

ABSTRACT

CREAGER, JAMES H. Agency and Pacing in a Professional Development Open Online Course with a Flexible Content Pathway and Release Schedule. (Under the direction of Dr. Douglas Gillan).

Massive Open Online Courses (MOOCs) have potential to offer scalable, relevant, and flexible professional development to practitioners, but most MOOCs to-date have been challenged by high dropout rates, declining engagement over time, and low certification rates. Prior research suggests traditional MOOC designs may not sufficiently accommodate the degree of flexibility many learners require to effectively self-direct their learning. The present research investigated the impact of a new course design that supported flexible pacing of participation and multiple pathways through content, relative to a traditional fixed-linear course design. In a professional development MOOC for educators, learners who worked as classroom teachers (the primary target audience) and were given a flexible course structure had significantly better course persistence, course engagement, and course certificate achievement than classroom teachers given a traditional course structure. However, learners with educational leadership and support roles (secondary target audiences) had similar course outcome metrics between the course structures. Examination of participation pace, jumps between units, and order of unit completion suggest learners who were classroom teachers took greater advantage of the enhanced flexibility than learners with leadership and support roles. Findings advocate the implementation of flexible course structures and further study of the impact of professional role on course outcomes. Implications for future design are discussed.

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Agency and Pacing in a Professional Development Open Online Course with a Flexible Content
Pathway and Release Schedule

by
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DEDICATION

To my loving wife and family. Thank you. This would not be possible without your faith, encouragement, and support.

BIOGRAPHY

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Introduction

Professional development is an essential component of education vocations (Darling-Hammond, Wei, Andree, Richardson, & Orphanos, 2009; Wei, Darling-Hammond, & Adamson, 2010). Education professionals at all grade levels and of all roles are consistently challenged to adapt to new circumstances, including new standards, new classroom technology, and new students with a variety of learning needs. Professional development provides educators the opportunity to acquire new knowledge, skills, and resources that can help them deliver high quality education amidst constant change.

Unfortunately, most formal professional development opportunities offered to educators in the United States are faced with effectiveness and administrative challenges. The National Staff Development Council has reported that nearly every educator has access to some form of professional development each year, but more than half consider the professional development they receive to be unrelated to their professional development needs and/or not in enough depth (Darling-Hammond et al., 2009). In addition, most formal professional development opportunities fail to provide long-term, job-embedded material and opportunities for collaboration with peers – all of which are commonly desired (Wei et al., 2010).

The most common formats of educator professional development, including in-person workshops and training sessions, are brief “sit and listen” events on predetermined topics that require substantial expense and coordination to implement (Darling-Hammond et al., 2009; G. M. Kleiman, Wolf, & Frye, 2013). Space must be allocated, a leader must be actively involved, professionals must collocate at the same time, and the aforementioned challenges scale with the numbers of attendees as learning needs become more diverse. Less common online alternatives, such as online teacher professional development (oTPD) and technology-mediated professional

learning (TMPL) distance education classes, eliminate the need for collocation and physical space but are still challenged by the need for multiple offerings to maintain relevance among diverse learning needs, the expense for active instructor involvement, and/or the coordination of multiple professionals to attend simultaneously (Brooks & Gibson, 2012).

In recent years, a new format of online education – the Massive Open Online Course (MOOC) – has emerged with the potential to offer scalable, relevant, and flexible education to large numbers of learners (Bond, 2015; Haggard, 2013; Yuan & Powell, 2013). MOOCs have overcome many financial and relevance challenges by designing environments that afford self-directed learning within pre-defined boundaries so instructor involvement can be minimal and individual learners can pursue their own learning goals (Hollands & Tirthali, 2014). MOOCs have also overcome many coordination challenges by making enrollment free of cost, making courses available to anyone in the world with internet access, designing courses around asynchronous communication, and allowing participants to catch-up if they miss part of a course (Hollands & Tirthali, 2014).

Whereas early implementations of MOOCs have shown great promise in both general education and professional development domains, challenges have been encountered with respect to learner persistence, engagement, and achievement in MOOC self-directed learning environments. MOOC literature reports that only a small percentage of registrants complete course requirements, while many follow a pattern of declining engagement over time and/or drop out before accomplishing their course goals (Ho et al., 2015; Jordan, 2014; Kolowich, 2013). Investigations report that early MOOC designs have not sufficiently accommodated for the degree of flexibility many learners require to effectively self-direct their learning, and there is

need for improvement in MOOC design (Bonk & Lee, 2017; Littlejohn & Milligan, 2015; Liu et al., 2014; Shapiro et al., 2017).

The present research contributes to a recent body of literature exploring the potential of new MOOC designs with flexible course structures that offer more opportunity for learners to engage with course material and self-direct their learning. MOOC literature is reviewed for a deeper understanding of MOOC design, the MOOC learner population, and design principles for MOOC interventions and supports. Then a new course structure is investigated in the context of a professional development MOOC for educators with respect to persistence, engagement, achievement, and various navigation behaviors related to the new course structure.

The following research questions are addressed:

RQ1 – Does a flexible course structure, which provides control over pacing and pathway, improve learners’ persistence, engagement, and achievement?

RQ2 – What individual differences, if any, moderate the impact of flexible course structure on course outcomes?

RQ3 – How do learners navigate through a flexible course structure?

Massive Open Online Courses

Massive Open Online Courses, or MOOCs, originated in 2008 as a new format of online courses making education more scalable and accessible than traditional alternatives (Ferguson & Sharples, 2014; Flynn, 2013). Similar to traditional online courses, MOOCs provide an online environment for learning about a topic over a period of months and offer some form of credit or certification for completing course requirements. However, unlike traditional online courses, MOOCs are freely available to anyone with internet access and are intended to host thousands of

learners with limited instructor involvement (Haggard, 2013; Mohamed & Hammond, 2018).

Large, distributed audiences afford new opportunities for instructors to leverage the knowledge and experiences of learners. They also encourage instructors to plan for diversity in advance and promote learner autonomy so instructor involvement is reduced during the course. These attributes introduce new design considerations unique to MOOC learning environments.

MOOC structure. The structural details of a MOOC define an overarching framework within which instructional materials can be designed. Structure can outline many organizational properties of a course, including the methods of decomposing content, pacing content, and evaluating certification requirements. Ideal course structures enhance the definitional properties of MOOCs by promoting learner autonomy and introducing flexibility that accommodates many learners, while simultaneously providing guidance and enforcing boundaries in the absence of an instructor (Bonk & Lee, 2017; Littlejohn & Milligan, 2015).

Most existing MOOCs are designed with a simple organizational structure reminiscent of traditional online courses, even though there is no prescribed structure by definition (Margaryan, Bianco, & Littlejohn, 2015; Yeager, Hurley-Dasgupta, & Bliss, 2013). An overarching topic is broken up into a linear series of units, and each unit contains a combination of learning resources, such as reading materials, videos, activities, social tools, and assessments. Units are gradually opened as a course progresses, and they remain accessible for the duration of the course. At the end of a course, some form of certification is awarded based on a combination of participation and assessment grades throughout all of the course material. Deviations from this overarching organizational structure are in the minority, but have received attention in recent experimental research (Crosslin, Dellinger, Joksimovic, Kovanovic, & Gasevic, 2018; Mullaney & Reich, 2015; van Cooten, 2017; Vigentini & Clayphan, 2015).

The typical MOOC structure diverges from traditional online courses in the requirements for completion. Although MOOC units are released at a predefined pace, learners are not required to complete units at the rate they are released. Unlike traditional courses where assignments must be completed in lockstep with the course progression, most MOOCs only necessitate that requirements be met at some point before the course ends. This gives MOOC learners the ability to slow their pace when necessary and later catch up if they have fallen behind. In addition, some MOOCs do not mandate an order of completion for resources within a unit and/or make some resources optional. This gives learners some autonomy within a unit.

Overall, MOOC structure has thus far changed very little from that of traditional online courses. MOOCs have yet to widely implement innovative course structures that accommodate diversity, promote learner autonomy, and reduce instructor involvement, with the exception of some flexibility in meeting certificate requirements as mentioned above. There is room for innovation and broad impact in this domain because structure is one of the most generalizable design traits across courses.

MOOC types. MOOCs support a variety of instructional approaches within their overarching structure because they are not bound to a particular philosophy of learning or pedagogical strategy. Three different types of MOOCs have been documented in the literature, each rooted in a separate epistemology with a unique approach to promoting learner autonomy and leveraging the knowledge and experience of participants during the learning process (Anderson & Dron, 2011; Crosslin, 2016; Moe, 2015).

