percent of goals achieved as a measure of persistence. While this approach provided some interesting insights, there was no way to confirm whether participants have actually achieved those goals or whether they were able to apply what was learned to their personal and professional practices. Thus, longitudinal studies in which researchers follow up with participants at different points after their participation in a MOOC would be one approach to validate the effectiveness of such outcome measures.

Prior research has indicated that the influence and role of motivational beliefs and SRL strategies in informal online learning environments such as MOOCs might be different than those established in formal learning settings (DeBoer et al., 2014; Fontana et al., 2015; Greene, 2014; Hood et al., 2015; Kop, 2011; Littlejohn et al., 2016; Rovai, 2003). Consequently, this study utilized a correlational design to explore the nature of these relationships in MOOCs with no prior hypotheses stated. While no causal relationships can be inferred from such studies, they are an important first step in identifying variables that can be included in future casual-comparative and experimental studies (Warner, 2013), especially in a novel learning environment such as MOOCs. Thus, a natural next step is to study the significant variables that emerged in this study in more well-designed and controlled studies that examine their causal role and their influence on learners' success and persistence in MOOCs (e.g. structural equation modeling and mediation and moderation analyses). Keeping in mind that the current study is correlational in nature and no causal effects can be inferred, study findings nonetheless hint at the possible mediational role that motivational beliefs play in motivating persistence and academic achievement through the utilization of SRL strategies (Multon et al., 1991). For instance, while online learning task value was the strongest predictor of persistence in step 2 of the regression analysis, it was no longer significant when SRL strategies were added in the final step. Further, the addition of SRL strategies resulted in the reduction of the standardized regression coefficient of online learning self-efficacy in the final model. These findings suggest that the positive effects that online learning self-efficacy and task value beliefs have on persistence might be partially or fully mediated by other variables such as the SRL strategies and behaviors that these positive motivational beliefs activate. In other words, while positive task value beliefs did not predict persistence to self-set goals in the HumanMOOC in the final regression model, it may have had a role in facilitating the use of time management, effort regulation, peer learning, and help seeking. These self-regulatory learning strategies, in turn, may be more directly tied to learners' persistence in the HumanMOOC. This explanation, while tentative, is consistent with previous research

(Neuville et al., 2007) and the basic assumptions of the social-cognitive framework of SRL that highlight the indirect effect of motivational beliefs on academic performance through the enactment of the behavioral skills needed to self-manage and regulate one's learning (Cleary & Zimmerman, 2012; Pintrich, 2000a; Zimmerman, 2000a, 2000b).

Further, findings from this study can be used in the development of digital SRL interventions (such as the Weekly Learning Calendar) that can be tested in MOOCs and refined iteratively through design-based research cycles that incorporate different data sources and research designs (Bannan, 2013; Kelly, 2013). Of special interest is the role of learners' goal orientation and self-efficacy for learning in MOOCs on learners' persistence to self-set goals in MOOCs, as the results found in this study are unique and deviated from what has been reported in the literature on the relationship between these motivational belief variables and learning outcomes in MOOCs. Additionally, future research should include different SRL processes that have not been included in this study and examine their role in learners' persistence in MOOCs. For instance, future research should examine the role of goal setting behavior in learners' persistence in MOOCs as the results of this study point to the possible role it has in supporting learners' persistence to self-set goals in MOOCs. This suggestion is supported by MOOC research that examined differences in completion rates between learners who did not state any goals for joining the MOOC and those who did, regardless of their stated goals and intentions, in nine MOOCs. Across all nine MOOCs, the average completion rate for all participants was 6% compared to 16.5% for participants who stated a specific goal for their participation (Ho et al., 2015).

This study was mainly quantitative in nature as learners' motivational beliefs and use of SRL strategies were assessed by means of predesigned survey items. Current research on SRL calls for the integration of diverse measurements in order to effectively and comprehensively understand SRL. Thus supplementing these findings with qualitative procedures might yield additional insight into the process of SRL in MOOCs. Another promising source of data that can be used to assess SRL in MOOCs is microanalytical measures. In general, microanalytic assessment refers to a highly specific form of measurement that targets different behavioral, cognitive, and/or affective processes as they naturally occur in a particular context (Cleary et al., 2012). This approach has been used in many domains such as education (DiBenedetto & Zimmerman, 2010) and medicine (Cleary et al., 2014) using different measures and procedures such as structured interviews consisting of specific questions targeting specific SRL processes as they occur in context or direct observations of students' SRL processes as they engage in authentic activities. Within SRL research, the difference between SRL microanalysis and other SRL measures such as self-report measures is that the former is used to systematically target individuals' SRL processes and beliefs prior to, during, and after engaging in a specific learning task and activity rather than retrospective or prospective reports such as the one used in this current study.

