THE IMPACT OF MOOC PARTICIPATION ON MOTIVATION TO ENROLL IN GRADUATE EDUCATION

By

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ABSTRACT

This study examined ways in which participation in Massive Open Online Courses (MOOCs) influenced aspects of learners' achievement motivation and decisions to enroll in a master's degree program by offering low-cost and low-commitment ways to sample the learning experience. Participants in this study (*n* = 197) were enrolled in two MOOC courses associated with a data science master's degree program, and were surveyed pre- and post-course to measure motivational and self-regulated learning strategy variables, as well as intentions to enroll in a degree program. Self-efficacy and intrinsic value significantly increased as learners progressed through the course, as predicted. However, attainment value increased and utility value did not change, which were unexpected. Opportunity costs declined unexpectedly, while effort and psychological costs remained stable. Self-efficacy had a negative relationship with intentions to enroll in a degree program, which was unexpected. However, attainment value had a positive relationship with intentions to enroll, as expected. Gender, age, first-generation student status, and underrepresented minority status among learners did not moderate the relationship between motivational variables and intentions to enroll, as predicated. Self-regulated learning strategies such as goal setting, strategic planning, and help seeking did not have a statistically significant relationship with intentions to enroll in a degree program when controlling for motivational variables.

This study examines learning in innovative, non-traditional learning environments, with a population of learners that has different characteristics and motivations for pursuit of learning. The difference in contexts between MOOC and formal degree environments, as well as differences in the learners engaging in each of these learning experiences, likely contributed to the many unanticipated findings. Researchers should carefully evaluate assumptions regarding how the new context establishes similar or different affordances and constraints that enable the same relationships between constructs as have been seen in traditional educational

environments. Measurement of constructs should also be critically evaluated to ensure established measures are applicable to these new environments and populations.

To Joshua, who made this possible.
And to Riley, who makes everything more meaningful.

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CHAPTER 1:

Introduction

There has been an enduring need to study graduate school choice in recent decades. Kallio (1995) notes how changes in graduate school conditions, including shifting enrollment patterns and availability of funding, make it challenging for institutions to maintain a stable graduate student learner population. At the same time, students' decisions to pursue graduate educational opportunities have been considered complex and difficult to model due to concerns relating to ability, income, expense, employment, and opportunity costs (Stoecker, 1991). While graduate students are more greatly influenced by spouses, families, and work considerations, models for undergraduate student decision making are often used to study graduate school choice as there are similarities in student choice factors at both levels (Kallio, 1995). These models primarily focus on economic or sociological approaches, which focus on rational decision-making and how individuals' thoughts, beliefs, and perceptions are informed by their immediate environment. However, these approaches do not consider self-beliefs regarding ability and how they influence choice. An individual's perception of their academic ability serves as an additional source of information that shapes predisposition to pursue college, and those with greater perceived ability have increased likelihood of planning to attend college when effects of attitudes, social norms, and academic achievement are controlled (Carpenter & Fleishman, 1987).

Developments in recent decades have continued to shift the context of graduate school, particularly related to master's degree programming, in important ways that may influence student choice. Workforce demand for graduate education has surged, with the number of occupations requiring master's degrees for entry into a profession in the U.S. increasing substantially over the last decade (Torpey, 2018). Workers are increasingly required to pursue additional educational opportunities to upgrade and broaden existing skill sets to stay current or advance in their career (Schwab, 2018; Mehrotra et al., 2001). With individuals working and living longer, society is placing greater value on engagement with opportunities for lifelong learning (Weise, 2020). As a result, older, nontraditional learners are returning to graduate school after spending time in the workforce, with some hoping to advance in their current field while others are hoping education will allow them to pursue careers in new disciplines (Wendler et al., 2010).

At the same time, institutions are responding to this greater need for master's degree programming with more flexible offerings that meet the needs of new learners. Institutions have diversified the array of master's degree programs available, with the number of distinct master's degree program fields rising significantly in recent decades (Blagg, 2018). Technology now allows institutions to offer more flexible programs so learners can pursue graduate while also balancing employment and family obligations (Mehrotra et al., 2001; Bickle & Carroll, 2003). The result is a proliferation of online master's degree programs that create greater access to graduate education, with online programs making up more than 21% of all master's programs during the 2017-2018 academic year (Miller, 2019).

Over the past decade, some institutions started offering learners opportunities to sample portions of their graduate program curricula prior to enrolling in an online degree program via participation in massive open online courses (MOOCs). MOOCs allow a large, global audience of learners to engage in full-length online courses with few registration requirements and a low cost, or no cost, to participate (Perna et al., 2014). In instances where MOOC courses are designed to provide a stackable pathway to a degree program, these courses will offer the opportunity to engage with some course elements—including readings, lectures, and assignments—that are similar to what would be encountered in the graduate education environment, but without the same level of commitment (Williamson & Pittinsky, 2016). These courses allow learners to sample the graduate school experience to some degree, and can create an alternative information source for learners considering whether graduate education is the right choice for them (Hein, 2021).

This information may be particularly meaningful for certain individuals. For instance, those who value current assessments of their academic capabilities as an information source when considering pursuit of graduate education, such as women (Hearn, 1987) or older individuals, may find the opportunity to assess current skills provided by a MOOC as a beneficial to making choices about whether to pursue graduate education. Those who have less social or cultural connections that can share information related to attending graduate school may find the ability to sample some graduate course content via MOOCs to be meaningful (Perna, 2006).

However, some characteristics of the MOOC environment that differ from graduate educational experiences may also make the use of self-regulated learning strategies more important toward learners' success and motivation. The lack of support and guidance from instructors and peers, an absence of timelines creating pressure to progress, and the absence of social norms to complete in a specified timeframe within MOOC contexts requires learners to have stronger self-regulated learning skills to succeed (Kizilcec et al., 2017). In particular, goal setting and strategic planning have been found to be critical for learners achieving their goals within a MOOC, as there is limited scaffolding within the MOOC that provide this type of support for learners (Kizilcec et al., 2017). Use of help seeking strategies was found to negatively predict goal attainment, as learners may not find the support necessary for success within a MOOC (Kizilcec et al., 2017).

Changes in demand for graduate education, new learner populations returning to school to pursue graduate programs, and the introduction of new stackable learning environments, creates an interesting new opportunity for understanding whether lower-cost chances to sample learning experiences can influence motivation and contribute to students' choices about pursuing online master's degree programs when considered through an achievement motivation lens. Framing this study through the lens of situative expectancy value theory creates an opportunity to explore how learners assess their self-beliefs related to their academic capabilities as well as their subjective task values—which include associated costs—while pursuing learning in a MOOC.

This dissertation study examined the ways in which participation in MOOCs, which create low-cost and low-commitment ways for an individual to engage with content that comprises a graduate degree program, can influence different learners' decisions to enroll in an online master's degree program. Specifically, I examined how various motivational constructs—self-efficacy, intrinsic value, attainment value, utility value, opportunity cost, effort cost, and psychological cost—change as learners progress through a MOOC course. I also examined how these constructs related to intentions to pursue a master's degree program after learners had engaged with the course. To better understand how learners with different characteristics might be impacted by their experience engaging with a MOOC and whether that impacted intentions to enroll in master's degrees, I examined how various personal characteristics (gender, age, first-generation status, race/ethnicity) moderated the relationship between motivational variables and intentions to enroll. I also considered how use of self-regulated learning strategies with the MOOC context contributed positively or negatively toward intentions to enroll once motivational variables were controlled. This research adds to the field of research around achievement motivation by extending the examination of these constructs in innovative new learning environments, and with different learner populations, to better understand how differences in the context and learners may help promote graduate school pursuit.

CHAPTER 2:

Review of Literature

In this chapter, I outline the theoretical framework used for examining how motivational constructs, framed through situated expectancy value theory (SEVT), relate to students' choices to pursue graduate education, as well as how self-regulated learning (SRL) strategies can impact motivation and may therefore influence graduate school choices. Next, I summarize literature regarding how graduate school choice has historically been studied. Finally, I explain how the contextual changes in the landscape relative to master's degree programs create new opportunities to understand how learners who are considering graduate school choice in today's environment are impacted by opportunities to sample the curriculum in a low-commitment environment.

Theoretical Framework

Achievement Motivation Can Help Explain Student's Academic Choices

Achievement motivation frameworks offer a compelling perspective for examining whether participation in a MOOC influences graduate school choices. Motivation refers to the process of initiating and sustaining behavior (Schunk et al. 2014). Situated expectancy-value theory (SEVT) of motivation combines learners' expectancies for success with assessment of values, suggesting that these constructs combined are the most proximal psychological processes that determine moment-to-moment decision-making related to task and activity choice (Eccles & Wigfield, 2020). The comprehensiveness of the framework makes it particularly useful for exploring differences among choice decisions for today's prospective graduate students. SEVT integrates developmental processes that influence expectancies for success and subjective task values, as well as social experiences and individuals' personal characteristics that act as inputs into those developmental processes; these elements create the social and experiential background that help explain within- and between-person differences in cognitive, affective, and behavioral aspects of the rest of the model (Eccles & Wigfield, 2020).

Expectancies for Success Address the Question "Can I Do This?"

Expectancies for success (ES) are defined as "individuals' beliefs about how well they will do on upcoming tasks, either in the immediate or long-term future" (Eccles & Wigfield, 2002, p. 119). Expectancies for success have been shown to have a strong, direct influence on performance, achievement, cognitive engagement, effort, and persistence, and an indirect influence on an individual's choice to pursue an activity (Wigfield & Cambria, 2010; Schunk & Pajares, 2005).

ES focus on personal and efficacy expectations and are measured in a manner similar to self-efficacy expectations (Eccles et al., 1998; Schunk & Pajares, 2005). Wigfield and Eccles (2000) identified similarities and differences in their ES construct in SEVT and Bandura's concept of self-efficacy, most notably calling attention to Bandura's tendency to measure self-efficacy at the task-specific level, whereas their ES construct tended to be domain specific and more generally conceptualized. However, there have been more domain-specific self-efficacy surveys developed, tested, and frequently used in recent decades, including the self-efficacy sub-scales of Midgley et al.'s (2000) Patterns of Adaptive Learning (PALS) survey and Pintrich and DeGroot's (1990) Motivated Strategies for Learning Questionnaire (MSLQ). Adaptations of these self-efficacy scales have been used to measure ES in recent studies of college students' motivation that are framed using SEVT (Mamaril et al., 2016; Robinson et al., 2019; Totonchi et al., 2021).

Academic self-efficacy beliefs are based on an individual's perceptions regarding whether they are capable of learning or performing academic behaviors at specific levels (Schunk & Pajares, 2005). Bandura (1977) suggests that individuals' perceptions of self-efficacy are informed by four sources of information: mastery experiences, vicarious experience, verbal and social persuasion, and emotional arousal. Mastery experiences are a particularly influential source, as they are based on an individual's previous experience successfully mastering a task (Bandura, 1977). Efficacy expectations increase as individuals experience repeated success, and eventually become strong enough to negate the negative impact created by occasional failure at a task (Bandura, 1977).

Verbal and social persuasion also support development of self-efficacy. Learners not yet capable of accurately appraising their own capabilities will rely on encouragement from teachers or peers to boost confidence in their academic capabilities (Usher & Pajares, 2008). When combined with conditions and instruction that help bring success, supportive messages from others can positively influence self-efficacy (Usher & Pajares, 2008).

This study focuses primarily on mastery experiences as well as verbal and social persuasion as sources of self-efficacy in MOOCs. MOOC engagement provides an opportunity for learners to engage in authentic tasks that either directly replicate or closely relate to tasks they would engage with if they enrolled in the master's degree program. The ability to attempt authentic tasks in a low-cost, low-commitment setting creates opportunities for learners to repeatedly attempt these degree-related tasks, with feedback provided if failure occurs. The ability to repeatedly attempt a task without penalty until a learner achieves success creates ideal opportunities for mastering the task, potentially creating opportunities for increasing self-efficacy and affirming "I can do this" when considering whether one will be successful at master's degree-related tasks. However, the lack of opportunities for verbal or social persuasion may undermine development of self-efficacy as well, given learners do not always have opportunities to engage with the instructor or their peers in the MOOC environment.

Values Help Students Determine "Do I Want to Do This?"

In the SEVT framework, subjective task values (STVs) are defined in relation to the qualities of different achievement tasks and how they influence one's desire to engage in the task (Wigfield & Eccles, 2020). They are considered subjective because they are unique; each individual may value the same activity differently (Wigfield & Eccles, 2020). STVs are broken down into four distinct subcomponents: attainment value, intrinsic value, utility value, and cost (Wigfield & Eccles, 2000). Values are important in predicting an individual's choice behaviors, including intentions to enroll in courses (Schunk et al., 2014), as students are more likely to choose to engage in activities that they value (Wigfield & Cambria, 2010). Cost is especially important for predicting choice, as all choices have a cost associated with them, and students are less likely to engage in activities that are associated with strong perceived costs (Wigfield & Cambria, 2010).

Attainment value refers to the value that results from pursuing a task seen as central to an individual's sense of self, due to the task providing a chance for the individual to confirm or reinforce important aspects of their identity (Eccles, 2005). Individuals attempt to confirm they possess qualities critical to their self-image; if an activity provides an opportunity to confirm one's self-image or is consistent with how they perceive themselves, they will be more likely to pursue the activity (Eccles, 2005).

The term *intrinsic value* is used to describe the enjoyment an individual experiences from participating in a task (Eccles, 2005; Wigfield & Eccles, 2000). SEVT suggests when an individual intrinsically values an activity, they can be subject to deep engagement and can persist for long periods of time (Wigfield & Cambria, 2010; Wigfield & Eccles, 2020).

Utility value refers to the value associated with how the task relates to present or future plans and goals, including career goals (Wigfield & Eccles, 2020). Utility value can have ties with an individual's personal goals or sense of self if the task being pursued helps achieve important goals the individual holds deeply and is therefore linked to attainment value (Wigfield & Cambria, 2010; Wigfield & Eccles, 2020).

Perceived cost refers to what is lost, given up, or suffered when performing a task (Wigfield & Eccles, 2020). The cost component of SEVT is often measured in three dimensions: perceived effort required to complete a task; loss of valued alternatives; and emotional or psychological costs of pursuing a task, particularly if one experiences failure (Flake et al., 2015; Wigfield & Eccles, 2020). Certain cost factors, such as the perceived loss of valued alternatives (i.e. opportunity costs) are particularly salient to college students and have been shown to impact behavior (Flake et al., 2015). Attainment value, intrinsic value, and utility value have had established measures for some time (Wigfield & Eccles, 2020) and recent work has identified new dimensions and measures that are useful for examining costs (Perez et al., 2014; Flake et al., 2015).

Certain characteristics of a task, such as task difficulty, can influence the extent to which they are valued (Wigfield & Eccles, 2020). Individuals' self-perceptions and identity can also impact the tasks they value; tasks resonating with how an individual broadly sees themselves are more highly valued (Wigfield & Eccles, 2020). These proposed connections to identity are helpful for understanding differences in STVs among students; aspects of a student's gender, racial, or ethnic identity can inform how they perceive whether an activity should be acceptable for them participate in (Wigfield & Eccles, 2020). Individuals' expectations for success when engaging in a task and their related affective reaction can also impact task value; when learners experience anxiety while engaging in a task it may lower the value of the task and make them less likely to engage (Wigfield & Eccles, 1992). Similarly, when learners anticipate a positive outcome from performing a task, they will likely value it more, as individuals tend to value things they are good at (Wigfield & Eccles, 2020).

Expectancies and Values Can Predict Achievement-Related Choices

Expectancies and values are posited as being strong direct predictors of achievement outcomes, performance, and choices (Eccles, 1983). Research supports this connection between expectancies, values, and choice, both in younger children and college students. While STVs generally more strongly predict both intentions as well as actual decisions to engage in activities, several studies find stronger connections between self-beliefs regarding ability and choice than values and choice (Wigfield & Eccles, 2020).

Several studies of learners in elementary school students provide evidence that ES and STVs can predict future choices. Students' perceptions of the importance of math (Meece et al., 1990) and English (Durek et al., 2006) predicted intentions to continue pursuing courses in these areas at later points in school. Students' expectancy and value for math and science activities related to participation in these courses later in high school, with expectancies more strongly predicting choice than value (Simpkins et al., 2006).

Relations between expectancies, values, and choice also extend to research in higher education and graduate school. Battle and Wigfield (2003) examined how STVs and costs impact intent to pursue graduate education for women, and found all STVs significantly predicted intentions to attend graduate school. A combined intrinsic-attainment value was the strongest predictor, and utility and cost values followed in prediction capabilities (Battle & Wigfield, 2003). The study's sample pulls from a population of junior and senior women engaged in undergraduate studies; these women likely anticipate pursing graduate education prior to joining the workforce, and the utility of graduate school may be undervalued if they have not experienced the need to pursue a master's degree for career growth or acceleration.

Perez et al. (2014) found attainment, intrinsic, and utility values predicted undergraduate students' intentions to leave science, technology, engineering, and mathematics (STEM) majors, as did task effort and opportunity cost sub-components of costs. However, emotional costs did not predict intent to leave a STEM major. While Perez et al.'s (2014) study was limited in the population and the variables examined, it is significant in that it is the first to identify perceived costs as a stronger empirical link to choice than to academic achievement, and also differentiates the impact of cost sub-components on student choices.

Estrada et al. (2011) examined data from a national panel of minority science students to determine whether self-efficacy, individuals' identity as a scientist, and internalization of scientific values predicted students' intentions to pursue scientific careers. The researchers found that undergraduates' identity as a scientist and internalization of values of a scientist were more predictive of longer-term behaviors of integration into science careers, including applying to graduate school. They also found self-efficacy is less related to long-term integration behaviors. Similarly, Estrada et al. (2018) examined integration of underrepresented minority

(URM) students into STEM communities by measuring development of science self-efficacy, identity, and values in a longitudinal study spanning from students' undergraduate junior year through their postbaccalaureate years. They found that mentorship and research experience occurring during students' junior and senior years positively related to their science efficacy, identity, and values during this period. Through longitudinal modeling they established that efficacy is an important and necessary predictor of engaging in STEM careers, but past efficacy experiences were not sufficient for maintaining long-term persistence in science professions. Science identity and values did continue to predict longer-term persistence in STEM career pathways up to four years after graduation.