First, connectivist MOOCs, or cMOOCs, utilize the principles of communal inquiry and connectivism to empower learners to discover and explore learning interests as a class community (Bond, 2015; Downes, 2008; Siemens, 2005). cMOOC pedagogy departs from many

traditional approaches to education because knowledge primarily emerges from learners themselves and the connections they make with external sources apart from an instructor (Couros, 2010). The role of a cMOOC instructor is merely to facilitate inquiry and learning processes, rather than to impart knowledge. cMOOC learning activities are typically group-based and involve the filtering and synthesis of distributed information sets from the internet to create blogs, wikis, and other compiled artifacts with up-to-date representations of knowledge (Bond, 2015; Downes, 2008). In this way, learning occurs through the collaborative connection of existing knowledge and the examination of shared information sets, instead of transmission from an instructor or peers.

Second, instructivist MOOCs, or xMOOCs, adopt a traditional teacher-student paradigm based on the principles of instructivism (Rodriguez, 2012). xMOOC course topics and resources are predetermined by an instructor, and the provided resources are expected to offer all of the information a learner needs to be successful (Moe, 2015). During the course, instructor interaction is typically limited to addressing common questions in support forums if the instructor is involved at all. xMOOC learning activities are primarily individualistic and consumptive, such as watching videos, reading lecture notes, and taking automatically graded assessments. In this way, learning occurs through the passive transmission of information from instructor to learner.

Lastly, social constructivist MOOCs integrate principles of social constructivism and instructivism to leverage personal experiences of the learner community in the learning process (Ferguson & Sharples, 2014; G. M. Kleiman & Wolf, 2016). Similar to xMOOCs, the topics and resources of social constructivist MOOCs are predefined by instructors, and resources often involve consumptive components. However, social constructivist MOOCs are distinguished by

activities that evoke experiential knowledge from learners and community discussions paired with activities to help participants learn through the experiences of their peers. During courses, instructor involvement is typically limited to encouraging and extending dialogue about curricular-related issues. In this way, learning occurs through a combination of transmission and creation in a social construct (DiStefano, 2018).

All three types of MOOCs provide valuable learning experiences, even though learning occurs in different ways (Anderson & Dron, 2011). All three types are implemented for general audiences (Belanger & Thornton, 2013; Ferguson & Clow, 2016; Yeager et al., 2013) and educator professional development audiences (Acree, Creager, Wiebe, & Wolf, 2018; Milligan, Littlejohn, & Margaryan, 2013; Mohamed & Hammond, 2018) with positive survey feedback from enrolled learners. However, instruction-oriented pedagogical formats seem to be preferred by learners because an overwhelming majority of learners avoid the cMOOC format when given a choice of format (Crosslin et al., 2018; Dawson, Joksimović, Kovanović, Gašević, & Siemens, 2015).

Professional development MOOCs. MOOCs provide a generalizable educational format that can deliver many different types of content to many different audiences. Underneath the pedagogical layer is a content layer with information selected by instructors. Information conveyed in lectures and assessed in quizzes can be framed in any fashion to make it more appropriate for different audiences. The distinction between general audience and professional development MOOCs is found in this content layer.

At some level, all MOOCs have the potential to serve as a professional development resource when the content is relevant to a learner's professional work. Many MOOCs appeal to a general audience and offer versatile knowledge that can be useful in a variety of contexts,

including professional work. In fact, a large percentage of general audience MOOC attendees are working professionals seeking knowledge that will help them solve problems encountered at their jobs (Ho et al., 2015). However, some MOOCs appeal specifically to a working professional audience and are branded as “professional development MOOCs” to indicate content is embedded in a professional context and focuses on the learning needs of working professionals.

Professional development MOOCs share a majority of their design with general audience MOOCs. The same structures and pedagogical styles are applied to both types of courses. Many of the resource types, such as lecture notes, videos, forums, and quizzes, are similar as well. Professional development MOOCs diverge from general audience MOOCs in the way information is framed and applied.

Professional development MOOCs are typically distinguished from general audience MOOCs by job-relevant content, applied activities and assessments, and professionally-relevant certifications (G. M. Kleiman & Wolf, 2016; Littlejohn & Milligan, 2015). Educator professional development MOOCs in particular cover pragmatic topics, such as best practices for instructional design, teaching students with learning differences, and implementing school-wide initiatives. Activities and assessments are often embedded in learners’ work context, such as modifying, implementing, and evaluating classroom lesson plans. Peers are often encouraged to interact by discussing content, sharing experiences, and reviewing submitted artifacts. Moreover, certifications have value in professional contexts, such as certificates that can be exchanged for job-mandated continuing education units (CEUs) and establish credibility with parents and principals.

In summary, MOOCs are still a relatively new format of online learning. Most MOOCs are still structurally modeled after their traditional counterparts, but they incorporate new qualities of open enrollment, limited instructor involvement, and plans for large numbers of learners. MOOC designers use different pedagogical approaches and content to promote learner autonomy, integrate peer interactions into the learning process, and target different audiences. The result is a self-directed learning environment where large numbers of distributed learners manage their own progression through course content (Kop, 2011).

Course Outcomes

MOOCs are created for the purpose of disseminating knowledge, developing skills, and in some cases certifying mastery, such as CEUs that help learners meet job requirements (G. M. Kleiman & Wolf, 2016). With these objectives in mind, desirable course-level outcomes from the designer's perspective include learners participating throughout an entire course, using many of the available resources, and earning certifications.

In turn, MOOCs are most commonly evaluated by three outcomes: persistence, engagement, and achievement. These outcomes capture a broad spectrum of learning factors, including exposure to course content, involvement in course content, and mastery of course content. In some cases, all three outcomes follow similar trends. For example, a learner who persists through an entire course is likely to engage in more content and get higher assessment grades than a learner who only attends the first week of a course (Lee, 2018). However, persistence, engagement, and achievement are not perfectly yoked, especially in self-directed learning environments. For example, MOOC learners have the freedom to participate regularly in a subset of the available resources (e.g. if they do not have time to commit to all resources in the course), which can lead to high persistence and engagement but low achievement (DeBoer,

Ho, Stump, & Breslow, 2014). New learning conditions in MOOCs warrant an investigation of all three outcomes.

Persistence. Persistence is broadly defined as participation over a period of time or set of content (Evans, Baker, & Dee, 2016; Gütl, Rizzardini, Chang, & Morales, 2014). In the MOOC literature, persistence is typically operationalized relative to the scope of an entire course offering as a binary value of whether or not a learner remained active through the last week/unit of the course, and the data is extracted from system logs of user activity, or trace data.

Studies in the MOOC literature have described learner persistence as a “funnel of participation,” where the number of active learners declines as courses progress (Clow, 2013). The first and largest drop in learners occurs between the start of enrollment and the start of courses. Between 25% and 50% of learners who enroll in MOOCs never show up to the courses after they start (DeBoer et al., 2014; Evans et al., 2016). These learners are commonly deemed “no-shows” and excluded from core outcome analyses due to their lack of presence in the course.

A second substantial drop in active learners occurs during the first few weeks of courses, and then dropout steadily declines throughout the remainder of courses. Roughly half of enrolled learners drop out within the first 20% of a course and only about one-quarter of learners persist into the final 20% of a course with the probability of dropout follows a U-shape curve throughout the runtime of a course (Reich, 2014). MOOC literature confirms this trend holds for both general audience and professional development MOOCs whether analyzing overall course activity or resource-specific activity, such as forum posts (Breslow et al., 2013; Koller, Ng, Do, & Chen, 2013; Kroll & Reed, 2017; Salmon, Gregory, Dona, & Ross, 2015; Wen, Yang, & Rosé, 2014).

Overall, persistence is strikingly different in MOOCs than traditional courses, regardless of whether MOOCs are oriented toward general or professional audiences. First, fewer learners make it to the end of MOOCs than would be expected in traditional courses. Sometimes more MOOC learners dropout than persist, which is the opposite of traditional courses. Second, the probability of dropout is consistently higher throughout the entirety of a MOOC than a traditional course. Although dropout is highest at the beginning, middle, and end of MOOCs, dropout is a common occurrence throughout. MOOC learners persist for different amounts of time and through different amounts of content before dropping out, as opposed to learners in traditional courses who have a tendency to dropout at specific times, such as in the first two weeks or just before a penalty free drop deadline.

Engagement. Engagement can be defined as “active involvement or deliberate investment of effort” in activities (Wiseman, Kennedy, & Lodge, 2016). In the MOOC literature, engagement is commonly operationalized as a quantity of resource utilization extracted from trace data. Aggregate engagement measures capture the utilization of multiple resource types to provide an overall picture of engagement in a course, while more focused measures isolate engagement with specific resource types, such as forums. Measures can also target the depth or breadth of engagement by focusing on frequency, duration, or variety of resource use.

Descriptive studies have investigated the funnel of participation with respect to engagement by considering the different types of resources learners use and the types of interactions performed with those resources (Clow, 2013). Most learners do not utilize the full breadth of resource types that MOOCs offer. Approximately 30% of MOOC learners tend to watch lecture videos and read lecture notes while avoiding assessments and forums (DeBoer et

al., 2014; Khalil & Ebner, 2016). Among learners who do engage in assessments and forums, passive interactions are much more common than active interactions (e.g. reading forum threads is more common than posting), even among learners who earn certificates (Sun, Rau, & Ma, 2014).