A number of studies reviewed in this paper have used different MSLQ subscales to examine learners' SRL adoption in MOOCs, however, these results should be interpreted with caution. In an attempt to highlight potentially problematic psychometric properties of the MSLQ items, Credé and Phillips (2011) conducted a meta-analytic review of the MSLQ subscales based on 2,158 correlations from 67 independent samples and 19,900 college students followed by factor analysis of the meta-analytic intercorrelations. While the researchers concluded that the MSLQ is a reasonably reliable measure of its various constructs and their results broadly supported some of the basic assumptions of the social-cognitive view of SRL, they found evidence that some of the specific learning strategies subscales (e.g. help seeking and peer learning) may be unrelated to academic performance. According to the researchers, this might be due to the fact that these constructs exhibit a nonlinear relationship with academic outcomes or due to poorly constructed items. Consequently, they suggest that alteration or elimination of items that exhibit undesirable psychometric properties could potentially increase the subscales' predictive utility for learning outcomes. Including such steps when reporting results of SRL studies using the MSLQ subscales might be even more necessary in a novel context such as MOOCs, as it has been suggested that the SRL and motivational constructs that are crucial for success in informal learning settings might be different than those in formal learning settings (DeBoer et al., 2014; Fontana et al., 2015; Greene, 2014; Hood et al., 2015; Kop, 2011; Littlejohn et al., 2016). This suggestion is supported by findings from this study. Exploratory factor analysis of the MSLQ subscales included highlighted some problematic issues regarding the unidimensionality of these subscales, which resulted in elimination of some of the items. Another possible research direction to overcome this shortcoming is the development of new SRL measures that are unique to informal online learning contexts similar to the efforts put forth by Hood et al. (2015) and Fontana et al. (2015).

Finally, the findings of this study are limited to the participants who responded to the survey in a cMOOC called The HumanMOOC. Consequently, replication of this study in other MOOC designs such as xMOOCs is needed. This polarization between cMOOCs and xMOOCs has become even more evident in the past year. The exponential rise in the number of MOOCs offered and learners who join these courses are accompanied by major changes to the MOOC landscape that is worth noting here (Cook, 2016). One major trend concerns the packaging of the courses offered by the major xMOOC providers such as edX, Udacity, and Coursera. While xMOOCs were previously offered as standalone courses, there seems to be a shift toward certificate programs in which learners are required to do a sequence of courses as the platforms offer their own credentials and degree programs such as Udacity's Nano degrees, Coursera's Specializations, and edx's Xseries (Cook, 2016; Shah, 2016a, 2016b). This shift toward more specialized MOOC programs and tracks has also reached the corporate sector. For instance, Coursera now offers Coursera for Business in which organizations can handpick the courses for their employees and track their progress (Shah, 2016a). Unfortunately, cMOOCs have not received as much media attention as their counterpart xMOOCs. However, this trend, while in part motivated by monetary reasons (Cook, 2016; Shah, 2016a), highlights a major difference between xMOOCs and cMOOCs that cannot be overlooked from an educational design or research perspective: the audience these MOOCs are targeting. While cMOOCs seem to be targeting lifelong learners and emphasize the learning process and connection made during a course, xMOOCs seem to have made a decisive shift toward professional learners who are seeking credentials that are acknowledged by organizations by focusing on assessment of high-demand skills in business and technology (Cook, 2016). Thus, SRL research in MOOCs should not only focus on research design and reporting of findings, but pay special attention in describing the MOOC's setting and its participants so that research can be replicated and findings can be compared and generalized.