The existing literature shows promising connections between expectancies, values, and choice to pursue or engage in certain educational opportunities. Applying the SEVT framework to evaluate this connection in relation to open learning experiences that stack into graduate degree programs may provide illuminating perspectives as to why nontraditional learners choose to engage in graduate degree programs due to online learning innovations in the context related to graduate school choice.

Developmental and Group Differences Exist for ESs and STVs

Research shows ESs and STVs typically decline over time for students in kindergarten through the beginning years of college (Fredericks & Eccles, 2002; Jacobs et al., 2002; Kosovich et al., 2017; Robinson et al., 2019). Research has also established group differences may exist in motivational factors among students with different group characteristics (Robinson et al., 2018; Robinson et al., 2019).

Students experienced declines in expectancy and value levels and increases in cost levels throughout various developmental periods (Barron & Hulleman, 2015). A longitudinal study of students' expectancies and values in the first two years of college found students typically indicated moderate to high levels of expectancies and values immediately before beginning college that declined during the first two years of college, while also experiencing low or moderate initial cost levels that increased over the first two years (Robinson et al., 2019). Attainment value demonstrated more relative stability, declining more slowly than other value components; this shows consistency with prior research suggesting attainment value is more stable due to its connection with identity. While effort cost increased at a quicker rate than psychological costs, the increase in opportunity costs was not significantly different from that of effort or psychological cost.

Robinson et al. (2018) found that while students from underrepresented racial/ethnic groups begin college with similar levels of motivation in comparison to racial/ethnic majority students, racial/ethnic majority students' attainment value remained high and stable throughout college in comparison to underrepresented racial/ethnic groups. Robinson et al. (2019) found that racial/ethnic minority students and first-generation college students began college experiencing initial levels of engineering expectancy and interest value that are higher than racial/ethnic majority students, and lower initial effort cost.

Estrada et al. (2019) examined differences between historically underrepresented and majority biomedical doctoral students during a one-year longitudinal study, and found that science identity mediated the relationship between professional network support and persistence after a year for majority students. But for historically underrepresented students, science identity mediated the relationship between instrumental, psychosocial, friend and family support, and persistence a year later.

SEVT suggests expectancy and value beliefs are influenced by gender norms and roles through socialization processes affecting identity formation (Eccles, 2009). While research has found female students tend to have lower expectancies for success in STEM domains, variations in value and cost between genders were inconsistent (Wigfield et al., 1997). A recent study found when race/ethnicity, first-generation status, and prior achievement were controlled, gender differences did not exist in engineering college students' motivational trajectories

(Robinson et al., 2019). More work is needed to evaluate potential gender differences in ES and STVs across domains.

While research shows expectancy and value beliefs may change over time and are likely influenced by socialization processes associated with identity formation, much of the research around these variations occurs in K-12 or traditional undergraduate or graduate college environments. Better understanding what group differences exist in expectancy and value beliefs, and how these beliefs develop while participating in non-credit MOOCs may provide useful insights as to whether these learning experiences effectively support specific groups of students in terms of increasing motivation toward pursuing a master's degree program.

Lack of SRL Supports Within MOOCs May Impact Motivation

While multiple models exist to study SRL, a recent review of the most prominent models defines SRL as the activation of cognitive, metacognitive, behavioral, motivational, and affective processes to persist until successful when an individual encounters a learning situation (Panadero, 2017). Models converge in suggesting SRL occurs in three phases, each including its own sub-processes: the preparation or preliminary phase, which includes task analysis, planning, and goal setting activities; the performance phase, including strategy use and monitoring activities; and the appraisal phase, where evaluation of outcomes occurs (Puustinen & Pulkkinen, 2001). Feedback plays an important role as a catalyst for SRL processes; as learners monitor their performance, they receive internal and external feedback that is used to calibrate further use of SRL strategies (Butler & Winne, 1995).

Several models of SRL emphasize the connection between SRL and motivational processes. Self-regulated learners also have higher self-efficacy, as they believe their SRL skills will help them be successful at learning (Zimmerman, 2000). Those with greater interest in topics being covered and those who perceive an activity as useful are more likely to use SRL strategies to aid learning (Pintrich & Zusho, 2002).

The ability to self-regulate one's learning is viewed as a skill that can be trained or developed through practice and application of SRL strategies rather than a fixed trait (Azevedo & Cromley, 2004; Pintrich, 2004). Based on this concept, Pintrich and colleagues established three categories of strategies that students use to self-regulate their learning: cognitive strategies, used for the acquisition, storage, and retrieval of information; metacognitive strategies, used to plan, monitor, and regulate processes to accomplish goals; and resource management strategies, used to manage the learning environment and external resources (Duncan & Mckeachie, 2010). Instruments have been established to measure strategies falling under each category of strategies, including: cognitive subscales, focused on rehearsal, elaboration, organization, and critical thinking; metacognitive subscales, focused on goal setting, monitoring, and regulation; and resource management subscales, focused on time management, study environment, regulation of effort, peer learning, and help seeking (Duncan & Mckeachie, 2010).

SRL models suggest that individuals' self-regulation of their cognition, motivation, and behavior mediates the relationship between the individual, their context, and their achievement (Pintrich, 2000); research shows that learners' use of certain cognitive, metacognitive, and resource management strategies can be critical to successful learning in traditional online learning and MOOC learning environments due to characteristics associated with these contexts (Broadbent & Poon, 2015; Kizilcec et al., 2017). Given the close relationship between SRL strategies and motivational components, as well as the potential for SRL strategy use to impact achievement, it is relevant to consider whether use of SRL strategies in the MOOC environment may also moderate the relationship between motivational elements and intentions to enroll in a degree program.

Graduate School Choice is Typically Studied from Economic and Sociological Lenses

Despite a continued call for the need to better understand graduate school choice, studies describing why learners pursue graduate programs are relatively limited in comparison to those regarding choice decisions of undergraduate students, which have been widely studied (Kallio, 1995; DesJardins et al. 2006; Stoecker, 1991). Research shows graduate student decisions are impacted by similar factors as those influencing undergraduate student decisions, with exceptions around graduate student choices being more greatly influenced by spouses, family, and work considerations in comparison to undergraduates (Kallio, 1995). Studies focusing on choice at the graduate school level draw heavily from models outlined in the extensive body of work related to undergraduate students' choice decisions due to similarities in student choice factors at both levels (Kallio, 1995).

These undergraduate models of choice are rooted in economic and sociological perspectives, and generally suggest the decision-making process involves multiple phases or stages, during which individual and organizational factors contribute to outcomes that influence the next stage or phase (Hossler et al., 1989; Paulsen, 1990; Perna, 2006). While scholars have proposed as many as seven stages related to the process of college choice, most models suggest three broad stages comprise the college choice process: predisposition, search, and choice (DesJardins et al., 2006; Perna, 2006). In the predisposition phase, individuals become interested in or predisposed toward attending college; in the search phase they search for information about college; and in the choice phase they choose the institution in which they are going to enroll (Perna, 2006). Much of the empirical work related to college choice focuses on the choice phase, in understanding how students choose which school they ultimately attend (DesJardins et al., 2006; Perna, 2006). Most research relating to student choice is framed through an economic model, a sociological model, or a combination of the two (Perna, 2006).

Economic Approaches Assess Benefits Versus Costs

Economic models assume additional education leads to gains in productivity by developing knowledge, skill, and problem-solving abilities, and productivity gains are rewarded with an increase in earnings (Perna, 2006). These models suggest an individual's decision to pursue additional education involves a rational comparison of the anticipated lifetime benefits versus expected costs related to the educational experience (Paulsen, 2001). Benefits may include increased earnings or non-monetary things such as less chance of unemployment, while costs may include the costs of attendance, opportunity costs related to missed earnings and leisure time, and costs of traveling to the institution (Perna, 2006).

Bedard and Herman (2008) took an economic approach to investigating whether enrollment in graduate school increases during periods of economic restriction, such as during a recession, and found unemployment rates impacted fluctuations on enrollment decisions for males pursuing master’s degrees, but not for women. Kennedy et al. (2016) examined how students assess information regarding what financial resources are available for pursuing graduate education, and found that students feel financial support available for graduate school is significantly less than what is available for undergraduate education.

Economic approaches are helpful for understanding how individuals weigh potential effects of costs versus benefits, but do not consider the nature of the information available to learners (Manski, 1993) or the cognitive processes that occur in students as they are making decisions about what school to attend (Simões & Soares, 2010). These approaches cannot account for differences across individuals due to non-monetary and intangible factors (Paulsen, 2001). Individuals’ understanding of benefits and costs associated with pursuing college is informed by the quality of available information (Perna, 2006), and students may lack or have differential access to information (Kane, 1999). These models assume factors such as preference, uncertainty, or risk tolerance exist among individuals, and create differences in how they make choices, but do not examine how they are formed or why they differ in individuals (DesJardins & Toutkoushian, 2005). When students are uncertain about whether they can succeed at their studies, principles of rational behavior cannot explain choice on its own; additional explanation is required, including a more precise understanding of beliefs, how they shape preferences, and how students respond to uncertainty (DesJardins & Toutkoushian, 2005).

Sociological Approaches Explain Variations Due to Context

Traditional sociological models suggest educational aspirations are based on academic preparation, achievement, and socioeconomic status (SES), as those who exhibit higher academic preparation and achievement receive greater support and encouragement from important individuals in their lives, which promote higher aspirations that lead to higher educational attainment (Perna, 2006). Recent research focuses on how cultural and social capital influence college choice, by providing access to resources that influence educational attainment and by shaping the social context in which decisions are made (Perna, 2006). Emphasis is placed on an individual’s habitus, or their internalized system of thoughts, beliefs, and perceptions, which is acquired from their immediate environment, as it informs college-related expectations, attitudes, and aspirations (McDonough, 1997). These approaches suggest that rather than relying on rational analyses, as occurs in economic models, students instead make reasonable decisions based on their habitus, which will reflect boundaries and constraints they have internalized from information provided within their school, social, or cultural context, and will determine what is possible (Perna, 2006). The involvement of parents or guardians is often central as a form of social capital in these frameworks; for instance, Perna and Titus (2005) explore variables such as parental involvement, parental education, parental educational expectations, and family income when examining how structural context impacts enrollment decisions.

Hearn (1987) investigated how a variety of sociological variables impacted aspirations and intentions to pursue graduate education, and found prior academic performance, parental supportiveness, major department context, and faculty-student interaction are all significant. Mullen et al. (2003) found the pursuit of graduate education remained indirectly dependent upon parental education level for students entering into some disciplines. A student's likelihood of entering a selective private or public institution, their educational expectations, and their academic performance all influenced the likelihood of pursuing postgraduate education.

Sociological approaches allow researchers to identify ways in which context can influence an individual's perspective about graduate school choice, suggesting that individuals obtain information by observing decisions made and outcomes experienced by others around them (Manski, 1993; Perna, 2006). But sociologists do not attempt to explain how people use information to make decisions, and these frameworks do not explain how individuals determine whether they wish to pursue graduate education, apply for admissions, or enroll (Manski, 1993; Perna, 2006). These models do not account for the information gained when an individual experiences something themselves, how it impacts self-beliefs about abilities, and how self-abilities might impact choice to pursue further educational attainment.

Integrated Models Consider Context in Addition to Benefits and Costs

Integrated models combine economic and sociocultural frameworks to consider assessments of benefits versus costs, while also accounting for influences within social contexts that impact individuals' choices (Perna, 2006). These models combine explanations of how individuals make decisions gained from economic models with the understanding of how individuals gather information gained in sociological models (Manski, 1993).

As an example, Kallio (1995) identified differences in influential factors relating to attending undergraduate versus graduate education, with residency, academic environment factors, and financial aid playing a significant role for both types of students. However, graduate students indicated the ability to accommodate work and spousal influences played a more significant role in their choices, and social considerations played a less significant role.

Combined models show ways in which economic and sociological frameworks can be effectively integrated to create a more complete picture of the factors that influence an individual's decision to pursue graduate education.

Choice Processes Differ Due to Personal Characteristics

A focal point for college choice research has been the impact of a variety of personal characteristics—including gender, race, and ethnicity—on pursuit of college. Research suggests the student-college-choice process varies across gender as well as racial and ethnic groups (Perna, 2006).

Pascarella et al. (2004) suggested general models may mask important differences in factors that influence graduate school plans by race, and found a wide variety of variables relating to experiences during undergraduate collegiate years impacted ambitions to attend graduate school differently for students from different races. For example, work experiences and on-campus living inhibited African American students' plans to attend graduate school, whereas effective teaching—or students' perceptions of instructional skill/clarity and perceived instructional organization—boosted intentions of pursuing a graduate degree. African American, Hispanic, and White students bring different combinations of background experience, social and cultural capital, and educational and career expectations to their undergraduate experience, which likely impacted their intentions to pursue graduate education differently (Pascarella et al., 2004).

Hearn (1987) found decisions to enter graduate school did not predictably relate to a series of data points (i.e., plans to attend graduate school and GPA) dating back to freshman year of college with women, as it does with men. For women, attainment of a master's degree is more contingent on year-to-year developments in comparison to men (Hearn, 1987).

More recent reports noted distinct challenges women encounter throughout undergraduate experiences that potentially impact pursuit of graduate education. Although women earned better grades and were more likely to complete their undergraduate degree, they evaluated their own academic abilities lower than men (Wendler et al., 2010). Women also experienced persistently high levels of stress and depression while pursuing their undergraduate degrees, in comparison to men (Wendler et al., 2010). Men expressed more interest in careers that pay well, which may allow them to more easily justify costs for further education (Wendler et al., 2010).

Research suggesting women's pursuit of graduate education may depend on conditions more proximal to entry into a master's program (Hearn, 1987), combined with indications that women's self-evaluation of their academic abilities and emotional state are factored into consideration when making decisions to pursue graduate education (Wendler et al., 2010), suggests current models for examining choice to pursue graduate education may not be sufficient to explain differences among male and female nontraditional learners in the current context. Information students gain about their abilities while they are learning, including self-beliefs regarding their ability to be successful at a particular educational pursuit or assessments of how learning about a particular subject impacts them emotionally, are absent in these models and may play an important role when considering groups differences in decisions to pursue graduate education.

Access to Information is a Critical Factor in the Decision-Making Process

Information available to students plays a critical role in each of the models related to college choice processes. In economic models, the availability of information regarding resources for subsidizing education and information regarding potential benefits of educational attainment are important for influencing student choice decisions (Perna, 2006). Sociological models focus on how information regarding college-going is gathered—primarily through students' observation of cues provided within their social or cultural contexts (Manski, 1993; Perna, 2006). Information provided from guidance counselors regarding a student's chances of being admitted to college, or marketing and recruitment information provided by an institution that shares information about the campus context, can be powerful influences on decisions to pursue college or choices to attend a particular school (Serna, 2015).

Access to information is critical to the college choice process, but the full higher education experience is not observable to prospective students (Winston, 1999; Serna, 2015). The cost of experiencing college is substantial, and those without access to relevant information from social or cultural connections—such as first-generation students—may be particularly disadvantaged in making decisions (Perna, 2006).

Carpenter and Fleishman (1987) identified an individual’s perception of their academic ability as an additional source of information that shaped predisposition to pursue college, and found those with greater perceived ability had increased likelihood of planning to attend college when effects of attitudes, social norms, and academic achievement are controlled. Despite this, models for choice do not include consideration of the impact self-assessments of academic potential may have on the college choice process, instead choosing to look at relationships between academic achievement and predisposition or choice to pursue college (Hossler et al., 1989). These self-assessments may play an important role in today’s graduate education context, where students have access to the learning experience, and an opportunity to affirm their self-beliefs regarding their ability to learn prior to making a choice to attend graduate school or enroll in a program.

Recent Contextual Changes May Impact Graduate Student Choices

There have been many changes in how master's degree programs are offered in recent decades. Greater demand for master’s degrees has led institutions to offer more master’s degree programs, in more diverse fields, and through more innovative online formats. These contextual changes have the potential to influence the choices students make.

Employers Increasingly Seek Individuals with Master's Degrees

Employers are demanding a more educated and skilled workforce, comprised of individuals who understand how to learn and a willingness to continuously upgrade and adapt their skill set to be able to efficiently create and use knowledge (Chen & Dahlman, 2005; Peters & Humes, 2003). Existing skill sets within the workforce are expected to become obsolete quickly in coming years, with employers estimating at least 54% of all employees will require additional learning opportunities to learn new skills or advanced their existing skill set to remain competitive in their jobs (Schwab, 2018).

Increasing numbers of workers are seeking graduate education, hoping an advanced degree will ensure continued employability or career advancement (Wendler et al., 2010). Workforce demand for master's degrees has increased tremendously in recent decades; the number of occupations requiring a master's degree for entry into a profession in the U.S. increased nearly 23% between 2010 and 2018, with projections anticipating 17% growth in occupations requiring a master's degree between 2016 and 2026 (Wendler et al., 2010; Torpey, 2018).

Workers are encouraged to continuously upgrade and broaden their existing skill sets through participation in additional formal educational experiences and lifelong learning opportunities to stay current or advance in their career (Mehrotra et al., 2001; Peters & Humes, 2003). The result is a growing trend in students returning to graduate school after spending time in the workforce (Wendler et al., 2010). Some of these students hope to enhance their existing knowledge or skill sets within their current field, but there are also a growing number of "career changers" who see graduate degree attainment as a way to ensure continued employment or career advancement (Wendler et al., 2010). These students are considered nontraditional because they engage in work, family, and school activities at the same time, and many are also older (Wendler et al., 2010). Flexibility and ease of access to graduate programs has increasingly become a priority to meet the needs of these nontraditional graduate students.