Researchers have also investigated the engagement trajectories learners follow throughout a course. When modeling engagement as being on- or off-track to certificate video and assessment requirements at different points in the course, learner trajectories can be classified into one of four major groups: completing, auditing, disengaging, and sampling (Bergner, Kerr, & Pritchard, 2015; Ferguson & Clow, 2016; Kizilcec, Piech, & Schneider, 2013). Learners in both the completing and auditing trajectories follow the pace of the course, but completers attempt almost all assessments while auditors rarely attempt assessments. Learners in the sampling and disengaging trajectories both tend to disappear from the course, but disengaging learners look like completers early on while samplers only watch videos for one or two weeks before dropping out. When modeling engagement as the variety of resources used, i.e. independent of certificate requirements and impartial to the types of resources, five common trajectories emerge (Creager, Wiebe, Thompson, & Behrend, 2019). A high-stable group is heavily engaged and uses almost all available types of resources through the entirety of the course, while mid-rise and mid-decline groups are more and less engaged in the middle of the course respectively. Slow-decline and fast-decline groups started with high engagement across resource types but reduce their breadth of engagement to fewer resource types, often leading to dropout late or early in the course respectively.

Collectively, engagement research shows MOOC learners choose to engage with different types of resources and different amounts of resources, rather than unanimously utilizing

virtually all prescribed resources as would be imposed by a traditional course. Some MOOC learners do not use all of the available resources, and in some cases, this can lead to sustained participation without progress toward a certificate. In addition, MOOC learner engagement fluctuates over time and in different ways depending on the learner. Persistent learners have trajectories with peaks and valleys at different points in the course, and disengaging learners decrease engagement at different rates and points in time.

Achievement. Achievement refers to a demonstration of mastery of course content. Achievement can be measured by performance on assessments and/or attainment of certifications, including quiz scores, final exam scores, and whether or not a course certificate is earned. Performance and attainment are tightly related in some cases, such as a quiz that is passed when a minimum score is reached. However, they can be decoupled, such as course certificates that involve a variety of participation requirements (e.g. forum posting, activity completion, etc.) in addition to multiple assessment requirements.

Studies reporting assessment performance indicate the score distributions of learners who take assessments are fairly similar to traditional courses (Admiraal, Huisman, & Pilli, 2015; Davis, Chen, van der Zee, Hauff, & Houben, 2016; Onah, Sinclair, & Boyatt, 2014). Considering only learners who attempted quizzes, courses with weekly quizzes report a fairly normal pattern with average scores near 80% and the lowest score typically between 50% and 70%. Considering only learners who attempted exams, courses with exams report fairly normal distributions with average scores a little lower in the range of 57% to 70%, perhaps because of partial participation throughout the courses.

Certificate attainment analyses, however, show the majority of MOOC learners do not earn a certificate of course completion. When all enrolled learners are included in analyses, the

certification rate is near 10% on average (Ho et al., 2015; Jordan, 2014). When excluding no-shows, certification rates approach 30% on average, but certificate earners are still a minority (Bonk & Lee, 2017; G. Kleiman, Kellogg, & Booth, 2015; Laurillard, 2016; Salmon et al., 2015). Since certificate requirements generally include requirements for passing assessments, low certification has been tied to failing to pass assessments in many cases. As mentioned in the studies of engagement, many learners have a tendency to avoid assessments, and even those who take assessments tend to take fewer as a course progresses (Rieber, 2016; Staubitz, Willems, Hagedorn, & Meinel, 2017).

MOOC achievement research suggests a small proportion of learners demonstrate mastery through assessments and certification avenues. Learners who engage with quiz-like assessments tend to perform well on those assessments, but most learners only engage with a fraction of assessments, which leads to lower final exam scores and low certification rates. A typical certification rate of under one-third of learners is drastically different from traditional courses, where the majority of learners are expected to meet passing requirements.

In summary, MOOC persistence, engagement, and achievement patterns are much different from what would be expected in traditional courses, and the outcomes seem to fall short of designer expectations, particularly in the case of professional development courses. MOOC learners exhibit engagement patterns that do not align with designated certificate requirements. Instead, partial participation, such as focusing on specific resource types or specific units of content, is the norm. Recent literature has investigated the characteristics of MOOC learners to understand why outcomes are different and to identify potential design improvements that benefit both learners and course providers.

Learner Characteristics

Many characteristics of MOOCs – online availability, low barriers to enrollment, unrestricted class sizes, and self-directed learning – make education accessible to learners who would typically not be found in comparable traditional courses. This creates potential for a distinct audience with different learner characteristics from traditional courses. A deeper understanding of the life contexts, motivations, and goals possessed by this audience could help explain the aforementioned course outcomes and inform how MOOCs with a traditional structure can better designed to meet learners’ needs.

Demographics. Aggregate reports published by major MOOC providers offer insight to the demographics of the typical MOOC audience (Coursera, 2015; Ho et al., 2015; S. B. Kellogg, 2018; Walton, 2016). Notable characteristics, such as gender, age, education, and employment from Coursera, FutureLearn, edX, and The Friday Institute are summarized in Table 1.

Although demographics vary by provider, some general trends are present across providers. Both females and males are well represented in MOOCs overall. Females notably outnumber males in educator professional development courses, but this is likely due to the fact that most United States teachers are female (National Center for Education Statistics, 2018). With respect to age, most MOOC learners are adults over the age of 25, and age is fairly evenly distributed between 25 and 60+. This latter trend of age departs from the typical demographic of traditional classrooms dominated by younger learners.

A heavy skew toward employed and higher-educated learners is also documented, which deviates from the typical full-time students attending traditional courses. A portion of learners are unemployed and/or do not possess a college education, but the strong majority are both

employed and possess a college education ranging from undergraduate to various postgraduate degrees. The pattern is exaggerated in educator professional development MOOCs, where over 95% of learners possess college degrees (over half post-graduate) and employment.

Interestingly, the job responsibilities of these working professionals vary greatly, even within the audience of a particular course topic. For example, an educator professional development MOOC may attract classroom teachers, special education instructors, teacher preparation specialists, school-based administration, and many other roles (S. B. Kellogg, 2018).

Table 1. Demographics from major MOOC providers.

Provider	Sample	Gender	Education	Employment	Age
edX (Ho et al., 2015)	68 general & PD MOOCs w/ 1.7 million learners	32% female	70% at least Bachelor's degree	20% employed teachers ^a ; other roles not mentioned	Median 28 years
FutureLearn (Walton, 2016)	327 general & PD MOOCs w/ over 3 million learners	62% female	73% at least Bachelor's degree	-	Ten-year wide age brackets from 25 to 65 evenly represented
Coursera (Coursera, 2015)	1,000 general & PD MOOCs w/ 15 million users	42% female	32% Bachelor's as highest degree; 51% postgraduate as highest degree	70% employed	25% in the 30-39 age bracket and between 16% and 18% in older age brackets up to 60+
The Friday Institute (S. B. Kellogg, 2018)	33 educator PD MOOCs w/ over 15,000 learners	81% female	29% Bachelor's as highest degree; 67.2% postgraduate as highest degree	96% employed educators; < 2% unemployed	Years professional experience as proxy for age; 24% 20+ years and between 18% and 20% for 5-year bins 1-20 years

Note. MOOC = Massive Open Online Course. w/ = with. - = no response. PD = professional development.

^a Separate sample from 21 MOOCs.

Working professionals. A variety of contextual factors differentiate working professional learners from traditional students and lead to distinct learning experiences. Two of these factors are particularly relevant to the present study because they have a strong relationship to the aforementioned observations of course outcomes.

First, job responsibilities influence learners' motivations, goals, and behaviors in a course. Working professionals tend to be more task-oriented and focused on the application of knowledge and skills than traditional students who primarily focus on attaining a degree. Professionals tend to have course goals related to job performance, such as learning new job-required skills, preparing tools and resources for use at work, and earning credentials that meet job requirements (Milligan & Littlejohn, 2014, 2017). In turn, professionals tend to exhibit different course behaviors than traditional students. For example, professionals are more likely to exhibit control and direct their learning to resources beneficial to their job (Hood, Littlejohn, & Milligan, 2015). Professionals are also more likely to pursue micro-credentials that certify mastery of specific topics embedded within a course (Hodges, Lowenthal, & Grant, 2016).