Study Limitations

Given the time and financial constraints of the researcher, only a single population from one MOOC was selected for inclusion in this study. The sample from this population was recruited using a convenience sampling technique, meaning it was not randomly drawn from a well-defined population but rather consisted of a sample that was readily available to the researcher (Warner, 2013). Convenience sampling techniques suffer from a number of biases that must be considered when interpreting and understanding the results of this study. Such sampling technique may lead to overrepresentation or underrepresentation of a particular group within the sample, which affects the generalizability and external validity of the findings from this study. However, such sampling technique allows for a quick and cost-effective way to explore hypothesis that can serve as basis for future testing using probability sampling techniques. For this study, the generalizability of the results is only limited to the 33.23% of HumanMOOC participants who responded to the survey. The sample included was not diverse as participants in this study were mostly White/Caucasian (77.5%), older (78.3% were 35 and older), and highly educated (75.7% had a Master or Doctoral degree). Additionally, SRL theory and research emphasizes the contextual nature of SRL processes and practice, which has been echoed in SRL research in MOOCs. For instance, Milligan and Littlejohn (2016) found evidence of the influence of MOOC design and delivery on participants' motivational beliefs, which in turn shaped the learning strategies participants used in the MOOC. The HumanMOOC design was more aligned with the principles of connectivism and its design features. Thus, this study requires replication not only in cMOOCs, but also in other MOOCs that adapt different design and delivery strategies, such as xMOOCs, to determine whether these findings can be generalized to other participants and contexts or if it is specific to the sample and context examined here.

Another limitation is that the study included a sample population that was difficult to predict. Van Selm and Jankowski (2006) provide a number of suggestions that can be used to increase response rates in situations where response rates are impossible to calculate. They suggest that understanding the populations' attitudes, decisions, and behavior may have implications for how surveys are prepared and delivered. Both open enrollment and high dropouts that happen throughout MOOC offerings make predictions of numbers difficult. This is evident by the consistent low response rates in postsurveys compared to presurveys in MOOC studies that involve pre- and posttests (Poellhuber et al., 2014). For this reason, one survey called "The HumanMOOC Experience Survey" that participants were asked to fill out whenever they ended their participation in the HumanMOOC was available to participants at the start of the MOOC to accommodate the different ways in which participants chose to engage with the MOOC. Further, Van Selm and Jankowski suggest the use of respondents' incentives to increase participation.

In this study, a $10 e-gift card from either Amazon or Starbucks was awarded to survey participants who consented by providing their email addresses.

In terms of the scales used, a number of issues must be pointed out and considered when interpreting and understanding the findings from this study. First, the MSLQ subscales had low reliability coefficients. While the removal of some items from the subscales as a result of the exploratory factor analysis resulted in improved reliability, the reliability coefficient for the effort regulation subscale in particular remained very low ($\alpha = .54$). Second, the online learning self-efficacy and task value scales adapted in this study were designed to measure efficacy and task value beliefs as it relates to online learning (Artino & McCoach, 2008) rather than a contextual measure that is specific to informal online learning contexts such as MOOC. In addition, the self-report nature of the instrument used in this study is another source of limitation because it relies on the truthfulness of participants responding to the survey. Such data sources suffer from inherent limitations with the grain size of the instrument (i.e. aptitude vs. event measures) that puts forward issues of validity and utility, cognitive distortions, and recall difficulties (Pintrich, 2004; Winnie & Perry, 2000). To mitigate the effect of these limitations, a number of design issues have been considered. Respondents were asked in the informed consent to answer the questions thoughtfully and were reminded that all necessary procedures would be taken to ensure the confidentiality and anonymity of their responses, which hopefully increased the truthfulness of their responses. Further, the survey was available to participants to access at any time they decided to stop engaging with the MOOC, thus overcoming some of the problems associated with memory and cognitive distortion in their responses. Finally, while self-report measures are less able to capture the ongoing dynamics of SRL processes at a micro level, that does not necessarily mean that such data sources are biased or less effective than objective forms of measurement (Cleary et al., 2012). For instance, Pintrich argues that other process-oriented measures of SRL, "have less practical utility than self-report questionnaires, so questionnaires still have a role to play in research on self-regulated learning" (2004, p. 401). Further, SRL researchers assert that the key issue to consider in self-report measures of SRL is their reliability and validity in capturing SRL as a contextualized process (Cleary et al., 2012) as well as the construct validity and empirical evidence that is offered in support of the instrument (Pintrich, 2004). Pintrich (2004) asserts that while self-report measures such as the MSLQ are less able to capture at the micro level in terms of actual events or strategies used by learners, a basic assumption of the MSLQ is that motivational beliefs and SRL strategies measured by the instrument are course and domain dependent and thus should be measured at some level below the college or university level. Consequently, this study asked participants to respond to the survey in relation to their learning experience within this specific MOOC, which provided a good compromise between a global-level measurement of learning in general and a more microanalytic level focused on individual tasks within a MOOC (Pintrich, 2004).