Institutions are Changing Program Offerings to Meet Changing Needs

Institutions are responding by offering a greater number of master's degree programs designed to meet workforce and student needs.

An Increasing Number of Programs are Offered, in More Diverse Fields

In recent decades, higher education institutions have increasingly aligned the educational opportunities offered with workforce needs, in part by increasing the number of overall degree programs offered to students (Wendler et al., 2010). Institutions are also significantly diversifying the array of master's degree program fields available to better address diverse needs found in workplace settings (Wendler et al., 2010). Between 1995 and 2017, the number of distinct master's degree program fields conferring 100 degrees or more annually has risen from 289 to 514 (Blagg, 2018).

Institutions Offer More Flexible Programs Through Distance Education

Information and communication technologies now allow institutions to offer more flexible learning experiences for individuals to pursue graduate education while maintaining employment. Increased access to personal computers, the internet, and more stable synchronous and asynchronous communication technologies has increased feasibility for institutions to deliver high-quality online educational experiences allowing students to interact with each other and instructors directly from homes or offices (Mehrotra et al., 2001). Opportunities to study via distance education provide flexibility for those who are balancing career and family obligations to engage with coursework and submit assignments in a way that is convenient for their schedule (Bickle & Carroll, 2003).

Distance education has become critical to many institutions' long-term strategy in recent decades (Allen & Seaman, 2015). As a result, tremendous growth has occurred in the number of online master’s degree programs offered; online programs made up more than 21% of all master’s programs during the 2017-2018 academic year (Miller, 2019).

Students pursuing master’s degrees now have a more diverse array of programs from which to choose, and those programs are offered in varied modalities the create flexibility to meet their needs.

Students Can Sample Courses Before Enrolling in a Graduate Degree Program

Proliferation of online learning has led some institutions to experiment with offering open online learning experiences that have lower barriers to entry as compared to traditional graduate educational experiences. More recently, institutions began offering stackable master’s degree programs, which allow learners to engage with sample learning experiences prior to enrolling in a degree program. These innovative new offerings create opportunities for learners to gain a better understanding of whether they can be successful in a graduate program.

Open Online Courses Introduce Low-cost Opportunities for Learning

Many institutions now offer massive open online courses (MOOCs) in addition to fully online master’s degree programs. MOOCs are full-length courses delivered online; accommodate a large, global audience of learners; and are “open” in that they require little or no financial commitment and have minimal requirements to register for the course (Perna et al., 2014). While students pursuing a graduate degree program typically must submit an application and may be required to meet minimum requirements before matriculating, any learner with internet access who wishes to engage in a MOOC may do so without encountering barriers to entry.

Several institutions in the United States began offering MOOCs in 2011 and 2012 (Perna, et al., 2014), and today the Coursera MOOC platform—just one MOOC provider—hosts over 4,600 courses created by over 200 university and industry partners, with over 76 million registered learners (Coursera, 2020).

Stackable Degree Programs Connect Non-credit and For-credit Learning Experiences

More recently, institutions began offering stackable degree programs, sometimes referred to as MOOC-based degree programs. The term “stackable” refers to the concept of one learning experience building or expanding upon the learning that occurs in another learning experience (Williamson & Pittinsky, 2016). These degree programs are offered fully online, with some of the content comprising the degree program openly available through MOOCs (Shah, 2018). Stackable degree models provide prospective students the opportunity to sample content and try learning in the online environment prior to enrolling in a degree program without a significant financial commitment if they do not wish to persist in the course (Shah, 2018). If a learner determines they wish to enroll in a degree program, they participate in the application process established by the institution offering the online degree program (Ledwon, 2021). At least 27 institutions currently partner with MOOC-hosting platforms to offer more than 70 MOOC-based degree programs (Ledwon, 2021), and by January 2019, at least 10,000 students were enrolled in MOOC-based programs (Shah, 2019).

The experience of learning in a MOOC may create opportunities for learners sampling courses to gain information that informs their thinking regarding whether they should pursue a degree program (Hein, 2021). However, how MOOC learners’ motivation changes and how choices regarding pursuit of graduate education are impacted has never been studied.

MOOC Learners are Motivated by Personal and Career Benefits

MOOC learners have expressed a variety of motivational factors contributing to enrollment in and completion of courses.

Watted and Barak (2018) found personal benefits—such as general interest in the course content and personal growth and enrichment—were the major motivating factor for individuals participating in a MOOC. They found career benefits such as increasing professional competence related to a current job and enhancing future employment possibilities also frequently contributed to enrollment, suggesting some individuals found MOOCs valuable for updating professional skills needed to stay relevant in or advance their careers.

Hollands and Kazi (2018) studied individuals pursuing a series of MOOCs, and found a variety of motivators, including: improving performance in a current job (44%), starting a business (27%), learning something new (26%), improving an application for another job (23%), improving an application to a degree program (12%), wanting a job promotion (11%), and wanting a pay raise (9%).

Of the 3,086 responders to Hollands and Kazi's survey, only 23% indicated they do not have intentions of applying to continue their studies in a master's degree program. Approximately 5% of respondents planned to apply to a degree program that was formally associated with MOOC content; 5% intended to apply to a different program offered by the same institution that offered the MOOC; 5% planned to apply to a degree program at another institution from the one that offered the MOOC (Hollands & Kazi, 2018).

In a broad survey of nearly 52,000 MOOC completers, Zhenghao et al. (2015) investigated actual (rather than expected) career and educational benefits learners experienced following MOOC completion. Fifty-two percent of respondents reported their primary goal for taking the MOOC was to improve their current job or find a new one. Of these individuals motivated by career benefits, 87% indicated they experience some sort of career benefit, with 33% reporting a tangible benefit such as finding a new job, receiving a promotion, or receiving a pay increase. Twenty-eight percent of respondents indicated they enrolled to achieve an academic goal. Of those seeking educational benefits, 87% indicated they receive an intangible benefit, such as: gaining knowledge essential to a field of study (64%); help deciding what field to study (38%); refreshing key concepts prior to returning to school (36%); improving admissions application (17%); identifying which institutions they should apply to (11%); help preparing for a standardized examination (8%).

It is clear from these studies that many MOOC learners engage with MOOCs in hopes of reaping career and personal benefits. Findings in Hollands and Kazi's (2018) and Zhenghao et al.'s (2015) studies suggested that some learners also saw MOOC learning experiences as a way of establishing readiness for a degree program. What remains unclear is to what degree learners gain the information needed via their MOOC participation to feel motivated to pursue a master's degree program.

Data from the University of Michigan's (U-M) stackable Master of Applied Data Science (MADS) degree program suggested individuals who participate in MOOCs may go on to pursue a degree program. During the first two semesters admitting students, an average of 66.5% of students enrolled in the MADS program engaged with a MOOC prior to enrolling, and 52% of enrolled MADS students enrolled in a MOOC that related closely to the MADS program curriculum (Hanley, 2020). These MOOC learning experiences provide students with opportunities to sample content (including video lectures, readings, and assessments) extracted directly from MADS courses, or with content aimed at building skills and capabilities that will support students' success in the program.

Characteristics of the MOOC Environment May Inhibit Learning for Some Learners

Certain characteristics of MOOC learning environments differ from the traditional structure that exists within conventional courses in higher education, including traditional face-to-face or online courses. MOOC learners are not required to adhere to a fixed schedule, as learning is not structured around course start and end dates; learners determine when, how, and with what parts of the course they choose to engage (Hood et al., 2015; Kizilcec et al., 2017). Learners can engage selectively in parts of the course that appeal most to their interests and learning goals, rather than progressing sequentially or entirely through the course (Perna et al., 2014). MOOCs also generally lack opportunities to interact or engage directly with the instructor, as feedback on assignments is often offered through automatically graded assessments or through peer graded assessments; this can create a perceived absence of support or guidance within the course (Hood et al., 2015; Kizilcec et al., 2017).

Self-regulated learning (SRL) strategies play an important role in learning and are context dependent in that specific features of the learning environment can impact whether or not they are engaged (Kitsantas & Dabbagh, 2004). As online learning environments have attracted more students, studies of SRL have extended to examine how use of SRL strategies supports academic success in online learning environments (Broadbent & Poon, 2015). Success in online learning environments requires that students have a stronger self-generated ability to control, manage, and plan their learning activities, as the environment relies on students' ability to be more self-directed, autonomous, and actively engaged in their learning (Broadbent & Poon, 2015).

Differences between traditional online courses and MOOC learning environments create an even greater need for learners to effectively self-regulate their learning while engaged in a MOOC (Hood et al., 2015). Kizilcec et al. (2017) posited that the lack of support and guidance, the absence of timelines that create pressure to progress, and the absence of social norms to complete in a specified timeframe within MOOC contexts required learners to have stronger self-regulation capabilities. Studies of learners' experiences in MOOC environments suggested metacognitive, as well as resource and task management strategies were critical for success for MOOC learners (Kizilcec et al., 2017). Nawrot and Doucet (2014) found challenges with metacognitive strategies, such as goal setting and strategic planning, were common reasons for disengagement in MOOC environments. Kizilcec et al. (2017) found that while various SRL strategies related to achievement of personal goals, goal setting and strategic planning were both strong positive predictors toward goal attainment in MOOC environments. Help seeking was found to be a strong negative predictor, suggesting that those who are inclined to seek help as they are learning may not find adequate supports necessary to be successful in the MOOC environment (Kizilcec et al., 2017). Zheng et al.'s (2015) study of learners' MOOC experience found learners' ability to manage time needed for the course was a factor in their success, and learners missed the community found in traditional course environments, possibly limiting the ability to seek help among others.

The proliferation of opportunities to learn online in recent years, combined with the chance to engage with open online learning experiences that have low barriers for entry, has resulted in a significant number of learners choosing to enroll in online MOOCs and online master's degree programs. The ability to sample courses before enrolling in a degree program creates an intriguing new source of information for learners, which may help establish motivation for pursuing a master's degree program, but this potential benefit may be offset due to certain characteristics of the MOOC learning context that do not provide adequate conditions for learners to reach their learning goals.

Stackable Degree Programs Offer a New Source of Information for Potential Master's Degree Students

The ability to sample course content with little or no cost prior to deciding to apply to or enroll in a degree program is an important change to the graduate school decision-making environment for some learners. This capability creates an environment where new information is available to learners, and those learners can better observe and experience some aspects of what it is like to be enrolled in a master's degree program, which previously was a significant limitation.

Various types of information regarding students' choices to pursue graduate education may be gained through participation in a MOOC. Students can to some degree observe whether instructors teaching within the degree program are effective teachers—defined as whether they possess instructional skill/clarity and instructional organization and preparation—which was found to increase African American students' intentions to pursue graduate education (Pascarella et al., 2004).

Students also obtain information that can better provide a glimpse of what benefits can be gained through participation in a degree program. Perna (2006) noted that students consider benefits such as increased earnings, more fulfilling work environments, and less chance of unemployment when determining whether to pursue postsecondary education. Zhenghao et al. (2015) found many who pursue MOOCs for career-related benefits experience beneficial outcomes, which may include finding a new job, receiving a promotion, or receiving a pay increase. These experiences may reinforce perceived benefits of pursuing a master's degree program to the extent that perceived costs are justified.

MOOC participation may create an excellent opportunity to gain current assessments of perceived academic ability within a particular domain, as content and assessments are, to some extent, drawn directly from the degree program. An individual's perception of their academic ability was an additional source of information that shapes predisposition to pursue college (Carpenter & Fleishman, 1987) and may be particularly valuable to women considering pursuit of a master's degree (Wendler et al., 2010). The proximity of perceived academic ability assessments in comparison to potential master's degree program participation may also be a particularly helpful information source for women, as Hearn (1987) found that attainment of a master's degree was more contingent on year-to-year developments for women in comparison to men. However, the impact of current assessments of academic ability on degree attainment may be especially important to examine due to several recent changes. As older populations of learners look to pursue master's degree programs to maintain or advance their career positioning (Wendler et al., 2010), more recent assessments of academic abilities may be an important factor that contributes to master's degree pursuit regardless of gender. Similarly, as an increasing number of career-changers look to attain advanced degrees in new disciplines to maintain employment or for career advancement (Wendler et al., 2010), current assessments of one's perceived academic ability in a new domain may be particularly informative.

The pursuit of undergraduate education created higher levels of stress and depression for women compared to men, which may have resulted in fewer women pursuing graduate degree programs (Wendler et al., 2010). Experience learning in a MOOC may provide an opportunity to assess emotional costs associated with pursuit of a graduate degree program.

In comparison to undergraduate students, graduate students put more significant consideration on the ability to accommodate work schedules and family commitments as a significant factor when choosing a school to attend (Kallio, 1995). While participation in a MOOC will not give a complete perspective of the time commitment and effort required when enrolled in a graduate program, it may provide learners with the opportunity to experience whether flexibility afforded by online coursework reduces opportunity costs to the extent that it allows them to balance coursework with work demands and familial commitments.

The recent emergence of these stackable degrees creates interesting opportunities to study factors that influence students' choices regarding whether to pursue graduate degree programs online, as the information gained through participation in a MOOC associated with a stackable online degree may contribute to student decision-making regarding whether to pursue the degree program. While preliminary data suggests that some MOOC learners do choose to go on to enroll in associated master's degree programs, it is unclear how the information gained during participation in a MOOC may influence that decision.

Critique of Prior Research

Existing Frameworks Regarding Choice Lack Perspectives Regarding Self-beliefs

Existing frameworks for evaluating graduate school choice rely on economic or sociological approaches, which have limitations in today's context. Economic models focus on rational decision-making and do not take individuals' beliefs and preferences into consideration, making it challenging to explain variations in choices across individuals. Sociological models provide additional insight regarding how individuals' thoughts, beliefs, and perceptions are informed by their immediate environment and inform their college-related expectations but do not consider self-beliefs regarding ability and how they influence choice.

While research shows graduate school choices are more greatly influenced by spouses, family, and work considerations (Kallio, 1995), research examining graduate education attainment has not evolved to consider that individuals can now engage in programs with less impact on spouses, families, and work due to the increase in flexibility afforded through distance education.

MOOC Experiences Offer New Information Sources for Learners that May Impact Choice

Prior research on graduate school choice also has not considered new ways in which individuals can gain important information about the graduate school experience by sampling the learning experience prior to degree program enrollment via engagement with MOOCs. With the development of these new stackable learning experiences, learners can gain information that may influence their motivation while engaging in a MOOC. However, research regarding how participation in MOOCs influences motivational variables and graduate school choices is limited. Research suggests learners engaged with MOOCs due to perceived utility value or as a stepping stone before pursuing a graduate degree (Watted & Barak, 2018; Hollands & Kazi, 2018).

MOOC Research is Not Framed Through an Achievement Motivation Lens

SETV suggests the new information encountered in a MOOC can influence self-beliefs related to one’s academic abilities and subjective task values, which ultimately may impact future choices related to education. But existing studies are not framed through an achievement motivation lens, so expectancies for success and emotional costs are not examined as part of these studies. Additionally, while research has identified developmental or group differences in ES and STVs in studies of individuals in K-16 educational settings, it is unclear how these constructs may vary among nontraditional learners—many who are older than traditional undergraduate or graduate school populations—as they progress through MOOCs that stack into degree programs. It is unclear how STVs change while pursuing a MOOC. Similarly, while traditional-aged undergraduate students experience declines in ES as they progress through a degree program, the experience throughout an undergraduate degree program and a MOOC or series is quite different. It is unclear whether the trend of decreasing ES would apply to progress through a series of non-credit learning experiences that gives learners an opportunity to participate in degree program-related learning activities before entering a graduate degree program.

Motivation Research has Focused on Traditional Learning Environments and Populations

Research focusing on how motivational constructs influence choices to pursue graduate education exists (Battle & Wigfield, 2003), however much of the work investigating how ESs and STVs impact choice focused on choices in grades K-16. There is a dearth of research around factors that influence nontraditional students' decisions to pursue graduate education. Similarly, while development of motivational variables has been examined in K-16 students, motivational changes for nontraditional learners engaged in MOOCs have not been studied through an achievement motivation lens.

Research Questions and Hypotheses

The purpose of this study is to better understand how participation in stackable MOOCs relates to individuals' decisions to pursue an online master's degree program. Specifically, the study examined how motivational variables, personal characteristics, and self-regulated learning strategies contribute to pursuit of graduate education (Figure 1).

Question 1: Do self-efficacy and subjective task values change after participation in MOOC courses?

Hypothesis 1a: Self-efficacy increases, with learners indicating mastery experiences are a positive source of self-efficacy, and lack of social persuasion hinders development of self-efficacy. I anticipated that learners would experience an increase in self-efficacy, as MOOCs provide an opportunity to experience content and assessments in a lowstakes environment where individuals can practice mastering a particular topic without concerns of being penalized. When individuals engage in academic tasks, they interpret and evaluate the results to either create or revise their judgement about their competence on that task; when they are successful at accomplishing a task their confidence is raised (Usher & Pajares, 2008).While mastery experiences are a particularly salient source of self-efficacy, social persuasion from others in the learning environment—including faculty or peers—can also support development of self-efficacy (Bandura, 1977). While MOOCs may provide opportunities to master specific content areas, interaction with peers and instructors is typically limited and may create a perceived lack of support or guidance for learners (Hood et al., 2015; Kizilcec et al., 2017).