Second, external life obligations influence the ways learners interact with a course. Working professionals tend to have more high priority obligations, such as job and family, competing with formal learning than traditional students who primarily focus on their education. Competing obligations introduce restrictions around when course participation can occur, which can test learners' motivation (Kizilcec & Halawa, 2015). Professionals are often challenged to make effective use of irregular timeframes while maintaining diligent progress toward larger course goals (Littlejohn, Hood, Milligan, & Mustain, 2016; Milligan & Littlejohn, 2016). They may cope by limiting participation to a subset of resources, such as videos only, in some units or by taking a break from participation during busy weeks (Sun et al., 2014). This is reflected in observations that, at the beginning of a course, most professional learners express a desire to participate in as much of the course as possible (Ho et al., 2014; Shapiro et al., 2017), but many reach the end of courses with partial participation and wish they could have participated more (Hood et al., 2015; Kizilcec & Halawa, 2015; Loizzo, Ertmer, Watson, & Watson, 2017).

Motives & goals. Studies of motives show learners enroll in MOOCs for different reasons, but those reasons can be described by a handful of common themes. Quantitative and qualitative accounts both indicate most learners enroll because they are interested and want to know more about a topic, desire an improvement in job performance or career status, or are curious to experience a MOOC for the first time (Hew & Cheung, 2014; Kizilcec & Schneider, 2015; Milligan & Littlejohn, 2014, 2017; Milligan et al., 2013; Salmon, Pechenkina, Chase, & Ross, 2017). In addition, the majority of learners choose to enroll in a MOOC, instead of a traditional class format, because they want a flexible class that lets them choose what they learn and participate at a pace that fits their personal schedule (Bonk & Lee, 2017; Liu et al., 2014; Loizzo et al., 2017; Milligan & Littlejohn, 2014; Park & Choi, 2009; Shapiro et al., 2017).

Learners also enter MOOCs with different goals for participation and achievement. Some intend to complete all requirements and earn a certificate – typically in the range of 25% to 50% per course – while others set goals for partial participation (Blackmore, 2014; Gray, Corley, & Eddy, 2016; Ho et al., 2015; Koller et al., 2013; Reich, 2014; Rieber, 2016). Partial participation goals are often strategic in the sense that learners target a subset of resources believed to be valuable and feasibly completed in the time available to the learner (Hodges et al., 2016; Milligan & Littlejohn, 2014, 2017; Sun et al., 2014). For example, a common tactic is to avoid resources requiring active participation, such as forum posting, and focus on resources allowing passive consumption, such as watching lecture videos and collecting tools and resources. However, a notable caveat is that partial participation goals are often rooted in an assumption that external obligations will interfere with course participation, rather than a lack of interest in other areas of the course (Liu et al., 2014; Loizzo et al., 2017; Milligan & Littlejohn, 2014; Shapiro et al., 2017).

With little surprise, learners who enter MOOCs with greater intentions for participation and achievement tend to access more course resources, complete more assignments, and earn more certificates on average (Creager, Wiebe, & Kellogg, 2018; Creager et al., 2019; Kizilcec & Halawa, 2015; Kizilcec & Schneider, 2015; Milligan et al., 2013; Phan, McNeil, & Robin, 2016; Wang, Baker, & Paquette, 2017). However, goals do not always equate to behavior. Some learners who enter a course with partial participation goals become deeply involved as the course progresses and end up earning a certificate (Creager et al., 2018; S. Kellogg & Kleiman, 2018). On the other hand, less than one-half of learners with an initial goal to earn a certificate typically complete certificate requirements, and more than half of all registrants drop out before the end of the course, regardless of their initial goal (Ho et al., 2015; Koller et al., 2013; Reich, 2014; Rieber, 2016). Thus, even goals which have been tempered by the expectation of competing obligations are often not attained.

Learners disengage from MOOCs for different reasons, but two key themes emerge in the literature. First, learners report not having enough time to participate due to competing obligations, which is consistent with the typical lives of working professional learners (Kizilcec & Halawa, 2015; Kop & Fournier, 2010; Liu et al., 2014; Nawrot & Doucet, 2014; Park & Choi, 2009; Shapiro et al., 2017). Most of these learners report a desire to participate more, but priorities, such as job demands and family illness take precedence. Second, many learners believe content is not attractively presented or they are dissatisfied with the degree of autonomy provided by the course (Chen & Jang, 2010; Kizilcec et al., 2013; Nawrot & Doucet, 2014; Shapiro et al., 2017; Yang, 2014; Zhou, 2016). These learners who are not captivated or are not given control early enough in the course to sustain motivation are likely to not form intentions to use and drop out. Given limited time for participation and a desire for content relevant to one's

job, it seems reasonable for working professional learners who are more interested in learning content than fulfilling certificate requirements to seek alternatives with more freedom of choice to maximize the limited time available (Shapiro et al., 2017).

In summary, MOOC literature has documented that working professionals comprise the majority of MOOC learners (virtually all in professional development MOOCs), and the distinct needs, motivations, and goals of working professionals potentially explain the low persistence, engagement, and achievement outcomes observed in MOOCs. For some learners, progress toward a desired certificate is stifled by conflicts with external obligations, and MOOCs have not offered sufficient accommodation and motivation for those learners to achieve their goals. Some other learners, particularly those who do not initially seek a certificate, find the value of MOOCs is limited by the control they have to access relevant content in the limited time they have available, and poor early impressions can lead to disengagement and drop out before experiencing content of value that could sustain additional engagement. An outstanding challenge faced by MOOC designers is identifying ways to give learners more flexibility and control over their learning to accommodate and motivate additional participation amidst competing demands.

Theoretical Framework

Educational and psychological theory provides insight into the mechanisms involved during the learning process and informs how the design of a learning environment, such as a MOOC, can support flexibility and control for learners.

Self-directed learning theory. Self-directed learning theory (SDL) is a theory of adult education which describes the role of the learner in the selection of a learning trajectory and in the act of learning itself, typically in work- or hobby-related contexts (Collins, 2004; Saks &

Leijen, 2014). In this way, SDL embodies principles of both student-centered learning and the principles of self-regulation (Schulze, 2014; Stubbé & Theunissen, 2008).

In the absence of a grade school or college curriculum, the education most adults experience is related to their work, and it involves the acquisition of practical wisdom with high application value (Merriam, 2001; Smith, 2002). Most adult learners gain experience in the real world and extrapolate an understanding of what they need to do to improve their performance in similar situations in the future. These experiences influence the learning trajectories learners pursue.

At the heart of SDL theory is a tenant that adult learners have control over their learning decisions (Stubbé & Theunissen, 2008). Adult learners use real-world experiences to diagnose their educational needs, form learning goals, identify what resources are needed to accomplish the learning, select and use learning strategies, and evaluate progress. Adult learners may need help making some informed decisions, but they are ultimately in control of handling information from their environment and choosing what to learn and how to achieve it.

Throughout a learning endeavor, adults exercise control over a breadth of processes internally and in their external environment. Bouchard (2009a) describes these in four categories: conative, algorithmic, semiotic, and economic. Conative factors refer to the internal dynamics within a learner that initiate and sustain learning, including life decisions to pursue a career change or prevent a bad work experience from happening again, as well as pursuing intrinsic and extrinsic motivators, such as autonomy, interest, or a raise in pay. Algorithmic processes regulate the cognitive components of learning, such as formulating learning goals, sequencing content in a favorable order, pacing learning, and evaluating progress (see also Kop & Fournier, 2010). Semiotic processes regulate selection and use of types of resources and

learning environments that promote autonomy and social connection (see also Song & Hill, 2007). Lastly, economic processes involve judgements of knowledge value and regulation of resources and learning environments based on opportunity costs of different learning approaches.

The degree of self-directed control a learner takes is a product of the relationship between a learner's self-directed learning skills and the structures and supports of the learners' environment (Merriam, 2001). In the right environment providing opportunity for autonomy with the proper supports, any learner can be self-directed (Stubbé & Theunissen, 2008). Though, self-directed learning skills vary between individuals, such as between learners with different education levels (Merriam, 2001), and can lead to problems if not enough autonomy is provided or not enough supports are provided.

In the design of formal learning environments, the balance of autonomy and constraints given to adult learners impacts both perception and behavior. SDL design principles indicate learners need options to pursue topics, resources, and tasks that apply to their personal experiences so they can select a relevant path, maintain motivation, and achieve beneficial outcomes (Bonk & Lee, 2017). In the context of distance education, adults are often drawn to distance course because of the flexibility to fit learning into their busy schedules, so if adults are not given enough control to regulate their participation, then their learning will be limited (Loizzo et al., 2017; Park & Choi, 2009; Waard, 2016). Learners also need flexibility to regulate the timing of their participation, particularly in internet-based ubiquitous learning environments, (Bouchard, 2009b; Stubbé & Theunissen, 2008). At the same time, if additional opportunities for autonomy are introduced, additional supports or default paths and timelines should be provided for learners who are not able to self-direct in the given context.

In summary, SDL theory suggests adult learners are heavily motivated and somewhat restricted by their life context. Experiences, typically work-related, drive not only learning objectives but also decisions about what paths to take during the learning process and how to regulate learning along the way. Comparing these tendencies to current standard of MOOC course structure with rigid, linear progression and fix, weekly release schedule, there is potential for MOOCs to offer learners more control over their learning pathways and participation schedules.