The last issue to consider is the scope of this study and persistence factors included. This study did not attempt to examine external factors affecting persistence in MOOCs (e.g. family responsibilities or work load) or test a model of persistence within MOOCs, but rather attempted to identify the most relevant factors of SRL in relation to persistence that can be used in future studies to test more complex informal learning and MOOC persistence models.

Concluding Remarks

This study is built on the premise that the success of MOOCs is more accurately measured by whether or not a course supports learners to reach the goals they have for joining a MOOC rather than traditional retention or completion measures. One model that addresses learners' ability to activate and sustain motivation, cognition, and behavior systematically oriented toward attainment of personal goals is SRL (Pintrich, 2000a; Zimmerman, 2000a). Hence, this perspective highlights the interrelations between motivational and behavioral factors in supporting positive learning outcomes and achievement of personal learning goals (Pintrich, 2000a, 2004; Zimmerman, 2000a, 2008), a gap that has been identified in MOOC research. Using the social-cognitive framework of SRL, this study explored the relationship between motivational beliefs (goal orientation, online learning self-efficacy, and online learning task value), the use of SRL strategies (time management, effort regulation, peer learning, help seeking), and learners' persistence to self-set goals in MOOCs. While some researchers suggest that the role of SRL strategies and motivational factors in informal learning settings and MOOCs are different than that found in formal online courses (Kop, 2011; Fontana et al., 2015), findings from this study mostly support existing literature on SRL in traditional and formal online courses and add important theoretical and empirical extension on SRL research in informal online learning settings such as MOOCs. This suggests that some SRL strategies and motivational beliefs that are necessary for learners' success in formal learning settings are also important for learners success in informal online learning settings such as MOOCs. Results of this study confirm the positive association between positive motivational beliefs and the use of different SRL strategies and the predictive power the combination of motivational and SRL factors have in predicting learners' persistence to self-set goals in MOOCs. This finding is noteworthy as it fills some of the gap in MOOC research that overlooks this connection by focusing on either motivational or behavioral factors in understanding learners' success and persistence in MOOCs (Poellhuber et al., 2014; Wang & Baker, 2015). Overall, results of this study suggest that the social-cognitive notion of SRL can provide a useful framework for examining learners' success and persistence in informal online learning settings. Future research efforts should continue to use contextualized and multidimensional SRL models to help understand the complex relationship between motivation, behavior, and cognition in informal online learning contexts. Ultimately, results from these studies can be used to generate and develop design interventions and examine whether such interventions can support learners' performance and persistence in MOOCs, thus moving both MOOC research and practice forward.

Appendix A

George Mason University Institutional Review Board Exemption Letter October 13, 2016

GEORGE MASON UNIVERSITY | Office of Research Integrity and Assurance

Research Hall, 4400 University Drive, MS 6D5, Fairfax, Virginia 22030
Phone: 703-993-5445; Fax: 703-993-9590

DATE:	October 13, 2016
TO:	Nada Dabbagh
FROM:	George Mason University IRB
Project Title:	[971882-1] Examining the Relationship Between Self-Regulated Learning Processes and Persistence to Goals in Massive Open Online Courses
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	October 13, 2016
REVIEW CATEGORY:	Exemption category #2

Thank you for your submission of New Project materials for this project. The Office of Research Integrity & Assurance (ORIA) has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

Please remember that all research must be conducted as described in the submitted materials.

Please note that any revision to previously approved materials must be submitted to the ORIA prior to initiation. Please use the appropriate revision forms for this procedure.

If you have any questions, please contact Bess Dieffenbach at 703-993-5593 or edieffen@gmu.edu. Please include your project title and reference number in all correspondence with this committee.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within George Mason University IRB's records.