Hypothesis 1b: Intrinsic value and utility value will increase. While studies have found that values can decrease during the first two years of college (Robinson et al., 2019), Battle and Wigfield (2003) suggested that perceived utility of additional education may be undervalued when there is not a present need for career growth or acceleration. Individuals engaging with MOOCs often indicate that they do so as a way to advance in their careers, prepare for graduate education, get a new job, or get a pay raise (Watted and Barak, 2018; Hollands and Kazi, 2018). Learners also indicate they enjoy participating in MOOCs simply to gain knowledge in a particular area (Hollands and Kazi, 2018; Zhenghao et al., 2015). The short nature of these learning experiences and the ability to apply them directly to various aspects of individuals lives may help learners experience increases in these value contructs throughout participation in a MOOC.

Hypothesis 1c: Attainment value will remain stable. Attainment value is often linked to an individual's identity, and research has shown that it remains relatively stable throughout an individual's undergraduate education (Robinson et al., 2019). Additionally, changes to attainment value tend to occur more slowly than other value components (Robinson et al., 2019). Given the relatively brief time-frame during which learners engage with a MOOC, I did not anticipate seeing a change in these scores.

Hypothesis 1d: Opportunity cost, effort cost, and psychological cost will increase. Research shows learners experienced low or moderate initial cost levels when beginning undergraduate education, and that these costs increased over the first two years (Robinson et al., 2019). Nontraditional learners participating in MOOCs are often also engaged in work, family, and learning activities at the same time (Wendler et al., 2010) and also potentially have not engaged in learning activities for some period of time. As a result, I anticipated that engaging in MOOCs concurrently with other priorities may result in an increase in how individuals perceive costs.

Question 2: Do self-efficacy and subjective task value beliefs contribute to intentions to pursue a master's degree program?

Hypothesis 2a: Self-efficacy positively contributes to intentions to pursue a master's degree program. While STVs typically more strongly predict future choices, studies have also found strong connections between self-beliefs regarding ability and choice (Wigfield & Eccles, 2020). Additionally, Estrada et al. (2018) indicate self-efficacy is an important predictor of longer term engagement in a discipline, and past efficacy experiences are not sufficient for maintaining longer term persistence. Learners' ability to engage in MOOC experiences allows them to more proximally affirm their capabilities, which may support persistence toward future goals to pursue a degree in a discipline.

Hypothesis 2b: Intrinsic value, attainment value, and utility value contribute positively toward intentions to pursue a master's degree program. STVs generally more strongly predict both intentions as well as actual decisions to engage in academic activities (Wigfield & Eccles, 2020). Additionally, Battle and Wigfield (2003) found that all STVs significantly predicted intentions to attend graduate school; combined intrinsic-attainment value was a strong predictor, and utility values followed in prediction capabilities.

Hypothesis 2c: Opportunity cost, effort cost, and psychological cost contribute negatively to intentions to pursue a master's degree program. Battle and Wigfield (2003) found that costs, while less influential in comparison to other task values, negatively predict intentions to pursue graduate study. Similarly, Perez et al. (2014) found that effort and opportunity costs predict intentions to leave STEM majors. As learners experience various types of cost throughout participation in a MOOC, they may become less motivated to persist in pursuing additional education, as costs within a graduate program are even greater.

Question 3: Is the relationship between self-efficacy, subjective task values, and intentions to pursue a graduate degree program after participating in a MOOC moderated by individual characteristics?

Hypothesis 3a: Women's estimates of self-efficacy while participating in a MOOC may more strongly relate to intentions to pursue graduate education in comparison to men's estimates. Research suggests women's intentions to attain graduate degrees rely on more proximal assessments of their academic capabilities in comparison to men (Hearn, 1987). Participation in a MOOC provides the opportunity to gain a current understanding of how an individual will perform on academic tasks that may be particularly informative for women who are considering pursuing graduate education.

Hypothesis 3b: There will be a stronger positive relationship between self-efficacy and subjective task values and intentions to enroll for learners who are first-generation status in comparison to those who are not. Those with access to relevant information about the experience or value of attending graduate school from social or cultural connections—such as those who have parents who attended college or graduate school—may not rely as strongly on beliefs that are elicited while participating in a MOOC (Perna, 2006). Alternatively, those who do not have these types of connections may find the information they gain by participating in a MOOC to be particularly informative.

Hypothesis 3c: As age increases, there will be a stronger positive relationship between self-efficacy and subjective task values and intentions to enroll. Learners are pursuing graduate education at later points in their lives (Wendler et al., 2010), and past experiences of some motivational constructs are not enough to maintain future persistence in a discipline (Estrada et al., 2018). As learners become increasingly separated from their undergraduate experiences, they may rely more strongly on beliefs elicited during the MOOC learning experience to inform decisions about whether or not to pursue a graduate degree.

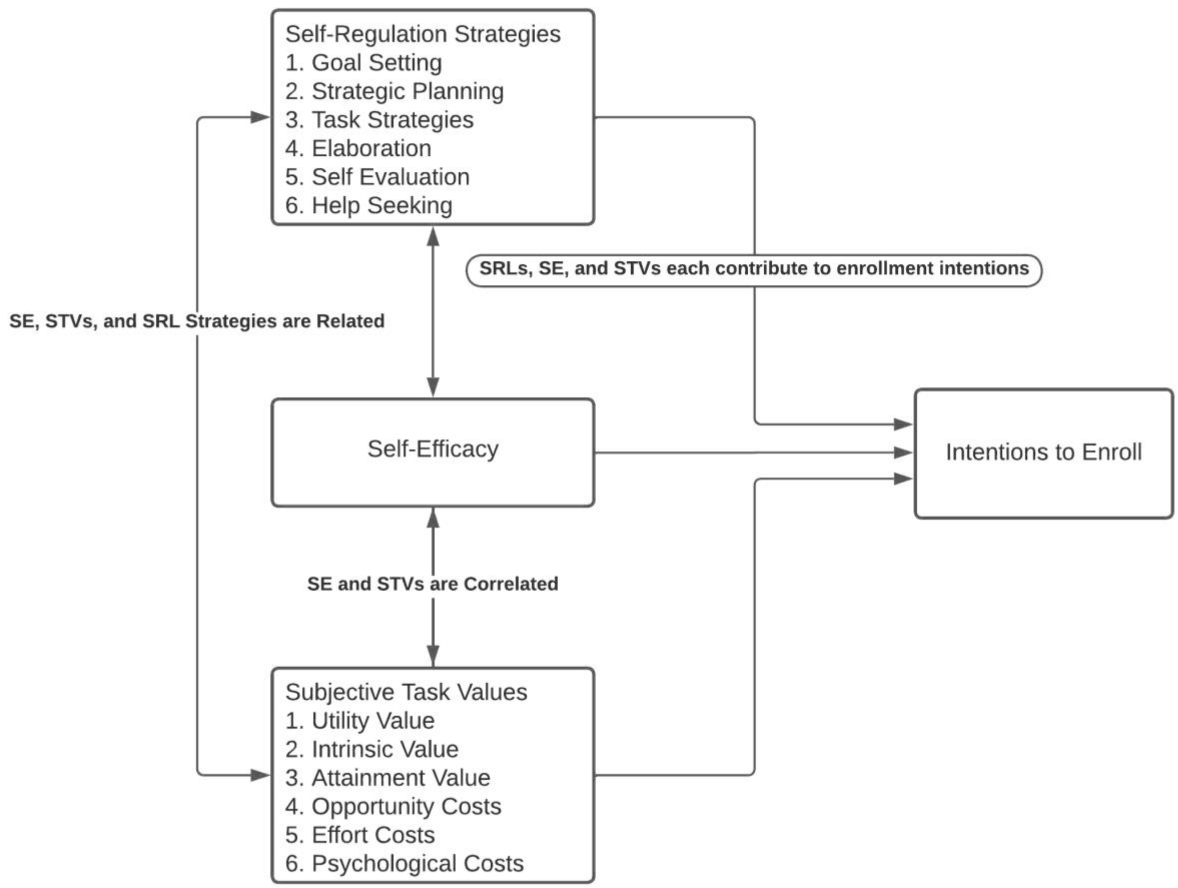
Question 4: Does use of self-regulated learning strategies contribute to intentions to enroll in a master's degree program?

Hypothesis 4a: The goal setting and strategic planning aspects of individuals' self-reported SRL strategies within the MOOC environment will contribute positively to intentions to pursue a graduate degree program after controlling for the relationship between self-efficacy, subjective task values, and intentions to pursue a graduate degree program. Studies of learners' experiences in MOOC environments suggest self-regulated learning strategies are critical to success for MOOC learners, with goal setting and strategic planning both being strong positive predictors toward goal attainment (Kizilcec et al., 2017). Those who indicate use of these strategies in their MOOC learning and achieve goals within this environment may be positively motivated to pursue further goals related to pursuit of a degree.

Hypothesis 4b: Help seeking will contribute negatively to intentions to enroll. Opportunities to engage with the instructor or other students are often limited within MOOCs, creating a perceived absence of support or guidance within the course (Hood et al., 2015; Kizilcec et al., 2017). Kizilcec et al. (2017) found that help seeking is a strong negative predictor of goal attainment in MOOCs, as learners who employ help seeking strategies may find that they are not able to access the help that they need to be successful. This may have a negative impact on whether these learners indicate that they intend to pursue graduate education.

Figure 1.

Hypothesized Relationship Between SE, STV, SRL Strategies and Intentions to Enroll



Positionality Statement

My work as an administrative leader in the field of online and distance education has significantly driven my interest in this research and the selection of the research hypotheses I pursued and the context in which I investigated them. Throughout my time engaging in this research I worked closely with academic unit leaders at U-M to lead the development of multiple stackable degree programs. The research hypotheses for this study stem from my interest in understanding the efficacy of the stackable learning strategy my work was implementing, and whether MOOC engagement might influence and motivate learners to pursue deeper, more meaningful learning experiences such as those encountered in a degree program.

Additionally, my identity as a non-traditional, first-generation, female learner who returned to college a decade after completing my undergraduate degree to engage in a hybrid Ph.D. program influenced my thinking on this project to a certain extent. My own experience as a prospective graduate student exploring information regarding what degree program I should apply to left me questioning what the experience of engaging in a graduate degree program would entail, and whether I was ready to engage in this challenging pursuit. I found that the opacity of the curriculum for each program I applied to made it challenging to make an informed choice as to what program was the right fit for my professional goals, and I feel I would have benefited from the opportunity to preview select curricular elements prior to making a decision to enroll in a degree program.

I share my positionality as a way to more clearly contextualize any motivations, biases, or assumptions involved in this research, particularly as I discuss implications of the findings within this study and potential directions for future research and practice.

CHAPTER 3:

Method

Participants

The purpose of this study was to examine how participation in stackable MOOC experiences relates to learners' choice to pursue a graduate degree program, specifically for those who have not yet enrolled in a degree program. Selection of the sampling frame was guided by Perna's (2006) definition of three college choice phases: the phase in which individuals become interested in attending college; the phase where they search for information about college; and the phase where they choose the institution in which they are going to enroll.

To understand how MOOC participation related to choice for those in the predisposition, search, and choice phases, the sample frame included learners who engaged in MOOCs associated with an online degree program. Specifically, participation for this study was solicited from individuals engaged in the most popular series of MOOCs related to U-M's MADS degree program. This program was selected due to its status as one of the largest-scale stackable degree programs offered through the Coursera platform, as well as consideration that the MADS program has a robust collection of related MOOCs available to learners wishing to engage in open content prior to pursuing the program.

Those engaged in the most popular series of MOOCs that are closely associated with the degree program (Python for Everybody) were able to participate in this study. These courses were taught by a faculty member who teaches in the MADS degree program, and were promoted to learners as opportunities to practice skills necessary for students to be successful in the program. Some portion of the content included in this series was also repurposed as part of courses in the degree program. When learners enroll in the series, a message was displayed indicating the courses are "Associated with the Master of Applied Data Science degree;" this message links to the degree program's information page for those who wish to learn more.

Recruitment and Eligibility

Pre-course surveys were made available to learners in all five courses that comprise the series, and at the conclusion of the pre-course survey learners were asked to indicate whether they would be willing to continue participating in the research. Learners who completed the pre-course survey and indicated they were willing to continue participating in research were eligible to be included in the study. Due to the significant drop-off in survey completion for those enrolled in the third, fourth, and fifth courses, no learners in these courses remained eligible to participate in the study. As learners encounter the same survey multiple times as they progress through the series, this drop-off may have been due to survey fatigue.

Learners who remained eligible were enrolled in the initial two MOOCs in the series, titled *Programming for Everybody* and *Python Data Structures*. A total of 901,273 learners were engaged in these two MOOCs during the study period. Of this population, 27% indicated their gender was female (*n* = 230,790), 72% indicated male (*n* = 658,123), and 1% indicated other (*n* = 12,360). Approximately 18% indicated they were between 18 and 24 years old, 53% indicated age between 25 and 34, 20% indicated age between 35 and 44, 6% were between 45 and 54, and approximately 3% were above the age of 55. The vast majority of learners enrolled in the course were physically located in Asia (52%) or the North America (23%). Many of those engaged in the course during the study period enrolled prior to initiation of the study; only those who enrolled after the study initiation period (*n* = 93,153) comprised the sample frame.

Those who completed the course during the study period (*n* = 28,319) may represent the most motivated and successful MOOC learners and may also be most motivated to pursue the master's degree program. To avoid participation bias from this group, learners were not required to complete all activities in the course to receive the post-course survey. Participation was solicited from both those who completed the course activities as well as those who did not within the three-month data collection window. Course completion reports were run weekly to identify those who had completed all required course activities, and emails were sent to new learners who had completed the course during the previous week. There were 1380 learners who completed all course activities and received the post-MOOC survey via email. A follow-up email was sent three days following the initial message, reminding individuals to participate in the survey.

To solicit participation from those who did not complete the course, an email was sent to solicit participation in the survey one week prior to the close of the data collection period for everyone who had enrolled in the course and completed all elements of the pre-course survey but had not taken action toward completing the course in the three weeks before the end of the data collection period (n = 393). To encourage participation, a follow-up email was sent three days later. Participation in the study was completely voluntary and learners received informed consent messages (Appendix B) that described how the data for each survey would be used at the start of both surveys. The combined total of those who completed the course and those who did not who received the post-course survey was 1773 learners.

An incentive was offered to all participants who were sent the post-MOOC survey due to the length of the survey and to encourage participation from those who may be less motivated to engage with the post-MOOC surveys, such as those who did not complete the course. The email soliciting participation from learners indicated that completion of all required items on the post-MOOC survey would make an individual eligible for a drawing for one of 10 $25 gift certificates. Given the ease of access to MOOC content and the large number of participants engaging with MOOCs, tactics such as asking individuals to proactively opt in to continue participating in the research by providing a valid email address and only making the post-MOOC survey available to those who completed the pre-course survey were implemented as ways to try to reduce the number of fraudulent responses from individuals who weren’t engaging with the MOOC to learn.

Those who responded to all required items on both the pre- and post-MOOC surveys between November 1, 2022 and February 4, 2023 were included in the study. As learners may have engaged in more than one course in the series, responses were filtered by contact information to identify any instances where learners participated in both the pre- and post-course surveys more than once. In instances where learners participated more than once, only responses from the most recent course learners engaged in was included. Complete responses were received from 178 unique MOOC completers and 19 unique non-completers, for a total number of 197 participants. Those agreeing to participate in the study were 32.5% Asian; 14.2% Black; 18.8% Hispanic, Latino or Spanish origin; 4.6% Middle Eastern or North African; 21.3% white; 29.4% female, 67.5% male, and 3% other. The percentage who were first generation college students was 39.6%. Learners ranged between 18 and 74 years old, including 33% in the 18 to 24 range, 38.6% were 25 to 34, 15.2% were 35 to 44, 10.7% were 45 to 54, and 2.5% were between 55 and 74.

Data Sources

Data regarding ESs, STVs, SRL strategies, intentions to enroll in a degree program, sources of self-efficacy, and learner demographic data were collected through surveys deployed to learners throughout the three-month data collection period. All survey items are available in Appendix A.

Expectancies for Success

Academic self-efficacy was used as a proxy for expectancies for success and was measured through questions adapted from the Academic Efficacy portion of Midgley et al.'s (2000) Patterns of Adaptive Learning Survey (PALS). PALS includes well-known measures developed and refined over time, which have been adapted for many studies. The PALS academic efficacy scale items have been used in studies of college learners pursuing studies in a specific domain (e.g. science; Totonchi et al., 2021) and are easily adapted to gauge learners' self-efficacy for learning the subjects taught in MOOCs (i.e. data science, Python coding).

Self-efficacy was assessed using a five-point Likert scale, anchoring at 1 = strongly disagree, 3 = somewhat agree, and 5 = strongly agree (Midgley et al., 2000). Cronbach's alpha was computed to assess internal reliability of the measures, with measures of self-efficacy showing high reliability (α = .874).

Subjective Task Values

Survey items measuring intrinsic value were adapted for the study from Conley (2012). These questions have previously been used in multiple studies, including being adapted for studying values in college students (Totonchi et al., 2021; Robinson et al., 2018; Robinson et al., 2019), and have demonstrated high internal reliability across studies.

Items measuring attainment value were adapted from Robinson et al. (2019); these items were originally adapted from Conley's (2012) attainment value scale and Pugh et al.'s (2010) science identity scale. Robinson et al.'s scale was chosen over Conley's (2012) due to the ability to adapt items to reflect different subject areas covered in the MOOCs as well as the broader domain of data science. For example, "it is important to me to be a person who reasons mathematically" (Conley, 2012) would be challenging to adapt to courses covering data science or Python coding.

Utility value survey items were adapted from Gaspard's (2017) utility for jobs scale. Many scales measuring utility value refer to utility of a domain in relation to a more distal time frame, as the learner perceptions being measured are typically K-16 (e.g., those who have not yet begun their career); for example, Conley's (2012) items refer to utility "in the future" or "later in life." Battle and Wigfield (2003) found that framing utility value as applicable to the long-term nature of a task in question will likely affect subjects' ability to fine-tune perspectives regarding its usefulness. As MOOC learners may be engaging with the learning experience because they perceive it will offer utility for their existing professional career, items with framing adaptable to measure utility within a more proximal timeframe (e.g., Gaspard's utility for job scale items) will likely resonate more closely with the learner population and provide a more valid measure of perceived utility value.