The Present Study

The present study examined an educator professional development MOOC that implemented a new, flexible course structure offering learners more control over their pacing and pathway through units in the middle of the course. Content in the flexibly structured units did not have knowledge dependencies, so all flexibly structured units were made available at the same time, rather than one at a time. Learners were given freedom to regulate their rate of participation and the order in which they participated in different units with the aim of increasing persistence, engagement, and achievement by providing learners with more opportunities to participate and structure their learning, relative to the traditional course structure.

The primary focus was to evaluate the effectiveness of the flexible course structure relative to the traditional course structure, and the secondary focus was to explore navigation behaviors with intentions of understanding how learners interact with flexible course structures and providing design recommendations for future courses.

Proposed model. Course flexibility and learner characteristics were expected to impact course outcomes, but the impact of course flexibility was expected to be moderated by learner characteristics as shown in Figure 1.

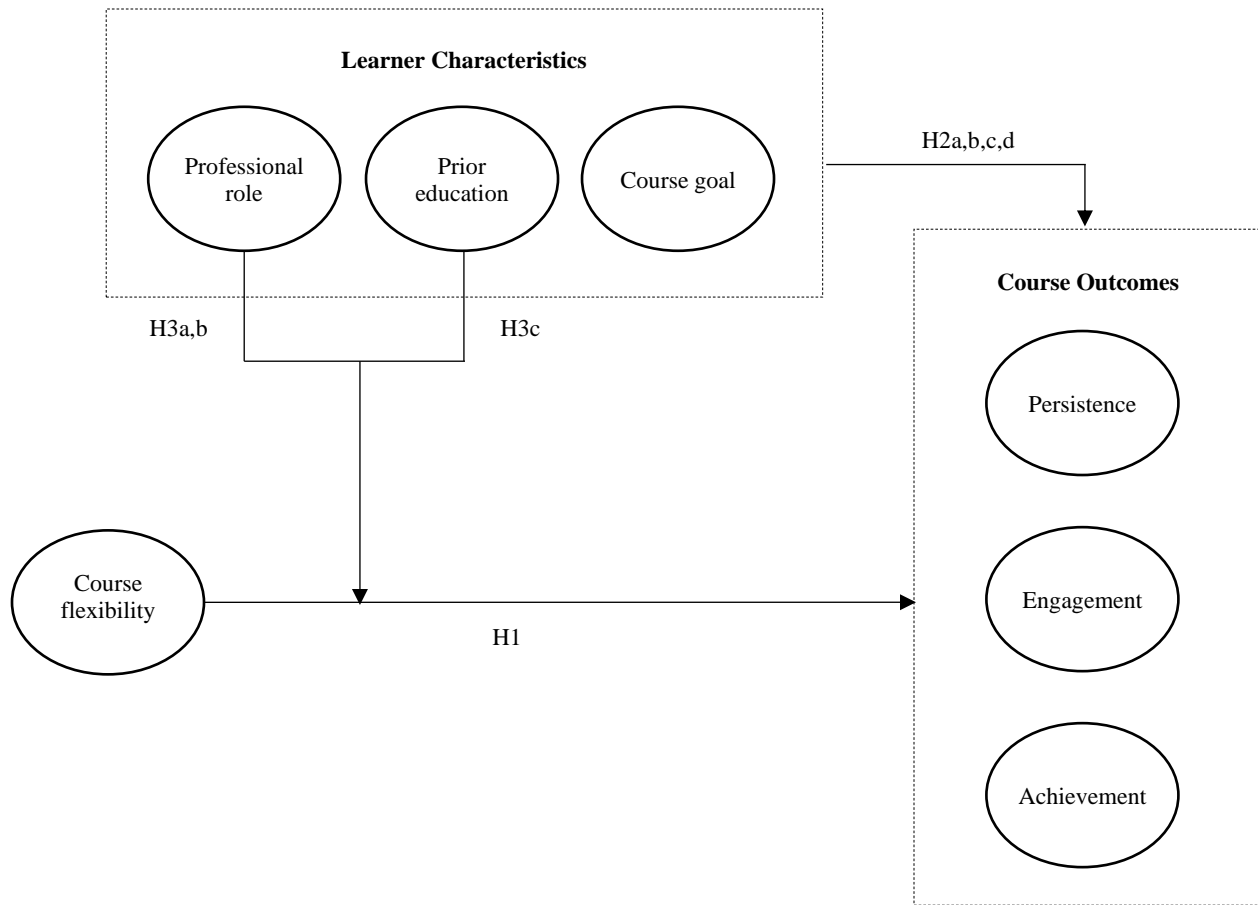


Figure 1. Initial model of course flexibility, learner characteristics, & course outcomes. In this model, course flexibility and learners’ professional role, prior education, and course goals are related to course outcomes of persistence, engagement, and achievement. Professional role and prior education also moderate the relationship between course flexibility and course outcomes.

MOOC learners need flexibility to schedule their participation and autonomy during the learning process (Nawrot & Doucet, 2014; Shapiro et al., 2017), and design principles based on self-directed learning theory suggest flexibility in course structure could address these needs (Park & Choi, 2009; Stubbé & Theunissen, 2008). In addition, studies of educator professional development MOOCs report that educators take advantage of flexibility in how they utilize resources (G. Kleiman et al., 2015). This led to the following hypothesis about the impact of flexible course structure:

H1 – Learners in a course with flexible structured units will persist longer in the course, engage more with course resources, and achieve more certifications than learners in a course with traditionally structured units.

Educator professional development MOOCs attract learners with a variety of professional roles, including leadership, such as principals and district management, classroom teachers, and support staff, such as instructional technology and library/media teachers (S. Kellogg & Kleiman, 2018; G. Kleiman et al., 2015). The job responsibilities of each role vary such that leaders tend to have the least consistent schedules and the least time available for professional development at an average 60 hour work week before professional development, followed by classroom teachers working an average 53 hour work week before professional development (Duignan, 2007; Gilson, 2008; Lavigne, Shakman, Zweig, & Greller, 2016; Scholastic & Bill & Melinda Gates Foundation, 2012). Conflicting job obligations and less dedicated time for course participation led to the following hypotheses:

H2a – Learners who work as classroom teachers will persist longer, engage more with course resources, and achieve more certifications than learners who work as educational leaders.

H2b – Learners who work as support staff will persist longer, engage more with course resources, and achieve more certifications than learners who work as classroom teachers.

Prior experience with formal education has been linked to future performance in education, and this holds in the context of MOOCs. MOOC learners with more prior formal education tend to have better lecture video engagement, assessment engagement, and

achievement in terms of course grades (Breslow et al., 2013; Kizilcec & Halawa, 2015; Morris, Hotchkiss, & Swinnerton, 2015), which led to the following hypothesis:

H2c – Learners who hold a postgraduate degree will persist longer, engage more with course resources, and achieve more certifications than learners with less formal education.

Studies of learner goals in the MOOC literature show learners who enter MOOCs with greater intentions for participation and achievement tend to access more course resources. Specifically, learners with the goal of earning a certificate complete more assignments and earn more certificates than learners with other goals (Creager et al., 2018; Kizilcec & Schneider, 2015; Milligan et al., 2013; Phan et al., 2016). This led to the following hypothesis:

H2d – Learners who possess a goal to earn a course certificate will persist longer, engage more with course resources, and achieve more certifications than learners with other goals.

The flexible course structure in the present study is designed to better accommodate inconsistent schedules by allowing learners to distribute their coursework during the modular units according to when time can be created. For example, if a learner has the most time during the week the modular units are released, that individual can complete more than one unit to compensate for less time the following weeks. The flexible course structure also allows busy learners to utilize resources most relevant to them in the limited time they have, which increases the likelihood of learners getting exposure to personally relevant content before dropping out because of low perceived value. Learners with less time to participate seem most likely to take advantage of and benefit from the flexibility offered by the course. As mentioned above,

educational leaders and classroom teachers are some of the most time-stretched educators, which led to the following hypotheses:

H3a – Learners who work as educational leaders will have greater gains in course outcomes between a flexible course structure and traditional course structure, relative to learners who are classroom teachers.

H3b – Learners who work as classroom teachers will see greater gains in course outcomes between a flexible course structure and traditional course structure, relative to learners who hold supporting staff roles.

Self-directed learning involves a process of self-regulation whereby professional practice is monitored, evaluated in the context of goals, and learning goals are set to improve practice that is short of desired performance (Saks & Leijen, 2014). Learners who have developed more self-regulation skills tend to exhibit more self-directed behaviors (Jo, Tomar, Ferschke, Rosé, & Gašević, 2016; Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Littlejohn et al., 2016) and seem more likely to take advantage of pacing and pathway flexibility in the flexible course design (Merriam, 2001). Learners with higher levels of formal education tend to have better self-regulated learning skills (Kizilcec et al., 2017), which led to the following hypothesis:

H3c – Learners who hold postgraduate degrees will see greater gains in course outcomes from a flexible course structure, relative to learners who do not have a postgraduate degree.