- 1 - Generated on IRBNet

Appendix B

The HumanMOOC Experience Survey

The HumanMOOC Experience Survey

Demographics and MOOC Experience

2. Select you gender

- ◯ Male
- ◯ Female

3. Choose your age group

- ◯ 18 to 19 years
- ◯ 20 to 24 years
- ◯ 25 to 29 years
- ◯ 30 to 34 years
- ◯ 35 to 39 years
- ◯ 40 to 44 years
- ◯ 45 to 49 years
- ◯ 50 years and over

4. What is your ethnicity?

- ◯ White/Caucasian
- ◯ African American
- ◯ African
- ◯ Hispanic/Latino
- ◯ Middle Eastern
- ◯ Caribbean
- ◯ South Asian
- ◯ East Asian
- ◯ Mixed

Other (please specify)

5. Where do you live?

- North America
- Central America
- South America
- Europe
- Africa
- Middle East
- Russia
- Australia

Other (please specify)

6. Choose your highest level of education completed

- Primary / Elementary School
- Secondary / Middle School
- High School or G.E.D.
- Associate's Degree
- Bachelor's Degree
- Master's Degree
- Ph.D. / Doctorate

7. Have you previously enrolled in and completed some or all of a different Massive Open Online Course (MOOC) in the past?

- Yes
- No

8. What was your primary goal(s) for enrolling in the HumanMOOC?

The HumanMOOC Experience Survey

Beliefs and Attitude

9. Please think about your general attitude toward, and goals for the HumanMOOC. Using the following scale (from 1=*Strongly Disagree* to 7= *Strongly Agree*), please select the number that indicates your degree of agreement or disagreement with the statements with respect to this MOOC.

1	2	3	4	5	6	7
Strongly Disagree	Moderately Disagree	Slightly Disagree	Neither Disagree Nor Agree	Slightly Agree	Moderately Agree	Strongly Agree

	1	2	3	4	5	6	7
I value what others think of my performance	○	○	○	○	○	○	○
It's important for me to impress others by doing a good job	○	○	○	○	○	○	○
I don't care what others think of my performance	○	○	○	○	○	○	○
I'm not interested in impressing others with my performance	○	○	○	○	○	○	○
I like to meet others' expectations of me	○	○	○	○	○	○	○
The opinions others have about how well I can do certain things are important to me	○	○	○	○	○	○	○
It's better to stick with what works than risk failing at a task	○	○	○	○	○	○	○
Typically, I like to be sure that I can successfully perform a task before I attempt it	○	○	○	○	○	○	○
I don't like having my performance compared negatively to others	○	○	○	○	○	○	○
I don't enjoy taking on tasks if I am unsure whether I will complete them successfully	○	○	○	○	○	○	○

	1	2	3	4	5	6	7
I avoid circumstances where my performance will be compared to others	◯	◯	◯	◯	◯	◯	◯
Most of the time, I stay away from tasks that I know I won't be able to complete	◯	◯	◯	◯	◯	◯	◯
I worry that I won't always be able to meet the standards set by others	◯	◯	◯	◯	◯	◯	◯
I avoid tasks that I may not be able to complete	◯	◯	◯	◯	◯	◯	◯
The opportunity to do challenging work is important to me	◯	◯	◯	◯	◯	◯	◯
I prefer to work on tasks that force me to learn new things	◯	◯	◯	◯	◯	◯	◯
If I don't succeed on a difficult task, I plan to try harder the next time	◯	◯	◯	◯	◯	◯	◯
In learning situations, I tend to set fairly challenging goals for myself	◯	◯	◯	◯	◯	◯	◯
I am always challenging myself to learn new concepts	◯	◯	◯	◯	◯	◯	◯
The opportunity to extend my range of abilities is important to me	◯	◯	◯	◯	◯	◯	◯
The opportunity to learn new things is important to me	◯	◯	◯	◯	◯	◯	◯

The HumanMOOC Experience Survey

Beliefs and Attitude

10. The following statements relate to your **beliefs in your ability to learn** with Massive Open Online Courses such as the HumanMOOC.

Using the scale below (from 1=*Completely Disagree* to 7=*Completely Agree*), select the extent to which you agree with each statement

1	2	3	4	5	6	7
Completely Disagree	Mostly Disagree	Tend to Disagree	Neutral	Tend to Agree	Mostly Agree	Completely Agree

	1	2	3	4	5	6	7
Even in the face of technical difficulties, I am certain I can learn the material presented in a Massive Open Online Course	○	○	○	○	○	○	○
I am confident I can learn without the presence of an instructor to assist me	○	○	○	○	○	○	○
I am confident I can do an outstanding job on the activities in a Massive Open Online Course	○	○	○	○	○	○	○
I am certain I can understand the most difficult material presented in a Massive Open Online Course	○	○	○	○	○	○	○
Even with distractions, I am confident I can learn material presented online	○	○	○	○	○	○	○