Items measuring effort cost, opportunity cost, and psychological cost were adapted from Perez et al. (2014). Perez et al.'s scales were originally adapted from Battle and Wigfield's (2003) Value of Education scale, which was developed specifically to measure costs perceived by postsecondary students considering enrollment in graduate programs, making the items particularly relevant for this context. The scale items are easily adaptable to address different types of educational experiences (such as MOOCs) and credentials awarded upon completion (including certificates), which makes these scales ideal for implementing in the MOOC experiences.

STVs were assessed using a five-point Likert scale that anchors at 1 = strongly disagree, 3 = somewhat agree, and 5 = strongly agree (Midgley et al., 2000). Cronbach's alpha was computed to assess internal reliability of each STV measure, finding the following: intrinsic value ($\alpha = .913$), attainment value ($\alpha = .863$), utility value ($\alpha = .764$), opportunity cost ($\alpha = .792$), effort cost ($\alpha = .690$), and psychological cost ($\alpha = .628$).

Self-Regulated Learning Strategies

Measures for goal setting, strategic planning, task strategies, elaboration, self-evaluation, and help seeking were used from Kizilcec et al. (2017). Kizilcec et al.'s instruments were drawn from those used by Littlejohn and Milligan (2015) and Barnard et al. (2008), and have specifically been established to study SRL strategies in MOOC learning environments. Littlejohn and Milligan (2015) and Barnard et al. (2008) adapted their measures from several other established measures of self-regulated learning strategies, including the Online Self-regulated Learning Questionnaire (OSLQ; Barnard-Brak et al., 2010), the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1991), the Metacognitive Awareness Inventory (MAI; Schraw & Dennison, 1994), the Learning Strategies Questionnaire (LS; Warr & Downing, 2000), and the Occupational Self-efficacy scale (OS; Rigotti et al., 2008). The measures have demonstrated strong reliability across all strategy subscales (Kizilcec et al., 2017).

While these statements as framed are measurements of general SRL strategies, learners were asked to consider how they applied to their MOOC learning experience with the following framing: “indicate the extent to which you agree with the following statements based on your engagement in this course.” SRL strategies were measured using a five-point Likert scale that ranged from 1= strongly disagree to 5= strongly agree (Barnard et al., 2008). Cronbach’s alpha was computed to assess internal reliability of each SRL strategy measure, finding the following alphas: goal setting (α = .868), strategic planning (α = .761), task strategies (α = .752), elaboration (α = .721), self-evaluation (α = .720), and help seeking (α = .653).

Sources of Self-efficacy

Quantitative measures of sources of self-efficacy such as “my teachers have told me I am good at learning data science” and “my classmates like to work with me in data science because they think I’m good at it” (Usher and Pajares, 2009) were considered but ultimately not used due to concerns about validity in the MOOC learning environment. These items would likely generate low scores for items associated with verbal persuasion for all participants due to the limited opportunities for social engagement and interaction with peers and instructors within MOOCs, regardless of whether or not that potential source was important for developing their self-efficacy.

Instead, learners were presented with statements asking whether specific sources of self-efficacy that align with the hypotheses—including the ability to perform well on assignments, comments from peers, and instructors’ encouragement—contributed to or undermined their confidence and success. The questions are loosely adapted from Milner and Woolfolk Hoy (2003), who asked “what sources (contributed most to/undermined) your sense of efficacy?” but are adjusted in two ways: 1) the phrase “confidence and success in this course” was substituted for “sense of efficacy,” as MOOC learners may not have a clear definition of what efficacy is; and 2) learners were asked specifically about the specific sources that were hypothesized to contribute to or undermine self-efficacy the most. These statements are available in Appendix A, and were measured using a five-point Likert scale that ranged from 1= strongly disagree to 5= strongly agree. Cronbach's alpha was computed to assess internal reliability of each source of self-efficacy measure, finding the following alphas which were very poor: instructor social persuasion (α = .266), peer social persuasion (α = .303), and mastery experiences (α = .412).

Enrollment Intentions

There is a dearth of research focused on the predisposition stage of college choice—which examines aspirations, expectations, and plans toward attending college—and the relevant existing research is limited by a lack of clear and consistent measurement of a dependent variable (Perna, 2006). However, Adelman (1999) argues that plans indicate a more realistic appraisal of future behavior in comparison to aspirations or expectations. This study adapts a similar approach to that of Adelman (1999) in using responses to a series of questions to establish five gradations of a variable indicating learners' plans (or intentions) to enroll in a degree program. While Adelman chose to treat the dependent variable as ordinal, Morgan's (1996) study used the same question responses to develop an educational expectation variable that is treated as a continuous dependent variable. Studies using factor analysis suggest ordinal variables with five or more categories and an approximately normal distribution may be treated as continuous (Rhemtulla et al., 2012; Robitzsch, 2020). In the present study, the gradations for the intentions to enroll variable were established to create a somewhat even progression between five categories, and the resulting distribution of responses was relatively normal. Thus, the intentions to enroll variable was treated as continuous in this study.

Specifically, MOOC learners were asked if they plan to apply for admission to U-M, what type of program they planned to apply to, and if they planned to enroll if they are admitted. Enrollment intentions were represented on a scale of one to five with the following coding: 1 = Does not plan to apply to U-M; 2 = Not sure about plans to apply; 3 = Plans to apply in the future; 4 = Already applied, not sure of intentions to enroll; 5 = Already applied, plans to enroll. Questions relating to enrollment intentions are available in Appendix A.

Demographic Data

Demographic data, including questions related to gender, race/ethnicity, age, and first-generation student status was collected via survey questions on the post-MOOC survey. The framing for demographic questions is available in Appendix A.

Procedures

MOOC Pre- and Post-Course Surveys

The pre-course survey included measures of self-efficacy, subjective task values, and demographic information as they began their course.

The post-course survey contained measures of self-efficacy, subjective task values, enrollment intentions, self-regulated learning strategies, and questions regarding sources of self-efficacy.

Survey items included on both surveys are available in Appendix A.

Data Analysis

To assess whether participation in MOOCs was associated with development of students' self-efficacy and subjective task values due to specific sources of self-efficacy (hypothesis 1), the following steps were taken:

- A composite score was calculated for pre- and post-MOOC measures of self-efficacy, intrinsic value, attainment value, utility value, opportunity cost, effort cost, and psychological cost.
- A dependent t-test was used to analyze differences before and after participation in the MOOC.

To determine whether each hypothesized source of self-efficacy contributed to development of self-efficacy in individuals, a multiple regression was used. Post-course self-efficacy scores were added as the dependent variable, and in the first step of the regression pre-course self-efficacy scores were added to treat them as a control variable. In the second step of the regression, composite scores for each source of self-efficacy was entered to establish whether these sources predict post-course self-efficacy. Composite variables were established for each source of self-efficacy—instructor persuasion, peer persuasion, mastery experiences—by reverse coding responses to each question regarding whether a particular source hindered development of self-efficacy and averaging these responses with the positively framed questions.

To determine whether learners' self-efficacy and subjective task value beliefs relate to intentions to pursue a master's degree program (hypothesis 2), a linear regression was performed to analyze the relationship between each motivational independent variable—self-efficacy, intrinsic value, attainment value, utility value, opportunity cost, effort cost, and psychological cost—as measured during the post-course survey and intentions to enroll in a degree program (the dependent variable).

To determine whether gender, age, and first-generation student status moderate the relationship between motivational independent variables as measured in the post-course survey and intentions to enroll in a degree program (hypothesis 3), a moderated multiple regression was performed. A hypothesis relating to URM status as a moderating variable was not included due to prior research providing unclear direction for specific ways in which URM status might moderate the relationship between motivational variables and enrollment intentions. However, URM status is included in the analysis as a potential moderating variable to determine whether it has a moderating effect due to research suggesting that African American, Hispanic, and white students bring different combinations of background experience, social and cultural capital, and educational and career expectations to their undergraduate experience, which may impact intentions to pursue graduate education differently (Pascarella et al, 2004).

The following steps were taken as part of the analysis:

- To analyze gender moderating effects, a dichotomous variable was created to distinguish the group of individuals indicating they are female versus those indicating they are non-female.
- To analyze whether first-generation student status moderates the relationship, a dichotomous variable was created to distinguish those who indicate they are first-generation student status versus those indicating that one or more parents had obtained a bachelor’s degree or higher.
- To analyze whether age has a moderating effect on the relationship, responses to the age categories were coded as a continuous variable, with the following coding: under 18 = 1, 18 to 24 = 2, 25 to 34 = 3, 35 to 44 = 4, 45 to 54 = 5, 55 to 64 = 6, 65 to 74 = 7, 75 to 84 = 8, and 85 and older = 9.
- To analyze whether race/ethnicity has a moderating effect on the relationship, a dichotomous variable was created to distinguish individuals reporting their race is considered an URM (including those who are African American/Black, Hispanic/Latino, and Native American/American Indian) versus those reporting those whose race is not considered underrepresented (all others).
    - Those indicating more than one race, including one or more selection that is categorized as URM, were coded as learners who are URM, in line with institutional reporting practices at U-M (University of Michigan Office of Budget and Planning, 2022).
- All continuous independent variables were mean centered and interaction terms were created between each moderating variable and each independent variable.

To analyze the effect of each moderating variable, a two-step process was carried out. The moderating variable was entered into the regression model at the first step with the independent motivational variables being analyzed (including self-efficacy, intrinsic value, attainment value, utility value, opportunity cost, effort cost, and psychological cost). Intentions to enroll in a degree program was added as the dependent variable. In the second step, each of the interaction terms between the moderating variable and the independent variables being analyzed were added to the analysis to determine if there was a significant increase in variance.

A hierarchical multiple regression was used to determine if SRL strategies employed within the MOOC learning environment contribute significantly to intentions to pursue a graduate degree program after controlling for the relationship between self-efficacy, subjective task values, and intentions to pursue a degree program (hypothesis 4):

- The initial model analyzed the relationship between self-efficacy, intrinsic value, attainment value, utility value, opportunity cost, effort cost, and psychological cost (independent variables) on intentions to enroll in a degree program (dependent variable).
- Each of the six self-regulated learning strategy variables (goal setting, strategic planning, task strategies, elaboration, self-evaluation, and help seeking) was added as the second step in the model as independent variables to determine if there was a significant increase in variance explained.

CHAPTER 4:

Results

Preliminary Analyses

Missing Data

Participant Inclusion and Exclusion Criteria

As noted in the procedures section, learners were included in the study if they: 1) enrolled in one of the courses during the study time frame, 2) completed all pre-course survey items, 3) indicated willingness to be included in ongoing research, and 4) completed all post-course survey items (regardless of whether they completed the course). Of the 93,153 learners who enrolled in the course during the study period, 5,240 (5.6%) completed all pre-course survey items, 1,773 (1.9%, including 1,380 course completers and 393 non-completers) agreed to be contacted about follow-up research, and 197 completed surveys including the post-course items. Of those who completed all pre- and post-course survey items, 178 were course completers and 19 did not complete the course in which they were enrolled.

Demographic Information

A summary of the self-reported gender and age among learners in the broader population of learners who were engaged in one of the participating MOOCs in comparison to those participating in this study (*N = 901,273)* is available in Table 1 in appendix A, including statistics for study participants broken down by those who completed the course and those who did not.

Participants in this study had similar gender composition to the broader population of learners engaged in the course, with approximately 29% of learners in the study reporting they are female and 27% in the broader population reporting the same. However, a larger proportion of the non-completer population participating in the study reported they are female (37%). Learners participating in the study skewed greater in the 18 to 24 age range (33%) and lower in the 25 to 34 age range (39%), as compared to the broader enrolled learner population (18% and 53% for each category, respectively).

A summary of statistics related to self-reported first-generation student status, race/ethnicity, and intentions to enroll in a master's degree program for learners participating in this study are also included in Appendix C, again with statistics for study participants also broken down by those who completed and those who did not. Note that data related to first-generation student status, race/ethnicity, and intentions to enroll in a master's degree are not collected and made available for the broader Coursera population of learners engaged in those courses, so these data are not included.

The majority of learners participating in the study (61%) indicated they are not first generation learners, approximately 33% of learners reported their race/ethnicity as one that is categorized as URM, and 70% of learners indicated they either did not intend to apply to a degree program (29.9%) or they were unsure of their intentions to apply (40%). Few learners had already applied to a degree program (2.5%).

Differences in SE and STV Scores Between Participants and Non-participants

An independent samples t-test was used to compare self-efficacy and subjective task value responses between two groups: those who only completed all items on the pre-survey and did not participate in the study (n = 5240), and those who completed the pre- and post-survey and were included in the study (n = 197). While those who participated in only the pre-survey do not fully represent the entire population of MOOC learners, this comparison helps understand how study participants compare in terms of motivational variables at the start of the course to a broader array of learners.

For these pre-course variables—self-efficacy, intrinsic value, attainment value, utility value, opportunity costs, effort cost, and psychological cost—outliers were identified through examination of box-plots, and no extreme outliers were identified. Visual inspection of the Q-Q plots for each variable show the assumption of normality was not violated for either the group.

Results of the comparison between scores for each construct between the two groups is available in Table 2. Those who participated in the study started with higher self-efficacy scores (*M* = 4.14, *SD* =.86) versus those who did not participate (*M* = 3.96, *SD* =.93), with the difference being statistically significant (*t*(5238) = 2.709, *p* = .007). Participants in the study also started with a lower effort cost score (*M* = 1.86, *SD* =.91) versus those who did not participate (*M* = 2.10, *SD* =1.02), with the difference being statistically significant (*t*(215.46) = -3.499, *p* < .001). Scores for other motivational variables did not show a statistically significant difference between populations.

Correlations

Table 3 includes correlations between each motivational variable and each SRL strategy. No correlation between variables was considered high. Values and self-efficacy all show positive correlations, as expected. Costs are positively correlated with each other, and are negatively correlated with self-efficacy and with value scores, as is also expected.

Table 4 includes correlations between pre-course self-efficacy, post-course self-efficacy, and the sources of self-efficacy composite variables. Correlations between variables were not considered high.

Differences in Pre- and Post-Course SE and STV Scores

Paired samples t tests were used to determine if there was a statistically significant difference in the mean self-efficacy, intrinsic value, attainment value, utility value, opportunity cost, effort cost, and psychological cost scores for learners before participation in the MOOC versus after engaging with the course (hypothesis one). Results are shared in Table 5.

Outliers for each test were identified by examining box-plots of difference scores for each variable. Between one and six extreme outliers were detected in the difference scores. For ~~these~~ cases the analysis was conducted with and without these cases in order to examine whether robustness of the results was influenced. While slight changes to the mean score, *t* value, *p* value and Cohen's *d* value occurred between analyses with and without outliers, the differences in results did not change determinations on statistical significance of the results or the effect size. The analysis results with extreme outliers removed is available in Table 6.

The assumptions of normality and homogeneity of variance were tested for each analysis with no violations.

Results show that learners reported lower self-efficacy scores in the pre-course survey (M = 4.14, SD = .86) as compared to the post-course survey (M = 4.29, SD = .75), indicating self-efficacy increased from pre-course to post-course. The difference was statistically significant ($t(196) = -2.04$, $p = .04$) and the effect size ($d = -.146$) is negligible. These results support the hypothesis that mean self-efficacy scores increase after engaging with the MOOC.

Results show that learners reported lower intrinsic value scores in the pre-course survey (M = 3.99, SD = .96) as compared to the post-course survey (M = 4.41, SD = .74). The difference is statistically significant ($t(196) = -5.98$, $p = <.001$) and the effect size was small ($d = -.426$). These results provide evidence supporting the hypothesis that intrinsic value increases when engaging with the MOOC.

The difference in utility value scores on the pre-course survey (M = 4.11, SD = .88) as compared to the post-course survey (M = 4.18, SD = .72) was not statistically significant ($t(196) = -1.18$, $p = .24$). Results of the test do not support the hypothesis that utility value increases when engaging in a MOOC.

Results show that learners reported lower attainment value scores in the pre-course survey (M = 3.43, SD = 1.00) as compared to the post-course survey (M = 3.73, SD = .94). The difference was statistically significant ($t(196) = -4.56$, $p = <.001$) and the effect size ($d = -.325$) was small. The results provide evidence that attainment value does not remain stable when engaging with the MOOC and that this hypothesis is not supported.

Results show that learners reported higher opportunity cost scores in the pre-course survey (M = 1.92, SD = .96) as compared to the post-course survey (M = 1.76, SD = .85). The difference was statistically significant ($t(196) = 2.09$, $p = .04$) and the effect was negligible (d =

.149). The difference in effort cost scores between the pre-course survey (*M* = 1.86, *SD* = .91) and the post-course survey (*M* = 1.76, *SD* = .82) was not statistically significant ($t(196) = 1.51$, $p = .13$). The difference in psychological cost scores between the pre-course survey (*M* = 2.30, *SD* = .94) as compared to the post-course survey (*M* = 2.18, *SD* = .88) was also not statistically significant ($t(196) = 1.67$, $p = .10$). These results provide evidence opposing the hypotheses that opportunity cost, effort cost and psychological cost increase when engaging with a MOOC.

Sources of Self-efficacy

A multiple regression was used to determine whether the hypothesized sources of self-efficacy contributed to development of self-efficacy in individuals. Post-course self-efficacy scores were added as the dependent variable, with pre-course self-efficacy scores added first as an independent variable to act as a control, and composite scores for each source of self-efficacy entered as a second step to establish whether these sources predict post-course self-efficacy when pre-course self-efficacy is controlled. Assumptions for independence of residuals, homoscedasticity, linearity, multicollinearity, and normality were all met.