Understanding navigation behaviors. In addition to evaluating the impact of the flexible course design on course outcomes, the present study aimed to describe how learners

utilized units with a flexible structure. Multiple behavioral patterns were investigated during the flexible parts of the course, including the rate of participation, transitions between units, and deviation from the default presented order of units, to better understand how flexibility was utilized.

Method

Course Description

Learning Differences was an 11-week course with a curriculum that covered strategies for education professionals to create a positive learning experience for students with diverse learning capabilities. The target audience was composed of teachers, administrative leaders, and support staff, but the course was available to anyone in the world, free of cost. The course implemented a social-constructivist design (Ferguson & Sharples, 2014; G. M. Kleiman & Wolf, 2016), which embedded course content in a combination of lecture notes, lecture videos, forums, supplemental resources, and assessments spread across multiple units. Three, non-exclusive methods of certification were offered, each of which could be exchanged for continuing education credits (CECs) or count toward other professional development requirements, if accepted by one's governing body (see Certification section below).

Course enrollment opened on August 28, 2017 and remained open until November 30, 2017 (the middle of the ninth week of the course). Beginning on October 2nd, 2017, content was gradually released in groups of one or more units over a period of six weeks. Weekly "spotlight" emails highlighted content as it became available to ensure participants were aware of the new content. After all content was released, the course remained open for an additional four weeks and five days, during which participants were encouraged utilize any resources they missed

during the initial release period and complete requirements for desired certifications. The last day of the course was December 15th, 2017.

Course content. Course content was divided into six units, which were made available to participants gradually throughout the content release period. The first unit, titled Thinking Differently about Student Learning (abbreviated TD), provided a foundational introduction to student capabilities, which was essential to the remainder of the course. The following three units released in the middle of the course, titled Working Memory (WM), Executive Function (EF), and Student Motivation (SM), each focused on a specific element of learning differences. These three units had modular content that only depended on the first unit and are hereafter referred to as the *modular units*. The final two units of the course, titled Strategies for Supporting the Whole Student (SS) and Internalizing a Growth Mindset (IG), integrated all of the previous material in the course, and thus were released last. All units were accessed through a central navigation interface located on the course home page, which indicated the release schedule of each unit.

The majority of resources in the six units were designed to help learners improve their personal professional practices. The exception was an optional, three-part coaching module for learners who wanted to coach their peers on how to account for learning differences. Coaching module content focused on peer-to-peer interactions and was thus topically independent and certified separately from the rest of the course. However, coaching module reflection activities asked participants to think about coaching in the context of the core course material, which made participation in the core course an essential complement to the coaching module. In fact, completion of core course content was a requirement for coaching certification, as discussed in the Certification section below.

Facilitation. The course instructor and two trained assistants monitored and facilitated forum and assessment activity throughout the course. Each day, facilitators reviewed new forum posts and replied to questions directed at facilitators. Facilitators also graded micro-credential submissions as they were received and, if points were deducted, facilitators added comments to the submission explaining which requirements were not met. Facilitator activity was not included in the archival data set.

Certification. The Learning Differences course offered three types of certifications: micro-credentials, a certificate of course completion, and a certificate of coaching module completion.

Micro-credentials were tied to unit assessments and certified the understanding and application of a single course topic. Each of the three modular units offered a micro-credential for achieving a 100% score on a three-question free-response quiz about the unit content. The “Strategies for Supporting the Whole Student” unit also offered a micro-credential for achieving a 100% score on a five-question free-response quiz about building plans of action to support students. Each micro-credential submission was manually graded by trained course facilitators according to a rubric established throughout previous iterations of the course. Feedback, including grades and comments, was given to participants, and participants had the option to adjust their responses and resubmit to get a higher score. The deadline for micro-credential submissions that counted toward course participation was the last day of the course.

Certificates of course completion were associated with participation throughout all core course content. To earn a certificate of course completion, participants had to view and post to at least one discussion per unit, attempt (but not necessarily earn) each of the four micro-credentials, participate in two course activities, complete a survey, and spend at least 25 hours

participating in the course – the last of which was on the honor system. The deadline for earning certificates of course completion was the last day of the course.

Certificates of coaching module completion were associated with participation in both the core course and the three parts of the coaching module. To earn this certificate, participants had to earn a certificate of course completion, participate in the coaching module for at least five hours, submit a completed coaching worksheet, and give another participant feedback on their coaching worksheet. The deadline for completing these requirements was the last day of the course.

Participants

A total of 1,078 people registered for the Learning Differences course. Seventy-six (7%) of the registrants enrolled under professional roles that were unrelated to practicing education or course goals unrelated to the course contents and were removed from the data set prior to analysis. Characteristics of the remaining 1,002 registrants are reported in Table 2 below. Of those who registered, 663 (66%) showed up to the course and used at least one resource. Of those who showed up to the course, 411 (62%) used at least one resource in the modular units and 177 (27%) earned a course certificate.

Table 2. Participant demographics.

Characteristic	Registered (<i>n</i> = 1,002)	Showed Course (<i>n</i> = 663)	Showed Mods (<i>n</i> = 411)	Earned Cert. (<i>n</i> = 177)
Role				
Teacher	468	318	204 (64%)	102 (32%)
Leader	181	112	68 (61%)	24 (21%)
Support	353	233	139 (60%)	51 (22%)
Post-grad Edu.				
No	408	267	171 (64%)	73 (27%)
Yes	594	396	240 (61%)	104 (26%)
Goal				
Earn	179	128	93 (73%)	58 (45%)
Collect	310	199	126 (63%)	49 (25%)
Learn	513	336	192 (57%)	70 (21%)

Note. Cert. = certificate for the course. Edu. = education. “Showed” refers to using at least one resource in either the course overall or the modular units specifically as specified by the accompanying qualifier. Percentages reflect the proportion of the number of course shows for that row. Some percentages may not sum to 100% due to rounding.

Materials

Navigational interfaces. As described above, the navigational interface, located on the course home page, controlled access to the six units. Twelve different navigational interfaces were constructed to manipulate (a) when the three modular units became available to participants and (b) the order in which the three modular units were listed. Six *traditional* interfaces provided access to one new unit each week of the six-week release period, similar to previous iterations of the course (see Figure 2). Each traditional interface listed and released the three modular units in a different order so all possible permutations were represented (WM-EF-SM, WM-SM-EF, EF-WM-SM, etc.). The remaining six *flexible* interfaces differed from the traditional interfaces in two ways. First, all three modular units were made available at the same time in the second week, instead of releasing modular units one at a time (see Figure 2). Second, flexible interfaces had text explicitly encouraging participants to choose the order they wanted to

complete the modular units. All navigational interfaces pointed to the same content, so only the timing and order of content varied between interfaces. The traditional interfaces released modular units one unit at a time while the flexible interfaces released all modular units at once.

Unit 1 Opens on 10/2	Thinking Differently About Student Learning Get acquainted with the concept of learning differences.	Unit 1 Opens on 10/2	Thinking Differently About Student Learning Get acquainted with the concept of learning differences.
Unit 2 Opens on 10/9	Working Memory Learn to support students' consumption, retainment, and use of information.	Units 2-4 Open on 10/9 Do all 3 units in any order. Choose your own path! Recommended pace is 1 unit/week.	Working Memory Learn to support students' consumption, retainment, and use of information.
Unit 3 Opens on 10/16	Executive Function Learn to support students' ability to plan, focus, and attend to tasks at hand.		Executive Function Learn to support students' ability to plan, focus, and attend to tasks at hand.
Unit 4 Opens on 10/23	Student Motivation Learn to foster students' intrinsic and extrinsic motivators.		Student Motivation Learn to foster students' intrinsic and extrinsic motivators.
Unit 5 Opens on 10/30	Strategies for Supporting the Whole Student Learn to identify the needs of students with multiple learning differences.	Unit 5 Opens on 10/30	Strategies for Supporting the Whole Student Learn to identify the needs of students with multiple learning differences.
Unit 6 Opens on 11/6	Internalizing a Growth Mindset Solidify and reflect on your understanding of learning differences.	Unit 6 Opens on 11/6	Internalizing a Growth Mindset Solidify and reflect on your understanding of learning differences.

Figure 2. Comparison of navigational interfaces. Traditional interfaces (left) released one unit per week over a total of six weeks. Flexible interfaces (right) released units over the same six-week period, but Units 2, 3, and 4 all became available in the second week and could be completed in any order. Note that the two interfaces shown represent only one of the six list orders. Ten additional interfaces (five traditional and five flexible) were created, so every permutation of the three modular units was represented.