11. The following statements relate to your opinions regarding the **value** of the HumanMOOC.

Using the scale below (from 1=*Completely Disagree* to 7=*Completely Agree*), select the extent to which you agree with each statement

1	2	3	4	5	6	7
Completely Disagree	Mostly Disagree	Tend to Disagree	Neutral	Tend to Agree	Mostly Agree	Completely Agree

	1	2	3	4	5	6	7
It was personally important for me to perform well in this Massive Open Online Course	○	○	○	○	○	○	○
This Massive Open Online Course provided a great deal of practical information	○	○	○	○	○	○	○
I was very interested in the content of this Massive Open Online Course	○	○	○	○	○	○	○
Completing this Massive Open Online Course moved me closer to attaining my career goals	○	○	○	○	○	○	○
It was important for me to learn the material in this Massive Open Online Course	○	○	○	○	○	○	○
The knowledge I gained by taking this Massive Open Online Course can be applied in many different situations	○	○	○	○	○	○	○

The HumanMOOC Experience Survey

Resource management Strategies

12. The following questions ask about your learning strategies and study skills for the HumanMOOC. There are no right or wrong answers. Answer the questions about how you study in this MOOC as accurately as possible. If you think the statement is very true of you, select 7; if a statement is not at all true of you, select 1. If the statement is more or less true of you, find the number between 1 and 7 that best describes you.

|…………..|…………..|…………..|…………..|…………..|…………..|

1 2 3 4 5 6 7

Not at all true Of me — Very true of me

	1	2	3	4	5	6	7
I usually study in a place where I can concentrate on my course work	○	○	○	○	○	○	○
I make good use of my study time for this Massive Open Online Course	○	○	○	○	○	○	○
I find it hard to stick to a study schedule	○	○	○	○	○	○	○
I have a regular place set aside for studying	○	○	○	○	○	○	○
I make sure I keep up with the weekly readings and assignments for this Massive Open Online Course	○	○	○	○	○	○	○
I participate in this Massive Open Online Course regularly	○	○	○	○	○	○	○
I often find that I don't spend much time on this Massive Open Online Course because of other activities	○	○	○	○	○	○	○
I rarely find time to review my notes or readings before an assignment	○	○	○	○	○	○	○

	1	2	3	4	5	6	7
I often feel so lazy or bored when I study for this Massive Open Online Course that I quit before I finish what I planned to do	○	○	○	○	○	○	○
I work hard to do well in this Massive Open Online Course even if I don't like what we are doing	○	○	○	○	○	○	○
When course work is difficult, I give up or only study the easy part	○	○	○	○	○	○	○
Even when course materials are dull and uninteresting, I manage to keep working until I finish	○	○	○	○	○	○	○
When studying for this Massive Open Online Course, I often try to explain the material to a classmate or a friend	○	○	○	○	○	○	○
I try to work with other students from this Massive Open Online Course to complete the course assignments	○	○	○	○	○	○	○
When studying for this Massive Open Online Course, I often set aside time to discuss the course material with a group of students from the class	○	○	○	○	○	○	○
Even if I have trouble learning the material in this Massive Open Online Course, I try to do the work on my own, without help from anyone	○	○	○	○	○	○	○
I ask the instructor to clarify concepts I don't understand well	○	○	○	○	○	○	○

	1	2	3	4	5	6	7
When I cant understand the material in this Massive Open Online Course, I ask another student in this class for help	◯	◯	◯	◯	◯	◯	◯
I try to identify students in this Massive Open Online Course whom I can ask for help if necessary	◯	◯	◯	◯	◯	◯	◯

The HumanMOOC Experience Survey

Persistence to goals

13. What percent of your primary goal(s) for joining this MOOC do you estimate you have achieved?

Please slide the marker to the percent of goals achieved

0% 50% 100%

14. If you wish to receive an e-gift card, please select the type of e-gift card you wish to receive

- $10 e-gift card from Starbucks
- $10 e-gift card from Amazon

15. If you wish to receive an e-gift card, please enter your email address so one can be sent to you during the first week of December

Appendix C

Recruitment Letter

Greetings!

My name is Maha Al-Freih and I'm a doctoral student at George Mason University under the supervision of Dr. Nada Dabbagh. You are being invited to participate in this research to explore the relationship between motivational beliefs, the use of self-regulated learning (SRL) strategies, and learners' persistence to self-set goals in Massive Open Online Courses (MOOCs).