Descriptive statistics indicate mastery experiences were highest among self-efficacy sources (*M* = 4.165, *SD* = .817), followed by instructor social persuasion (*M* = 3.967, *SD* = .830), and peer social persuasion (*M* = 3.581, *SD* = .785). Results of the regression analysis show the full model was not statistically significant, $R^2 = .019$, $F(4, 192) = .914$, $p = .457$, adjusted $R^2 = -.002$. The addition of sources of self-efficacy resulted in an increase in R^2 of .8%, which was not statistically significant ($F(3,192) = .535$, $p = .659$) in comparison to the model containing only pre-course self-efficacy scores.

The Relationship Between SE, STV, and Intentions to Enroll

It was hypothesized that learners' self-efficacy and subjective task value beliefs related to intentions to pursue a master's degree program, including: self-efficacy would have a positive relationship with enrollment intentions; intrinsic, attainment, and utility value, would also have a positive relationship; and opportunity, effort, and psychological costs would have a negative relationship.

A multiple linear regression model was used to determine if learners' intentions to pursue a master's degree program (dependent variable) can be predicted from learners' self-efficacy and subjective task value belief scores (independent variables) as measured in the post-course survey. Assumptions for independence of residuals, homoscedasticity, linearity, multicollinearity, and normality were all met. Four studentized deleted residuals showed outliers greater than ±3 standard deviations; examination of the data suggested these cases represented the four instances in which learners indicated intent to enroll in a master's degree program, suggesting the data is valid, therefore these cases were retained in the analysis.

The results of the multiple linear regression suggest a significant proportion of the total variation in intentions to enroll was predicted by self-efficacy, intrinsic value, attainment value, utility value, opportunity costs, effort costs, and psychological costs, with approximately 11% of the variance explained ($R^2 = .105$, $F(7, 189) = 3.164$, $p = .003$). Regression coefficients for each predictor variable are shared in Table 7.

The regression coefficients indicate that self-efficacy negatively predicted intentions to enroll ($b = -.262$, $t(189) = -2.41$, $p = .02$, $\beta = -.222$), while attainment value positively predicted intentions to enroll ($b = .175$, $t(189) = 1.98$, $p = .05$, $\beta = .186$).

The regression coefficients also indicate that intrinsic value ($b = .181$, $t(189) = 1.47$, $p = .15$, $\beta = .151$), utility value ($b = .120$, $t(189) = 1.17$, $p = .25$, $\beta = .097$), opportunity cost ($b = .120$, $t(189) = 1.33$ $p = .19$, $\beta = .115$), effort cost ($b = -.042$, $t(189) = -.45$, $p = .65$, $\beta = -.039$), and psychological cost ($b = -.143$, $t(189) = -1.75$, $p = .08$, $\beta = -.143$) were not statistically significant and do not predict intentions to enroll.

Moderation in the Relationship Between SE, STV, and Intentions to Enroll

It was hypothesized that the relationship between self-efficacy, subjective task values, and intentions to pursue a graduate degree program after participating in a MOOC would be moderated by individual characteristics such as gender, age, and first-generation student status in specific ways.

For each moderation analysis, a two-step regression was used. In the first step, each mean-centered motivation variable and the moderator variable were added as independent variables, and intentions to enroll was added as the dependent variable. In step two, interaction terms between each motivation variable and the moderator variable were added. For each analysis, assumptions related to linearity, multicollinearity, homoscedasticity, and normality were met, and there were no extreme outliers.

Results show that gender did not moderate the effect of self-efficacy on intentions to enroll in a master's degree program, as evidenced by an increase in total variation explained of 3.3%, which was not statistically significant ($F(7, 181) = 1.022$, $p = .417$).

First-generation student status also did not moderate the effect of self-efficacy and subjective task values on intentions to enroll in a master's degree program, as evidenced by an increase in total variation explained of 6.1%, which was not statistically significant ($F(7, 181) = 1.911$, $p = .070$).

Age also did not moderate the effect of self-efficacy and subjective task values on intentions to enroll in a master's degree program, as evidenced by an increase in total variation explained of 1.9%, which was not statistically significant ($F(7, 181) = .571$, $p = .779$).

An additional analysis was run to determine if status as an underrepresented minority would moderate the relationship between self-efficacy and subjective task values and intentions to enroll. Results of this analysis show that URM status did not moderate the effect of self-efficacy and subjective task values on intentions to enroll in a master's degree program, as evidenced by an increase in total variation explained of 1.9%, which was not statistically significant ($F(7, 181) = .563$, $p = .785$).

Adding SRL Strategies to the Regression Model to Explain Intentions to Enroll

It was hypothesized that the goal setting and strategic planning aspects of individuals' self-reported self-regulated learning (SRL) strategies within the MOOC environment would contribute positively to intentions to pursue a graduate degree program and intentions to pursue a graduate degree program, while help seeking would contribute negatively.

A hierarchical multiple regression was used to determine if the addition of self-regulated learning (SRL) strategies improved the prediction of intentions to enroll in a degree program over and above self-efficacy and subjective task value variables alone. Table 8 includes coefficients for each regression model. Assumptions related to linearity, independence of residuals, homoscedasticity, multicollinearity, and normality were met.

Results of the analysis show the full model (Model 2) of self-efficacy, intrinsic value, attainment value, utility value, opportunity cost, effort cost, psychological cost, goal setting, strategic planning, task strategies, elaboration, self-evaluation, and help seeking to predict intentions to enroll in a master's degree program was statistically significant, R^2 = .151, F(13, 183) = 2.504, p = .004, adjusted R^2 = .091. The addition of goal setting, strategic planning, task strategies, elaboration, self-evaluation, and help seeking led to a not statistically significant increase in R^2 of .046, F(6, 183) = 1.657, p = .134 in comparison to the model only containing SE and STV variables.

This finding contradicts the hypothesis that the goal setting, strategic planning, and help seeking aspects of SRL strategies will each contribute positively to intentions to enroll.

CHAPTER 5:

Discussion

While this study resulted in some anticipated outcomes, there were also many unexpected findings that are important to explore. The study hypotheses drew largely upon prior research findings that illustrated relationships between constructs examined in this study, but these prior studies were commonly situated within traditional educational contexts where traditional student populations were engaged in learning. This warrants further consideration regarding how differences between characteristics of the MOOC context and traditional educational contexts, as well as differences between characteristics of MOOC learners and traditional student populations, should be considered to potentially explain why many hypotheses were not supported.

Differences in the MOOC Context as Compared to Traditional Educational Contexts

Recognition that context plays an important role in education has existed for some time (Anderson et al., 1997). Situative learning—in which the knowledge is distributed among individuals, tools, artifacts, books, communities, and practices an individual engages with—requires consideration of constraints and affordances within a particular context (Greeno et al., 1996). Constraints are obstacles that need to be neutralized to support learning in an environment, while affordances are features that aid or facilitate learning, with both being present within any context (Tessmer & Richey, 1997).

MOOCs have specific context-related constraints and affordances that make them different in comparison to traditional graduate school environments. MOOCs require little or no financial commitment and minimal requirements—such as an application—to participate in comparison to graduate degree programs (Perna et al., 2014). MOOCs are designed to be completed in a short period of time and include a limited breadth and depth of content in comparison to a master’s degree program. MOOC learners are not required to adhere to a fixed schedule; course start and end dates are often nonexistent, and MOOCs generally lack deadlines by when specific course activities need to be completed (Hood et al., 2015). There are no expectations that learners will progress sequentially or entirely through a MOOC; learners can selectively engage in activities most aligned with their interests and learning goals (Perna et al., 2014). While completion of a MOOC does not earn the participant as substantial of a credential as compared to a master's degree, learners engaged in a MOOC also are not penalized and experience few consequences beyond not earning a certificate if they do not fully engage in all activities within a course. Additionally, learners often have the ability to attempt assignments or tasks within the MOOC multiple times if desired without penalty, providing an opportunity to practice a skill repeatedly if desired until one achieves mastery.

As MOOCs are offered to a massive audience of learners, they are designed in a way that limits opportunities to receive support, or interact and engage directly with, instructors (Kizilcec et al., 2017). Lower direct engagement with instructors means assessments, feedback, and evaluation of learning are often automated or require engagement with peers, such as with peer-graded assessments (Hood et al., 2015). Assessments that are automated often allow learners repeated attempts without penalization for failure.

The differences noted between the MOOC context and traditional educational environments can be considered as affordances for those who are uncertain of whether they would like to pursue a degree program. The low cost and commitment needed to engage in attempting tasks associated with a master's degree program may provide easier access to information regarding whether they are able to successfully engage with a limited amount of content and activities associated with a master's degree program.

Differences in Characteristics of MOOC Learners as Compared to Traditional Student Populations

The majority of studies examining motivational constructs and intentions to enroll in graduate education engage traditional undergraduate learners at a university, which typically involves individuals within the 18 to 23 year old range, and who have limited full-time work experience or obligations. However, in recent decades, increasing numbers of individuals with established careers are returning to seek graduate education, with hopes that an advanced degree will ensure continued employability, advance their careers, or allow them to change careers altogether (Wendler et al., 2010). These individuals are typically older and engage in work, family, and school activities concurrently (Wendler et al., 2010). Similarly, those engaged in MOOCs often are employed concurrently and find MOOCs to be a valuable option to support their goals, including improving their performance in their job, improving their application for another job, or receiving a promotion or pay raise (Hollands & Kazi, 2018; Watted & Barak, 2018). Research also shows that individuals engage in MOOCs for personal benefits such as personal growth and enrichment or due to the desire to learn something new (Hollands & Kazi, 2018; Watted & Barak, 2018). While data regarding participants' current career engagement was not collection as part of this study, the majority of those who engaged in the study were older than typical undergraduate student populations, with 67% of participants indicating they were 25 or above.

The open and low-cost nature of MOOCs typically results in a diversity of learners that enter into these courses, each with varying baseline knowledge and prior experience (Hood et al., 2015). While Hollands and Kazi (2018) found that many learners engaged in stackable pathways have interest in pursuing a degree program, the majority of learners engaged in this study (nearly 70%) indicated they either did not plan to apply or were unsure of plans to apply to a degree program. A university student's engagement in a credit-bearing course that comprises a degree program typically signals a learner's commitment toward complete the program, but engagement with a MOOC cannot be assumed to signal intent for a higher-order credential in the manner.

Traditional Motivational Constructs and Measurements Require Careful Application in New Contexts

The core motivational constructs examined in this study were developed in traditional educational contexts that involved different affordances and constraints in comparison to the MOOC context and enrolled different learners. Given these differences, it is necessary to consider applicability of previous research findings related to each construct based on characteristics of the new context and its learners. Respective measurements for each construct should also be considered to ensure they are appropriately applied in these new environments.

Self-efficacy

This study hypothesized that self-efficacy would increase after participating in a MOOC due to affordances present in is context. When individuals engage in an academic task, they interpret and evaluate the results to create or revise judgements about their competence on that task; when they are successful at accomplishing a task their confidence is raised (Usher & Pajares, 2008). Whereas in a degree course learners may only have one attempt to engage with a task on an assignment or a test before receiving a grade based on their performance, in the MOOC context, learners are able to engage with content and assessments and attempt particular tasks repeatedly until they are mastered without concerns that a grade will be recorded on their initial attempt. This hypothesis was confirmed in the data; while the effect size was negligible, engagement in a MOOC showed a statistically significant increase in self-efficacy for participants. While it was encouraging to see this increase in self-efficacy while participating in just one MOOC, it should also be considered that one MOOC is constrained in terms of the breadth and depth of tasks it offers to participants; learners engaged in a master's degree program would be required to master a much broader array of concepts within a discipline. Additionally, it is also important to consider that some learners likely entered into the MOOC with prior knowledge of the concepts being covered, and these learners likely did not see considerable gains in self-efficacy.

While it was also hypothesized that self-efficacy would positively contribute to intentions to enroll in a degree program, results of this study show that self-efficacy contributes negatively to intentions to pursue graduate education. It is feasible that this result is in part due to learners' understanding that tasks accomplished in the MOOC environment are a limited subset of tasks required in a master's degree. However, this could also be impacted by learners' motivation for pursuing the MOOC itself and the extent to which they value a MOOC certificate as a credential.

Theory and research suggest that feelings of self-efficacy can support learners' choice to pursue additional educational opportunities (Simpkins et al., 2006; Wigfield & Eccles, 2020). However, in considering prior research such as Simpkins et al.'s (2006) findings that elementary school students' expectancies for success predict choice of which courses to pursue later in high school, such results are situated within the context of traditional K-12th grade education, where the trajectory of one's anticipated educational journey is more clearly defined. In contrast, college and graduate school choice requires consideration of an individual's predisposition toward attending college or graduate school (Perna, 2006). Learners seeking out MOOC learning opportunities are at varying levels of predisposition toward pursuit of graduate education; data show that 70% of participating learners in this study either did not have plans to apply or were unsure of their plans to apply to a graduate degree program.

Learners engaging with MOOCs may also value the alternative credential itself as a way to achieve their goals related to advancing their career aspirations (Hollands & Kazi, 2018; Watted & Barak, 2018) and may have lower overall motivation to pursue a degree program. The increased perception by learners that these types of credentials are valid comprehensive alternative learning opportunities for individuals creates perceptions that alternative credentials are competing with graduate programs for enrolled learners (Krupnick, 2018; Purbasari Horton, 2020; Kato et al., 2020). It should be considered that those who experience increases in self-efficacy through engagement in a MOOC may feel this learning experience is a sufficient alternative to a master's degree when considering the best way to meet their learning goals.

Finally, the sources of self-efficacy adapted measure used in this study showed very poor reliability for those engaging with the MOOC. It was challenging to find appropriate measures for sources of self-efficacy for this study, as other measures considered were largely developed and used in K-12 environments where there is significant interaction among students and the instructor. For instance, questions such as “my Python coding teachers have told me that I am good at learning Python coding” would not make sense in a MOOC environment where the instructor does not interact directly with the learner. However, the lack of a reliable measure for this construct makes it challenging to draw any real conclusions from the analysis, which showed that mastery experiences and social persuasion did not have statistically significant contributions toward intentions toward post-course self-efficacy scores.

Attainment Value

The measurement chosen for this study plays a role in how the attainment value construct is framed in relation to identity, as adapted measures from Robinson et al. (2019) were used that specifically emphasized importance of a task on an individual’s identity. Prior research related to attainment value has indicated that attainment value tends to remain relatively stable over time due to it being a central, defining component of an individual’s identity (Eccles, 2009; Robinson et al., 2018), which informed the hypothesis that attainment value would remain stable for learners in the MOOC due to engagement in the course being relatively short. However, data suggest attainment value actually increased for those engaged with the MOOC, with the effect size being small.

Robinson et al.’s (2018) study of undergraduate college students found instances where attainment value starts low among students and rapidly declines. They posit that these learners potentially follow patterns consistent with identity development going from moratorium to identity diffusion (Marcia, 1993), with the decline experienced when students face uncertainty about their commitment to a subject area upon experiencing changes associated with college. Participants in MOOCs may be engaging with courses for a variety of reasons, including to explore new concepts or advance their careers in new, meaningful ways (Watted & Barak, 2018; Hollands & Kazi, 2018), and MOOC engagement may provide an opportunity for study participants to engage in a process of identity exploration in which they demonstrate qualities more closely associated with other trajectories for identity development. Waterman (1993) suggests individuals can experience progressive developmental shifts—such as shifting from moratorium to identity achievement, or from foreclosure into moratorium—when there is initiation of reflection of identity alternatives or development of personally meaningful commitments to specific goals and values, and the ease of enrollment and low-commitment necessary to engage with new concepts in MOOCs may provide an effective avenue for identity exploration.

Data showing that attainment value is a significant and positive predictor of intentions to enroll in a degree program confirms other studies examining the relationship between attainment value and choices to pursue graduate education, but through a new context for learning, and with a different population of learners. For instance, Battle and Wigfield (2003) found that a combined intrinsic-attainment value was the strongest predictor of choice to pursue graduate study among undergraduate women, Estrada et al. (2011) found that undergraduates' identity as a scientist and internalization of values of a scientist are more predictive of longer term behaviors of integration into science careers, including applying to graduate school, and Robinson et al., 2018 found that attainment value emerged as the strongest predictor of retention in undergraduate engineering majors. This study shows there is also consistency in terms of attainment value having a positive relationship with intentions to enroll among non-undergraduate learners engaged in the MOOC environment as well.

Utility Value

Studies related to MOOC engagement suggest learners engaging with MOOCs do so because of their perceived utility value, including their ability to help support job promotions, pay raises, or finding another job among those who participate (Watted & Barak, 2018; Hollands &

Kazi, 2018), and Zhenghao et al. (2015) found that many MOOC learners do actually realize such benefits relating to utility value. Yet findings in this study show no significant increase in utility value, and no significance in the relationship between utility value and intentions to enroll in a degree program.

This is another example where consideration of how a construct was measured, combined with contextual considerations such as the applicability of the content to current work or life tasks, may be important. Battle and Wigfield (2003) suggest framing utility value as applicable to the long-term nature of a task likely affects individuals' ability to fine-tune perspectives regarding usefulness; in this study Gaspard's (2017) utility for jobs scale was used, as it allows for framing that contextualizes utility value within a more proximal timeframe. Questions such as "a good knowledge of Python coding will help me in my job," allow the learner to consider usefulness toward their current job. Given that findings related to utility value were not significant, it is important to question whether individuals had the opportunity to see where the specific content, ideas, and skills covered within these MOOCs have obvious utility toward their jobs. Careful consideration should be used to determine if measures are appropriate for the current context, as well as for the learners engaged in the study.