Registration survey. When registering for the course, participants were required to complete a survey collecting demographics, goals, and information about their current teaching practices related to the course material (see Appendix A).

Embedded surveys. An optional survey was embedded at the end of each unit of the course. Surveys in the TD, WM, EF, and SM units asked participants to provide ratings of how much they learned in the units, estimates of time spent in the units, and identify if they had difficulties navigating through the units (see Appendix B). The survey in the SS unit asked participants to estimate their time spent in the unit and provide free response feedback about the usefulness of the materials, changes to their professional practice, and general course design feedback (see Appendix C). Lastly, the survey in the IG unit was a summative end-of-course

survey that asked participants to estimate time spent in the course, rate how much they learned, rate the impact of the course on their professional practice, and provide feedback on micro-credentials and other aspects of course design (see Appendix D).

Trace database. The online course platform passively collected and stored trace data logs of participants' interactions with the course in a MySQL database. Trace data captured the dates, times, and types of participants' administrative actions (e.g. logging in/out of the course) and interactions with course resources (e.g. viewing pages, posting to forums, submitting assessments etc.). Trace data also captured achievement outcomes, such as micro-credential grades and certificate completion.

Experimental Design

After registering for the course, participants were assigned to one of 12 experimental conditions and placed into one of four forum cohorts, as discussed below. The experimental condition determined which of the 12 navigational interfaces would be seen in the course. The forum cohort determined with whom each participant would be able to communicate in the course forums. That is, the course platform isolated each cohort, so participants could only interact with other participants in the same cohort.

The twelve experimental conditions were formed by assigning each participant to one of the two *interface types* (traditional or flexible) and one of six *presentation order* permutations, which determined the order that the three modular units were listed (A-F as shown in Table 3). Due to a limitation in the capabilities of the online course platform, different assignment procedures were used for people who registered before the course started and people who registered after the course started. Participants who registered before the course started were randomly assigned to one of the twelve experimental conditions (EC1-EC12 as shown in Table

3). Participants who registered after the course started were randomly assigned to either EC1, EC6, EC7, or EC12, which represented permutations A and F for each of the interface types.

Table 3. Experimental conditions.

Exp. Condition	Interface Type	Presentation Order	
		Name	Unit Order ^a
EC01	Traditional	A	WM, EF, SM
EC02	Traditional	B	WM, SM, EF
EC03	Traditional	C	EF, WM, SM
EC04	Traditional	D	EF, SM, WM
EC05	Traditional	E	SM, WM, EF
EC06	Traditional	F	SM, EF, WM
EC07	Flexible	A	WM, EF, SM
EC08	Flexible	B	WM, SM, EF
EC09	Flexible	C	EF, WM, SM
EC10	Flexible	D	EF, SM, WM
EC11	Flexible	E	SM, WM, EF
EC12	Flexible	F	SM, EF, WM

Note. Exp. = Experimental. TD = Thinking Differently about Student Learning. WM = Working Memory. EF = Executive Function. SM = Student Motivation. SS = Strategies for Supporting the Whole Student. IG = Internalizing a Growth Mindset.

^aReading left-to-right, units would be displayed top-to-bottom in the navigational interface.

Assignment to the four forum cohorts was determined by participants' experimental conditions. Participants in traditional interface experimental conditions (i.e. EC01-EC06) were randomly assigned to one of two forum groups (FC01 and FC02), and participants in flexible interface experimental conditions (i.e. EC07-EC12) were randomly assigned to one of two other forum groups (FC03 and FC04), as shown in Figure 3. The number of forum cohorts was selected based on (a) experience from previous iterations of the course, in which forums were most active with ~300 members and (b) a projected course enrollment of ~1200.

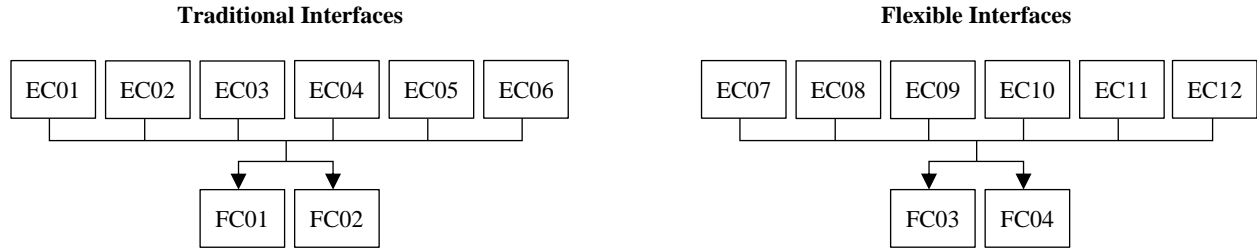


Figure 3. Experimental condition and forum cohort assignment. Participants exposed to traditional interfaces (EC01-EC06) were assigned to either forum cohort 1 or 2 (FC01 or FC02). Participants exposed to flexible interfaces (EC07-EC12) were assigned to either forum cohort 3 or 4 (FC03 or FC04).

Balance Checks

Distributions of professional role, prior education, and primary goal were examined between levels of the experimental variables to verify a reasonable balance of learner characteristics after random sampling. Nominal differences were observed between the course overall and levels of the experimental variables for all three learner characteristics as shown in Table 4.

Table 4. Learner characteristics by interface and presentation order.

Characteristic	Interface		Presentation Order					
	Traditional	Flexible	A	B	C	D	E	F
Role								
Teacher	224 (46%)	244 (47%)	135 (50%)	54 (45%)	45 (39%)	48 (45%)	53 (46%)	133 (48%)
Leader	94 (19%)	87 (17%)	51 (19%)	19 (16%)	25 (22%)	18 (17%)	22 (19%)	46 (17%)
Support	168 (35%)	185 (36%)	85 (31%)	46 (39%)	44 (39%)	41 (38%)	39 (34%)	98 (35%)
Post-grad Edu.								
No	199 (41%)	209 (41%)	114 (42%)	40 (34%)	51 (45%)	46 (43%)	40 (35%)	117 (42%)
Yes	287 (59%)	307 (59%)	157 (58%)	79 (66%)	63 (55%)	61 (57%)	74 (65%)	160 (58%)
Goal								
Earn	88 (18%)	91 (18%)	48 (18%)	22 (18%)	18 (16%)	25 (23%)	23 (20%)	43 (16%)
Collect	148 (30%)	162 (31%)	80 (30%)	33 (28%)	47 (41%)	30 (28%)	46 (40%)	74 (27%)
Learn	250 (51%)	263 (51%)	143 (53%)	64 (54%)	49 (43%)	52 (49%)	45 (39%)	160 (58%)

Note. Edu. = education. All participants who registered for the course are included (after data cleaning). Percentages reflect the proportion of the vertical total for role, post-graduate education, and goal respectively. Some percentages may not sum to 100% due to rounding.

Evaluation Study

In addition to the aforementioned experiment, an evaluation study with 49 participants (37 of whom showed up to the course and 14 of whom earned a certificate of course completion) was conducted during the same Learning Differences course on behalf of the course's funding agency. Data from evaluation study participants were not included in the archival data set, but the potential influence of the evaluation study on the archival data set is discussed below.

Precautions were taken to minimize the impact of the evaluation study on the experiment. Evaluation study participants were recruited separately from a population not expected to otherwise participate in the course. In addition, although evaluation participants were shown a traditional navigational interface similar to EC01, evaluation participants were not included in the experimental condition assignment process, so experimental group sizes were not affected by the evaluation study.

Still, there was potential for the evaluation study to impact experimental forum data. Evaluation study participants were placed into forum cohorts FC01 and FC02 with traditional interface experimental participants to ensure the evaluation participants experienced the social dynamics of a largely populated open online course. This created unequal opportunity for traditional interface experimental participants to interact with evaluation participants, relative to flexible interface experimental participants in other forum cohorts. However, given the small number of evaluation participants, forum interactions between evaluation and experiment participants were expected to be minimal and have a negligible impact on the data set.

Measures

Predictor variables. Two experimental variables and three measures of learner characteristics served as predictors during analysis: interface type, presentation order, professional role, prior education, and primary goal.

Interface type. A binary variable representing whether or not the course’s navigational interface offered a flexible course structure, as opposed to the traditional course structure.

Presentation order. A categorical variable with six levels (A-F) representing the order the three modular units were listed in the course’s navigational interface.

Professional role. A measure of *professional role* was constructed by categorizing responses to the “Primary area of responsibility” question on the registration survey (see Appendix A item 4). The three categories were classroom teaching, support staff (composed of curriculum and instruction, instructional technology, library/media, school counselor, special education, and other), and leadership (composed of school-based administration, school district administration, teacher preparation – college/university, professional development, and mentor).

Prior education. Participants' highest degree of education attained was extracted from responses to the level of education question on the registration survey (see Appendix A item 2). Based on the high percentage of educator professional development learners with advanced college degrees (G. Kleiman et al., 2015), the procedure of Kizilcec et al. (2017) was followed, where a single binary variable, *postgraduate*, was constructed based on whether or not participants possessed a postgraduate degree.