To conduct this study, an online survey called "HumanMOOC Experience Survey" has been created. If you decide to participate in this study, you are kindly asked to complete this survey at **anytime you decide to end your participation in the HumanMOOC**. Answering the survey will not impact your ability to access or participate in the HumanMOOC at a later point. This survey should take you **no more than 15 minutes** to complete. Questions in this survey include demographic information as well as questions related to your perception of your learning experience and the resource management strategies you used in this MOOC.

Please answer each question as accurately as possible, reflecting your own attitudes and behaviors in the HumanMOOC. Remember, this is completely voluntary. You can choose to be in the study or not. You can also opt out at any point during the study with no penalty. Although this study may not be of direct benefit to you at this time, we believe that any insights and knowledge generated will inform future MOOC design interventions that can help improve learners' experiences in Massive Open Online Courses. As an incentive for your participation in this study, you will be awarded a 10$ digital gift card from either Amazon or Starbucks. At the end of the survey, you will be asked to provide your email address and select the type of gift card you wish to receive so one can be sent to you via your email during the last week of December. Your email address will be removed from the dataset prior to analysis to protect your confidentiality.

If you'd like to participate and have any questions about the study, please email or contact one of research team member listed bellow. We will be more than happy to answer any of your questions or concerns.

Thank you very much for your time and consideration.

Sincerely,

Researcher:

Maha Al-Freih, College of Education and Human Development at George Mason University.
xxx-xxx-xxxx or maha.gmu@gmail.com

Follow-Up Email to Participants

One follow-up email at the end of the MOOC will be a resending of the original email with the following:

Greetings!

Please let us know if you would like to participate in this important study or learn more about it.

Thanks again,

Your research team:

Maha Al-Freih, College of Education and Human Development at George Mason University.
xxx-xxx-xxxx or maha.gmu@gmail.com

Appendix D

Informed Consent Letter

RESEARCH PROCEDURES

The purpose of this research is to explore the role of motivational beliefs and Self-Regulated Learning (SRL) strategies in learners' persistence to self-set goals in Massive Open Online Courses (MOOCs). Questions in this survey include demographic information as well as questions related to your perception of your learning experience and the resource management strategies you used in this MOOC.

If you decide to participate in this study, <u>you are kindly asked to complete this survey at anytime you decide to end your participation in the HumanMOOC</u>. Answering the survey will not impact your ability to access or participate in the HumanMOOC at a later point. This survey should take you no more than 15 minutes to complete.

RISKS

There are no foreseeable risks for participating in this research.

BENEFITS

There are no direct benefits to you for participating in this study, but we hope to learn more about motivational beliefs, SRL, and persistence to self-set goals in MOOCs from your participation.

CONFIDENTIALITY

No identifiable data will be collected in this study. However, if you decide to receive a **$10 e-gift card from either Amazon or Starbucks**, you will be asked to provide your email at the end of the survey so that a gift card can be sent directly to your email address. The email addresses will be removed from the dataset prior to analysis to protect your confidentiality and will be destroyed once the gift cards are distributed during the last week of December. All survey data will be concealed and stored in surveymonkey-secure database. Data in this study will only be accessible by the research team and will be kept confidential under password-protected folder. While it is understood that no computer transmission can be perfectly secure, reasonable efforts will be made to protect the confidentiality of your transmission.

PARTICIPATION

Your participation in this study is completely voluntary, and you may withdraw from the study at any time and for any reason. There are no costs to you or any other party. If you decide not to participate or if you withdraw from the study, there is no penalty or loss of benefits to which you are otherwise entitled. However, upon completing this survey you will receive a $10 digital gift card from either Amazon or Starbucks. This gift card will be sent to your email you provide at the end of the survey during the last week of December. You must be 18 years of age or older to participate.

CONTACT

This research is being conducted by Maha Al-Freih, College of Education and Human Development at George Mason University. Maha Al-Freih can be reached at xxx-xxx-xxxx or maha.gmu@gmail.com for questions about this study or to report a research-related problem. Dr. Nada Dabbagh is the principal investigator for this research and can be reached at xx-xxx-xxxx. You may contact the George Mason University Office of Research Integrity and Assurance at 703-993-4121 if you have questions or comments regarding your rights as a participant in the research.

This research has been reviewed according to George Mason University procedures governing your participation in this research.

CONSENT

I have read this form and agree to participate in this study. Please click 'I Agree' to continue to the survey.

- I Agree
- I Decline

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Biography

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