Misalignment between perceived utility and the content, ideas, and skills covered during the course of the study may be due to several factors, including: the timing of when content was encountered and whether an individual could see value of this knowledge in their jobs during that span of time; the depth of content and skill-building covered in the course, and whether it was substantial enough to have real utility; learners' prior knowledge of the concepts covered and whether they learned anything valuable from the contents of the course, and learners' expectations related to what outcomes they would see from learning about concepts in the course. Given the relatively short period in which the study took place, learners likely only had a chance to engage with one course with a limited depth of concepts covered, and engagement with these concept may not have had as strong perceived utility as might occur when an individual engages with concepts across several courses. Additionally, if individuals' definitions of utility includes being able to get a new job, promotion, or pay raise after learning these concepts, these things may not have been experienced quickly—or at all—upon completing the course, as they take time to come to fruition and typically require substantial increases in capability that might not be realistic given the limited scope of content covered in one course.

Costs

While research shows that students engaged in degree programs can experience increases in perceptions of costs throughout pursuit the program (Robinson et al., 2019), learners in this study did not experience statistically significant changes in effort or psychological costs, and they experienced a decrease in opportunity cost. Differences between the characteristics of MOOCs in comparison to degree programs may make learners' perceptions of cost constructs operate in a different way. For instance, affordances of the MOOC environment such as the ability to engage on an individual's desired timeframe and experiencing no penalties for not completing course assignments or activities may contribute to the decreased perceptions of opportunity cost. The more limited amount of time and energy that learners are expected to engage to cover concepts within the course may eliminate perceptions of effort cost. And lower perceived consequences of failure or success in completing course activities or earning credentials associated with MOOCs may eliminate some psychological cost of not succeeding.

The perceived elimination or decrease in costs among learners in the MOOC environment in comparison to those engaged in traditional degree programs is another example of how data from this study encourages us to look more closely at each of the constructs associated with cost. It is unlikely that learners in this context experience opportunity, effort, and psychological costs the same way that learners experience these constructs in a degree program, where there are greater consequences to failure and clear penalties for not completing course activities in a timely fashion. The results of the cost analyses being unexpected reminds us that it is important to become more critically aware of assumptions the constructs make relative to characteristics of the learning environment, and to consider ways in which these constructs may not be perceived similarly in this context as they were in other learning environments.

Differences Between Individual MOOCs Also Require Consideration

While MOOCs and degree program contexts have many differences, one thing they have in common is that each individual course can differ—in ways that range from small to significant—from other courses. It is important to consider these differences between courses and how they have the potential to impact how individuals experience motivational constructs within that context.

For example, there may be significant differences between the content and activities available in an introductory Python coding MOOC, such as the ones represented in this study, versus MOOCs aimed at more advanced concepts. Courses that address more basic concepts may allow learners to feel they can easily master certain tasks and may result in positive changes in self-efficacy, as occurred in this study. Courses that cover deeper, more challenging concepts may not create similar changes with regards to self-efficacy. The basic concepts covered in introductory courses may also be quite abstract, which serves the purpose of providing learners with an easy entry into understanding a new area of study, but also may be too far removed from concepts and skills providing authentic connections to meaningful tasks in a learner's situation, which may impact perceptions of utility value. The basic level of the concepts covered in Python for Everybody and Python Data Structures may have limited the utility value for learners participating in this study.

Results also may differ when considering course offerings across disciplines. Concepts covered within a computer programming MOOC may attract different learners who have different motivations in comparison to those engaging in a MOOC that covers social work-related content. Perceived value of the credential earned and competencies gained through a

MOOC—by learners, employers, and accrediting bodies—may factor into an individual's perceptions of utility value. For instance, practicing as a social worker in many states within the U.S. requires completion of a master's degree in social work, whereas many jobs requiring computer programming skills do not require a formal master's degree education as a required qualification.

Learners May Not View MOOCs as Adequate Information Sources

Results of the moderated multiple regression show that gender, age, first-generation status, and URM status among learners do not moderate the relationships between self-efficacy or each of the subjective task values with intentions to enroll in a master's degree program, as hypothesized. These hypotheses were framed around the suggestion that MOOCs may serve as an important information source for individuals. It was hypothesized that women may find more proximal assessments of their academic capabilities valuable for determining whether a master's degree program is the right educational next step, based on findings by Hearn (1987). Similarly, older learners who have not engaged in formal education for some time may also value more recent assessments of self-efficacy and subjective task values when considering master's degree pursuit. And finally, those who are first-generation student status may find information encountered or gained through engagement with a MOOC as helpful for confirming the value of a master's degree or may help them better understand the experience they will encounter as part of the master's degree experience based on literature from Perna (2006).

There are some logical reasons related to the study design that may explain why moderating effects were not found during this study, including the limited duration of time learners had to engaged in the MOOCs and the limited selection of MOOCs included in the study. The lack of any potential moderating effects may be due to the short time span in which individuals engaged with the learning experience, or due to these particular courses not providing helpful information necessary to the populations of learners who it was hypothesized might benefit most from it.

An alternative explanation for why no moderating effects were found may be due to learners having a more comprehensive understanding of how the context of the MOOC environment and a master's degree program differ. Learners may not view assessments of their academic capability when engaged in a MOOC as a valid assessment of their ability to be successful when engaging in a master's degree program because they understand that the conditions under which they were successful in the MOOC environment do not apply within the context of the degree program. Learners may also question the extent to which content available within the MOOC aligns with the rigor and difficulty of content available within the degree program.

The Relationship Between SRL Strategies and Intentions to Enroll Remains Unclear

The fourth hypothesis suggested that the goal setting and strategic planning SRL strategies individuals implement when learning in a MOOC environment should contribute positively toward intentions to enroll after controlling for the relationship between SE and STVs and intentions to enroll, and help seeking strategies will contribute negatively. However, the addition of SRL strategies to the regression model once SE and STVs were controlled showed no statistically significant difference in R^2, suggesting SRL strategies do not contribute significantly toward intentions to pursue a master's degree program

While Kizilcec et al. (2017) found that goal setting and strategic planning can be strong positive predictors of goal attainment in MOOC environments, and help seeking is a strong negative predictor, it is ambitious to assume that findings related to goal attainment within a MOOC and intentions for master's degree program pursuit would be similar. As noted previously, learners engaged with MOOCs come from a variety of backgrounds, have differences in baseline knowledge around a particular area of study, and their motivation for achieving goals within the MOOC may not be in aligned with intent to continue on to pursue a master's degree program, as suggested by a significant (70%) proportion of participants indicating that they either had no intentions to pursue a degree program or were uncertain if they would apply.

Additionally, the measures for SRL strategies were adapted for online learning in a MOOC context specifically, and learners were asked to consider the applicability of each statement when considering their learning in the course. Responses to questions such as “I set personal standards for performance in my learning” may vary for the same learner if they are enrolled in a non-credit MOOC where there are no consequences or penalties for poor performance in comparison to a credit-bearing course where grades are recorded on a transcript. Learners may possess the ability to self-regulate their learning but not use those strategies in this environment because their goals for the course may be less ambitious and achieving those goals may not require strong use of SRL strategies.

Implications

Implications for Research: Future Opportunities to Explore Motivation Within Stackable Learning Environments

This study contributes to the field of achievement motivation research in that it examines how learners experience various aspects of motivation within novel and nontraditional learning environments, but also in that the learners participating in the study are different from the learner populations examined within studies of achievement motivation situated within K-12, college, or graduate school environments. Serving the life-long learning needs of individuals is a critical goal for institutions of higher education and institutions continue to look for innovative ways to provide learning opportunities that meet these needs (Weise, 2020). Further studies regarding how achievement motivation differs across traditional and non-traditional learning contexts, as well as across traditional and non-traditional learner populations, should be considered.

However, several surprising findings from this study suggest that when investigating achievement motivation in innovative educational environments that attract new learner populations, researchers should carefully evaluate assumptions regarding how the new context establishes similar or different affordances and constraints that enable the same relationships between constructs as have been seen in traditional educational environments. Measurement of constructs should also be critically evaluated to ensure established measures are applicable to these new environments and populations. Assumptions based on findings of prior studies may seem perfectly reasonable, but also may not be applicable based on changes within the context of a new learning environment. Assumptions should be carefully reconsidered to account for contextual differences, and validated through exploration in future studies.

Several personal characteristic variables were examined to determine if they moderate the relationship between motivational variables and intentions to enroll in a master's degree program. However, perhaps the most important variables were not considered as potential moderators in this relationship: background knowledge or experience within the particular area of study that the MOOC covers, and motivation for pursuing the MOOC. Future studies should ways in which these variables affect the relationship with intentions to enroll. For instance, the finding that attainment value increases through participation in a MOOC is exciting, and suggests that individuals may use MOOCs as an avenue for identity exploration. Further exploring this phenomenon through future research would be worthwhile. Similarly, understanding whether individuals are already predisposed to pursuing graduate education or if they value the MOOC credential as an end toward meeting their professional training and development needs may help better explain the relationship between self-efficacy and intentions to enroll in a degree program. This relationship being negative in this study is reasonably explained if individuals feel MOOCs are a valid alternative to meet their learning goals in comparison to a master's degrees, but without this data the result is challenging to interpret.

Hypotheses in this study are based in part on suggestions from college choice literature regarding the importance of information as a critical factor in the decision-making process regarding whether to pursue a degree program. Information sources for those who are returning to graduate education may be limited to marketing and recruitment materials (Serna, 2015) and the full experience of participation in a degree program is not observable to prospective students (Winston, 1999). While it was hypothesized that MOOC participation may act as an important information source for certain groups of learners in particular (e.g. women, non-traditional students, or older students) data are inconclusive in terms of helping to explain whether specific learners consider the information gained through MOOC participation when considering degree program pursuit. To this end, it would be beneficial to understand the extent to which learners perceive stackable MOOC pathways toward degree programs as similar or different in terms of rigor, level of difficulty of learning activities, and prospective value of the respective credentials. Such additional research would help better explain whether learners participating in MOOCs truly view information gleaned through MOOC engagement as valid indicators of what to expect as part of the graduate school experience.

The predisposition phase of students' choice process is not well studied and therefore there is a lack of clear and consistent measurements for accurately establishing intentions to enroll in a degree program (Perna, 2006). This study draws upon several prior studies to establish a measure of enrollment intentions, including Adelman's (1999) and Morgan's (1996) approaches in measuring and evaluating enrollment intentions. However, further studies would benefit from having a more established, reliable, and valid measure around intentions to enroll. More specifically, replicating this study with alternative data analyses that treat intentions to enroll as a categorical variable should be considered to determine whether findings remain consistent when the intentions to enroll variable is treated differently.

Implications for Practice: Interpreting Findings to Inform Practices for Those Supporting Stackable Online Pathways

As these stackable programs have proliferated in recent years, it is important to understand the potential impact they are having on learners' motivation and choices. This study provides initial insight into how these motivation-related constructs are impacted as individuals participate in stackable learning experiences.

Since their inception, MOOCs have been considered as an opportunity to provide marketing for institutions due to their ability showcase the talented instructors who teach within universities. This study also shows that the impact of MOOC participation goes beyond the ability to influence prospective consumers' perceptions of the institution, but also serve as potentially valuable opportunities for learning for those who are engaged, as data from this study shows MOOC engagement influences individuals' perceptions of self-efficacy, attainment value, and intrinsic value. When evaluating return on the substantial investment required to develop and offer these courses, evaluating whether these courses are successful at increasing prospective students' perceptions of the institution is only one facet that should be considered—considering how they influence motivational constructs is another. More clearly understanding the diverse ways in which MOOC courses can benefit participating learners allows institutional leaders to more clearly define the full impact that offering these courses can have on global online learners.

Limitations

This study examines the experience of learners engaging with a limited number of MOOC experiences that stack into a single degree program, all offered by one institution. As noted previously, differences between MOOCs and the content areas they cover may have influenced the outcome of this study in particular ways. Specifically, the primary content areas for the participating degree program and related MOOC experiences, Python coding and data science, are in high demand by employers, and demand for employment significantly outnumbers existing formal opportunities for learning in the data science field (Henke et al., 2016). The areas of focus for these learning experiences likely impacted perceived utility value for learners, and may impact the types of learners drawn to the program and related learning experiences; as Python coding and data science are STEM-related disciplines, there may be less participation among women or underrepresented minority participants in comparison to learning portfolios that address other topics, such as social work or education. Similarly, learners may value the MOOC credential more in this area of study as employers may not require more formal credentials to advance in their professional fields, as may be the case in fields such as social work or education.

As noted throughout the discussion, the measurements used to examine constructs within this study were established and have been used primarily within traditional educational environments and among traditional student populations. This limits applicability to some degree for these measurements within the MOOC environment, with a non-traditional population of learners.

Questions remain about whether intentions to enroll can be treated as a continuous, rather than categorical, variable. As noted previously, clear and consistent measurement of dependent variables has been lacking in research related to the predisposition phase of college choice, and variables related to intent to pursue further education have been treated both as categorical (Adelman, 1999) and continuous (Morgan, 1996) in previous studies. While I have chosen to treat this variable as continuous, it can be questioned whether the interval between each possible intention to enroll response is equal. For instance, is the same distance present between those indicating they do not plan to apply and those who do not know if they plan to apply, in comparison to the distance between those who have applied and plan to enroll and those who have already been accepted an plan to enroll? Further studies that replicate this work using different variable types would help validate the robustness of the findings in this study.

Relatively few individuals who enrolled in the course (n = 1773, or 1.9% of enrolled learners during the study period) actually completed the pre-course survey measures necessary to be considered as participants in the study. In considering the broader population of MOOC learners, the majority of those who enroll in a course do not complete all course activities. However, there was a large difference in engagement with the research between learners who completed (n = 178) and those who did not complete (n = 19) their course, suggesting the participants in this study do not appropriately represent the broader MOOC learner population in terms of their persistence and time to completion for learning activities in the course. Those who participate may represent the most self-efficacious learners, as demonstrated in the missing data analysis that showed participants had statistically significantly different, and higher, self-efficacy scores at the start of the course.

This study aggregates students who are considered to fall within a traditionally defined underrepresented minority populations (African American/Black, Hispanic/Latino, and Native American/American Indian) into one group to form a dichotomous variable for the purpose of evaluating whether URM status impacts the relationship between motivational constructs and intentions to enroll. Lumping individuals within these racial groups together into a catchall category can hide differences and inequities in how they experience engagement in a MOOC and prevents practitioners from more closely considering that factors contributing to equity gaps or differences in experiences for these students are likely to be distinct in some ways (McNair et al., 2020). An ANOVA of post-MOOC scores for each motivational variable and the intentions to enroll variable showed there was a statistically significant difference between groups for the effort cost ($F(12, 183) = 2.27$, $p = .01$) and psychological cost ($F(12, 183) = 2.18$, $p = .02$) variables. However, Tukey post hoc tests were not able to reveal the groups between which there were significant differences for these variables as there were groups with less than two cases. Means for each construct disaggregated by race/ethnicity selection are available in Table 11. While this study is just beginning to examine differences between learners, further analysis should disaggregate based on selections made to the race/ethnicity question as there are significant differences in mean scores between groups for some variables and moderating effects for one racial/ethnic group may not be illuminated in the data if it is aggregated with other groups.

The study collected data from MOOC participants for three months, which may not be a sufficient time period to see the impact of participation in MOOCs on self-efficacy and subjective task values and these variables' relationship with intentions to pursue graduate education. As MOOC participants do not have clear time limits within which they need to complete a course or a series of courses, those who have other life priorities may take longer to engage with course work or may never complete the course.

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APPENDIX A: TABLES

Table 1

Summary of Participants' Self-reported Gender, Age, First-generation Student Status, Race/Ethnicity, and Intentions to Enroll

	Enrolled Learner Population	All Study Participants (*n* = 197)	Completers (*n* = 178)	Non-completers (*n* = 19)
		Gender		
Female	230,790 (27%)	58 (29.4%)	51 (28.7%)	7 (36.8%)
Male	658,123 (72%)	133 (67.5%)	121 (68%)	12 (63.2%)
Other	12,360 (1%)	6 (3%)	6 (3.4%)	-
		Age		
Under 18	-	-	-	-
18 – 24	159,254 (17.7%)	65 (33%)	58 (32.6%)	7 (36.8%)
25 – 34	478,936 (53.1%)	76 (38.6%)	71 (39.9%)	5 (26.3%)
35 – 44	183,229 (20.3)%	30 (15.2%)	25 (14%)	5 (26.3%)
45 – 54	53,806 (6.0%)	21 (10.7%)	19 (10.7%)	2 (10.5%)
55 – 64	17,124 (1.9%)	3 (1.5%)	3 (1.7%)	-
65 – 74	8021 (.89%)	2 (1.0%)	2 (1.1%)	-
75 – 84	-	-	-	-
85 and Above	-	-	-	-
		First-generation Student Status		
First Generation		78 (39.6%)	69 (38.8%)	9 (47.4%)
Not First Generation		119 (60.4%)	109 (61.2%)	10 (52.6%)
		Race/Ethnicity		
Asian		64 (32.5%)	62 (34.8%)	2 (10.5%)
Black		28 (14.2%)	21 (11.8%)	7 (36.8%)
Hispanic, Latino, Spanish Origin		37 (18.8%)	34 (19.1%)	3 (15.8%)
Middle Eastern or North African		9 (4.6%)	8 (4.5%)	1 (5.3%)
White		42 (21.3%)	37 (20.8%)	5 (26.3%)
North American Indigenous		-	-	-
Hawaiian & Pacific Islander		-	-	-
Prefer to self-describe		8 (4.1%)	7 (3.9%)	1 (5.3%)

Table 1 (cont'd)

Prefer not to say	2 (1.0%)	2 (1.1%)	-
Multiple Chosen	7 (3.5%)	7 (3.9%)	-
		Intention to Enroll	
Does Not Plan to Apply	59 (29.9%)	54 (30.3%)	5 (26.3%)
Not Sure About Plans to Apply	79 (40.1%)	71 (39.9%)	8 (42.1%)
Plans to Apply in the Future	54 (27.4%)	49 (27.5%)	5 (26.3%)
Already Applied, Unsure of Enrollment Intent	1 (.5%)	1 (.6%)	-
Already Applied, Plans to Enroll	4 (2.0%)	3 (1.7%)	1 (5.3%)

Table 2

Analysis Results for Differences in SE and STV Scores Among Study Participants and Non-participants

Motivation variable	Participants		Non-participants		*df*	*t*	*p*	Cohen's *d*	Levine's test *p*
	M	*SD*	*M*	*SD*					
Self-efficacy	4.144	.861	3.962	.926	5238	2.709	.007	.197	.350
Intrinsic value	3.992	.962	3.864	.965	5238	1.828	.068	.133	.558
Attainment value	3.426	.997	3.340	1.038	5238	1.146	.252	.083	.415
Utility value	4.113	.876	4.058	.928	5238	.814	.415	.059	.374
Opportunity cost	1.915	.959	2.034	.998	5238	-1.635	.102	-.119	.519
Effort cost*	1.861	.913	2.095	1.018	215.46	-3.499	<.001	-.230	.026
Psychological cost	2.300	.940	2.380	1.011	5238	-1.094	.274	-.222	.254

Note. * Results of the Welch's t-test due to violation of the assumption of homogeneity.

Table 3

Correlations for Motivation and SRL Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Intentions	—												
2. T2 Self-efficacy	.01	—											
3. T2 Intrinsic Value	.17**	.64***	—										
4. T2 Attainment Value	.23***	.45***	.61***	—									
5. T2 Utility Value	.18**	.32***	.39***	.50***	—								
6. T2 Opportunity Costs	.02	-.22**	-.17**	-.07	-.17*	—							
7. T2 Effort Costs	-.03	-.20**	-.07	-.03	-.23**	.54***	—						
8. T2 Psychological Costs	-.11	-.24***	-.22**	-.10	-.07	.47***	.41***	—					
9. Goal Setting	.18**	.45***	.47***	.47***	.28***	-.25***	-.18**	-.25***	—				
10. Strategic Planning	.19**	.46***	.44***	.50***	.38***	-.20**	-.19**	-.26***	.71***	—			
11. Task Strategies	.19**	.43***	.47***	.51***	.37***	.-17**	-.17*	-.28***	.61***	.70***	—		
12. Elaboration	.01	.38***	.37***	.35***	.34***	-.24***	-.19**	-.23**	.53***	.58***	.68***	—	
13. Self-evaluation	.17**	.44***	.45***	.45***	.34***	-.20**	-.16*	-.24***	.47***	.62***	.64***	.55***	—
14. Help Seeking	.14*	.32***	.33***	.39***	.29***	-.13*	-.03	-.16*	.33***	.40***	.45***	.46***	.47***

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

Table 4

Correlations for Self-efficacy and Sources of Self-efficacy Variables

Variable	1	2	3	4	5
1. Post-course Self-Efficacy	—				
2. Pre-course Self-Efficacy	-.102	—			
3. Instructor Social Persuasion	.073	.152*	—		
4. Peer Social Persuasion	.029	.077	.480***	—	
5. Mastery Experiences	.014	.242***	.348***	.289***	—

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

Table 5

Results of Analysis Examining Pre- and Post-Course SE and STV Scores

Motivation Variable	Pre-course		Post-course		$t(196)$	p	Cohen's d
	M	SD	M	SD			
Self-efficacy	4.144	.861	4.286	.748	-2.044	.042	-.146
Intrinsic Value	3.992	.962	4.405	.735	-5.982	<.001	-.426
Attainment Value	3.426	.997	3.725	.937	-4.563	<.001	-.325
Utility Value	4.113	.876	4.178	.717	-1.177	.241	-.084
Opportunity Cost	1.915	.959	1.761	.845	2.087	.038	.149
Effort Cost	1.861	.913	1.756	.822	1.506	.134	.107
Psychological Cost	2.300	.940	2.184	.882	1.666	.097	.119

Table 6

Results of Analysis Examining Pre- and Post-Course SE and STV Scores with Extreme Outliers Excluded

Motivation variable	Pre-course		Post-course		*t*	*p*	Cohen's *d*
	M	*SD*	*M*	*SD*			
Self-efficacy	4.152	.833	4.317	.673	-2.723	.007	-.196
Intrinsic value	4.046	.890	4.424	.673	-6.709	<.001	-.485
Attainment value	3.439	.984	3.718	.935	-4.442	<.001	-.317
Utility value	4.142	.831	4.169	.715	-.554	.580	-.040
Opportunity cost	1.903	.937	1.749	.815	2.226	.027	.159
Effort cost	1.831	.866	1.764	.823	1.028	.305	.074
Psychological cost	2.286	.923	2.191	.880	1.433	.154	.102

Table 7

Multiple Regression Coefficients for Predicting Intentions to Enroll

Variable	*B*	95% CI	β	*t*	*p*
Constant	1.394	[.295, 2.493]		2.502	.013
Self-efficacy	-.262	[-.477, -.048]	-.222	-2.409	.017
Intrinsic Value	.181	[-.063, .425]	.151	1.465	.145
Attainment Value	.175	[.001, .350]	.186	1.981	.049
Utility Value	.120	[-.083, .322]	.097	1.166	.245
Opportunity Costs	.120	[-.059, .299]	.115	1.325	.187
Effort Costs	-.042	[-.225, .141]	-.039	-.453	.651
Psychological Costs	-.143	[-.304, .018]	-.143	-1.754	.081

Note. R^2_{adj} = .072 (N = 197, p = .003). CI = confidence interval for *B.*

Table 8

Hierarchical Multiple Regression Predicting Enrollment Intentions from SE, STV, and SRL Strategy Scores

	Intentions to Enroll			
	Model 1		Model 2	
Variable	B	β	B	β
Constant	1.39*		1.30*	
Self-efficacy	-.262*	-.222	-.296*	-.251
Intrinsic Value	.181	.151	.159	.133
Attainment Value	.175*	.186	.093	.099
Utility Value	.120	.097	.128	.104
Opportunity Cost	.120	.115	.114	.109
Effort Cost	-.042	-.039	-.045	-.042
Psychological Cost	-.143	-.143	-.113	-.113
Goal Setting			.120	.111
Strategic Planning			.075	.063
Task Strategies			.153	.115
Elaboration			-.360*	-.267
Self-evaluation			.089	.068
Help Seeking			.083	.077

Note. N = 197. * *p* < .05

Table 9

Summary of Results Related to Changes in SE and STV

Construct	Hypothesized change	Mean change	Is the hypothesis supported?
Self-efficacy	Increases	Increase	Yes
Intrinsic value	Increases	Increase	Yes
Utility value	Increases	—*	No
Attainment value	Remains stable	Increase	No
Opportunity cost	Increases	Decrease	No
Effort cost	Increases	—*	No
Psychological cost	Increases	—*	No

**mean change was not significant.*

Table 10

Summary of Results Regarding the Relationship Between SE and STVs and Intentions to Enroll

Construct	Hypothesized relationship	Actual relationship	Is the hypothesis supported?
Self-efficacy	Positive	Negative	No
Intrinsic value	Positive	—*	No
Utility value	Positive	—*	No
Attainment value	Positive	Positive	Yes
Opportunity cost	Negative	—*	No
Effort cost	Negative	—*	No
Psychological cost	Negative	—*	No

**relationship was not significant.*

Table 11

Construct Means Based on Disaggregated Racial/Ethnic Selections

		Self-efficacy		Intrinsic value		Utility value		Attainment value		Opp cost		Effort cost		Psych Cost		Enroll Intentions	
Race/ Ethnicity	*N*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Asian	64	4.23	.60	4.31	.67	4.12	.71	3.60	.92	1.85	.89	1.88	.92	2.34	.83	1.91	.77
Black	27	4.28	.55	4.39	.68	3.93	.68	3.77	.91	1.52	.68	1.67	.80	1.78	.75	2.04	.94
Hispanic, Latino, Spanish origin	37	4.21	.91	4.40	.85	4.28	.67	3.55	.96	1.84	.88	1.72	.69	2.20	.84	2.16	.99
Middle Eastern or North African	9	4.29	1.05	4.44	1.24	4.17	1.00	3.94	1.07	1.70	.65	1.70	.42	2.33	.88	2.33	.50
White	42	4.35	.89	4.45	.71	4.22	.74	3.79	.95	1.80	.89	1.69	.79	2.06	.93	2.04	.99
Prefer not to say	2	4.40	.28	5.00	.00	4.50	.71	3.75	1.77	1.00	.00	1.00	.00	1.83	1.18	3.00	.00
Prefer to self-describe	8	4.75	.33	4.72	.34	4.63	.69	4.31	.75	1.33	.50	1.25	.46	2.08	.85	1.87	.99
Asian/White	1	4.40	—	5.00	—	4.5	—	3.75	—	3.33	—	4.33	—	4.00	—	3.00	—
Asian/Prefer not to say	1	4.60	—	5.00	—	5.0	—	5.00	—	1.00	—	1.00	—	1.00	—	3.00	—

Table 11 (cont'd)

Black/Hispanic, Latino, Spanish origin	1	4.00	—	5.00	—	5.0	—	4.75	—	1.67	—	2.67	—	3.00	—	2.00	—
Hispanic, Latino, Spanish origin/White	2	4.90	.14	4.50	.71	4.38	.53	4.38	.53	1.33	.47	1.83	.24	3.17	1.18	1.50	.71
Middle Eastern or North African/White	1	2.80	—	3.75	—	3.50	—	3.25	—	2.67	—	2.67	—	3.67	—	2.00	—
Hispanic, Latino, Spanish origin/White/ North American Indigenous	1	3.60	—	3.50	—	3.50	—	3.25	—	3.33	—	3.67	—	3.67	—	2.00	—

APPENDIX B: SURVEY QUESTIONS

Self-efficacy (adapted from Midgley et al., 2000)

I am certain I can master the skills taught in (data science, Python coding, statistics) courses.

I am certain I can figure out how to do the most difficult course work in (data science, Python coding, statistics).

I can do almost all the work in (data science, Python coding, statistics) courses if I don't give up.

Even if the work in (data science, Python coding, statistics) is hard, I can learn it.

I can do even the hardest work in (data science, Python coding, statistics), if I try.

Subjective Task Values

Intrinsic Value (adapted from Conley, 2012)

I enjoy the subject of (data science, Python coding, statistics).

I enjoy doing (data science, Python coding, statistics).

(Data science, Python coding, Statistics) is exciting to me.

I am fascinated by (data science, Python coding, statistics).

I like (data science, Python coding, statistics).

Attainment Value (adapted from Robinson et al., 2019)

Being someone who is good at (data science, Python coding, statistics) is important to me.

Being good in (data science, Python coding, statistics) is an important part of who I am.

Being involved in (data science, Python coding, statistics) is a key part of who I am.

I consider myself a (data science, Python coding, statistics) person.

Utility Value (adapted from Gaspard, 2017)

Good grades in (data science, Python coding, statistics) will bring many advantages for my job and my career.

A good knowledge of (data science, Python coding, statistics) will help me in my job.

For my working life it will pay off to be good in (data science, Python coding, statistics).

Knowing the contents in (data science, Python coding, statistics) will be helpful for my career.

Opportunity Cost (adapted from Perez et al., 2014)

I'm concerned my (data science, Python coding, statistics) (program/course) will take time away from other activities that I want to pursue

I'm concerned my (data science, Python coding, statistics) (program/course) may cause family relationships to suffer.

I worry that my (data science, Python coding, statistics) (program/course) will take time away from other activities that I want to pursue.

Effort Cost (adapted from Perez et al., 2014)

Considering what I want to do with my life, having a (data science, Python coding, statistics) (degree/certificate) is just not worth the effort.

When I think about the hard work needed to get through my (data science, Python coding, statistics) (program/course), I am not sure that getting a (degree/certificate) will be worth it in the end

Getting a (data science, Python coding, statistics) (degree/certificate) sounds like it really requires more effort than I'm willing to put in.

Psychological Cost (adapted from Perez et al., 2014)

My self-esteem would suffer if I tried my (data science, Python coding, statistics) (program/course) and was unsuccessful at it.

I would be embarrassed if I found out that my work in my (data science, Python coding, statistics) (program/course) was inferior to that of my peers.

I'm concerned that I won't be able to handle the stress that goes along with my (data science, Python coding, statistics) (program/course).

Self-Regulated Learning Strategies (from Kizilcec et al., 2017)

Goal Setting

I set personal standards for performance in my learning.

I set short-term (daily or weekly) goals as well as long-term goals (for the whole course).

I set goals to help me manage studying time for my learning.

I set realistic deadlines for learning.

Strategic Planning

I ask myself questions about what I am to study before I begin to learn.

I think of alternative ways to solve a problem and choose the best one.

When planning my learning, I use and adapt strategies that have worked in the past.

I organize my study time to accomplish my goals to the best of my ability.

Task Strategies

I try to translate new information into my own words.

I ask myself how what I am learning is related to what I already know.

I change strategies when I do not make progress while learning.

When I study for this course, I make notes to help me organize my thoughts.

I create my own examples to make information more meaningful.

I read beyond the core course materials to improve my understanding.

Elaboration

When I am learning, I try to relate new information I find to what I already know.

When I am learning, I combine different sources of information (for example: people, web sites, printed material).

I try to apply my previous experience when learning.

Self-Evaluation

I know how well I have learned once I have finished a task.

I ask myself if there were other ways to do things after I finish learning.

I think about what I have learned after I finish.

Help Seeking

When I do not understand something, I ask others for help.

I try to identify others whom I can ask for help if necessary

I ask others for more information when I need it.

Even if I am having trouble learning, I prefer to do the work on my own.

Sources of Self-Efficacy

Quantitative Questions

My instructor's encouragement by praising my ability contributed to my confidence and success.

The lack of encouragement from my instructor in this course undermined my confidence and success.

My peers' comments that I understood everything taught in this course contributed to my confidence and success.

The lack of comments from peers about my understanding of everything taught in this course undermined my confidence and success.

My ability to perform well on assignments in this course contributed to my confidence and success.

My inability to perform well on assignments in this course undermined my confidence and success.

MOOC Demographic Information

Gender

What is your gender?

- Female
- Male
- Non-binary/Third gender
- Prefer to self-describe
- Prefer not to say

Race/Ethnicity

Which categories best describe you? Please select one or more:

- Asian
- Black
- Hispanic, Latino, or Spanish origin
- Middle Easter or North African
- White
- North American Indigenous
- Hawaiian & Pacific Islander
- Prefer to self-describe
- Prefer not to say

Age

What is your age?

- Under 18
- 18 – 24
- 25 – 34
- 35 – 44

- 45 – 54
- 55 – 64
- 65 – 74
- 75 – 84
- 85 or older

First-generation Student Status

Please specify the highest level of education completed by your parents. Depending on your personal circumstances, your parents may be your birth parents, adoptive parents, extended parents or legal guardians

Parent #1 highest educational level completed:

- Some high school or less
- High school diploma or equivalent
- Associate's degree or equivalent
- Bachelor's degree or equivalent
- Graduate or professional degree
- Unknown

Parent #2 highest educational level completed:

- Some high school or less
- High school diploma or equivalent
- Associate's degree or equivalent
- Bachelor's degree or equivalent
- Graduate or professional degree
- Unknown

Enrollment Intentions

Are you currently enrolled as a student in an educational program?

- Yes, I am currently a full-time student.
- Yes, I am currently a part-time student.
- No, I am not currently a student.

Do you plan to apply for admission to the University of Michigan?

- I have already applied to U-M
- Yes, I plan to apply to U-M in the future
- No, I do not plan to apply to U-M
- I am not sure yet

Which school(s) or college(s) do you plan to/did you apply to? Select all that apply:

- Full listing of U-M's 19 academic units

What type of program do you plan to/did you apply to? Select all that apply:

- Doctoral degree program
- Master's degree program
- Undergraduate degree program
- Professional school program (i.e. programs offered through the Law, Medicine, Dentistry, Pharmacy schools)
- Certificate program

If admitted, how likely are you to attend the University of Michigan?

- I plan to enroll if I'm admitted
- I'll probably enroll if admitted
- I'm not sure if I intend to enroll if I'm admitted
- I don't plan to enroll if I'm admitted

APPENDIX C: PARTICIPATION MESSAGES

Pre-Course Survey Messaging

You have been invited to participate in this survey because you have registered for an online course administered by the University of Michigan. Any information you share will be used to conduct research to help us better understand the teaching and learning experiences, with the goal of supporting continuous improvement of our portfolio as well as enabling research.

Your participation is voluntary and your decision to participate will not affect your relationship with the University of Michigan. Your responses will be kept confidential, and the results from this survey will only be presented in aggregate form. We greatly appreciate your willingness to share your time by participating; this survey is expected to only take approximately 5-10 minutes to complete.

If you have any questions about this survey, please contact the University of Michigan Center for Academic Innovation: ai-surveys (at) umich.edu

Thank you for helping to make the University of Michigan online courses better!

University of Michigan Center for Academic Innovation (CAI)

Post-Course Survey Messaging

Welcome!

You have been invited to participate in this survey because you have registered for an online course administered by the University of Michigan. Any information you share will be used to conduct research to help us better understand the teaching and learning experiences, with the goal of supporting continuous improvement of our portfolio as well as enabling research.

The survey includes specific questions about your experience in this course. **You do NOT need to have completed this course to participate in this survey.** Whether you completed the course or not, please help us understand your experience in the course and provide feedback that will help us improve the experience of other students.

Your participation is voluntary and your decision to participate will not affect your outcomes in this course or your relationship with the University of Michigan. **Your responses will be kept confidential, and the results from this survey will only be presented in aggregate form.** We greatly appreciate your willingness to share your time by participating in this survey; we expect that it will only take 5-10 minutes to complete the questionnaire.

If you have any questions about this survey, please contact the University of Michigan Center for Academic Innovation: ai-surveys (at) umich.edu

Thank you for helping to make the University of Michigan online courses better!

University of Michigan Center for Academic Innovation (CAI)