Primary goal. Participants' *primary goal* for the course was collected in the registration survey question "Which of the following best describes your primary reason for enrolling in this course?" (see Appendix A item 8). Responses were categorized as learning (deepen my knowledge of the course topics), collecting (collect resources and tools for my practice), and earning (earn a certificate of accomplishment/renewal credits).

Criterion variables. Six types of criterion variables were formulated from behavioral data in the course: persistence, engagement, achievement, pace, transitions, and divergence. Variants of persistence, engagement, and achievement were calculated for both the course overall and the modular units, which allowed flexible and traditional course designs to be evaluated in the context of the entire course and the experimentally manipulated units. Pace, transitions, and divergence were only calculated for the modular units to describe different aspects of interaction with the experimentally manipulated units.

Persistence. Three binary measures of persistence were formulated from trace data: *persistence to week 2* when modular units were released, *persistence to week 5* when the fifth unit was released, and *persistence to week 6* when the final unit was released. Learners were considered persisting to a given week if they used at least one resource during or after that week. Resource use was operationalized as performing one of six types of interactions with the five

types of resources in the course: lecture note views, lecture video views, forum thread views, forum thread posts, supplemental resource views, and assessment submissions.

Engagement. Following prior research suggesting behavioral engagement is a complex construct with multiple facets (DeBoer et al., 2014; Lee, 2018), three types of engagement measures – frequency, variety, and duration of resource use - were formulated from trace data. The same six interactions mentioned above were used in the calculations. Measures were calculated at two levels of scope: *course engagement* from the course overall and *modular engagement* from the modular units.

Frequency of resource use was computed by counting the number of times resource interactions were performed. For example, if two lecture notes were viewed and two videos were viewed, the frequency score would be four. *Variety* of resource use was constructed by counting the unique types of resource interactions performed (Thompson, Wiebe, Creager, & Frankosky, 2016). For example, if two lecture notes were viewed and two videos were viewed, the variety score would be two. *Duration* of resource use was constructed by summing the number of hours spent performing resource interactions (see Appendix E: Duration Calculation for code and detailed explanation). If the length of an interaction was greater than 0.33 hours, or 20 minutes, the length was set to 0.33 hours to minimize the influence of noise on the data, such as a participant leaving the browser tab open while doing something unrelated to the course.

Achievement. Trace data from each learner was used to determine whether or not a *micro-credential* was earned during the modular units. Trace data was also used to determine whether or not each learner earned a *course certificate*.

Pace change. Trace data was used to formulate a measure of *pace change*, which captured the consistency of engagement in the weeks modular units were released. Pace change

was computed as the average absolute weekly differential in engagement duration during the weeks modular units were released (see Figure 4). In other words, two values were averaged: the absolute difference between weeks two and three and the absolute difference between weeks three and four. A smaller value represented a more consistent pace.

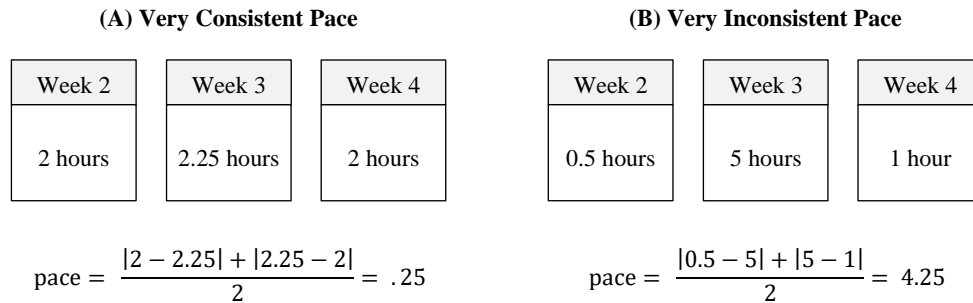


Figure 4. Pace change examples. Two examples of pacing participation during the weeks modular units were released – one very consistent (A) and one very inconsistent (B). In example A, a learner engaged in each of the three modular units on a different week, and participated for 2-2.25 hours each week. This was a very consistent pace over those three weeks, resulting in a pace change score of 0.25 hours. In example B, a learner briefly engaged in the first modular unit for 0.5 hours during the second week of the course, the first and second modular units for a total of 5 hours during the third week, and the third modular unit for one hour during the fourth week. This was an inconsistent pace, resulting in a pace change score of 4.25 hours.

Transitions. A count of *transitions* between modular units was constructed from trace data. A transition was considered to be between modular units if subsequent resource interactions occurred in different modular units (see Figure 5).

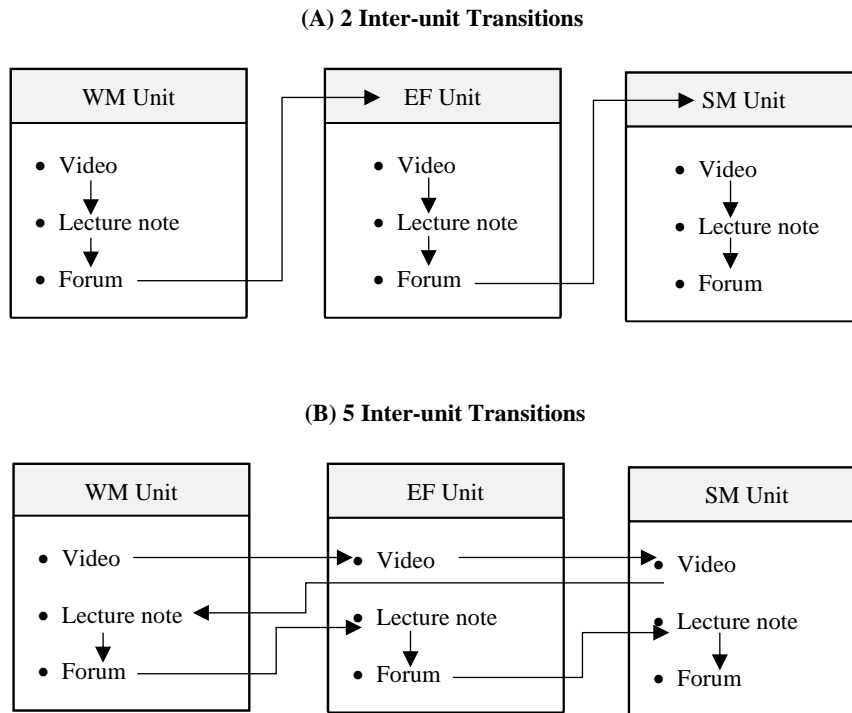


Figure 5. Transition examples. WM = Working Memory. EF = Executive Function. SM = Student Motivation. Two examples of resource utilization between modular units – one with two inter-unit transitions (A) and one with five inter-unit transitions (B). In these examples, each unit has three resources: a video, lecture note, and forum. The sequence of resource use is indicated by arrows. In example A, a learner used all resources within a unit before moving to the next unit. In example B, a learner watched a video in each unit before utilizing the lecture notes and forum in each unit.

Divergence. A binary measure of *divergence* was constructed from trace data to indicate whether or not the order learners utilized the modular units matched the order modular units were presented in the navigational interface (see Figure 6). The order learners utilized the modular units was determined by the following process. First, the duration of resource use in each unit was calculated for each learner. Second, units with less than five minutes of use were excluded. Third, the point in time at which a learner reached 95% of their duration in each unit was marked. Finally, the chronological order in which units were marked determined the order

of use. This result was compared to the presentation order to determine divergence (i.e., the orders were different).

(A) Divergent		(B) Not Divergent	
Presentation Order	Order of Use	Presentation Order	Order of Use
1. WM	1. EF	1. WM	1. WM
2. EF	2. WM	2. EF	2. EF
3. SM	3. SM	3. SM	3. SM

Figure 6. Divergence examples. WM = Working Memory. EF = Executive Function. SM = Student Motivation. Two examples, each showing the order modular units were listed in the navigational interface (presentation order) and the order modular units were used (order of use). In example A, a learner used the EF and WM units in the opposite order from their presentation, which was divergent. In example B, a learner used all modular units in the order they were presented, which was not divergent.

Results

Data from each course outcome were explored, and then hierarchical logistic regressions or hierarchical multiple regressions were performed to analyze the hypothesized relationships between the interface type, learner characteristics, and course outcomes with presentation order included as a control and an alpha level of .05. In each hierarchical analysis, a two-step approach was followed to examine hypothesized main effects (initial model) of each predictor and hypothesized moderation effects (second model) between predictors (Cohen, Cohen, West, & Aiken, 2003). The initial regression model was analyzed without interaction terms to determine if individual predictors had relationships with outcomes. The second regression model – containing both individual predictors and hypothesized interactions – was analyzed to determine (a) if moderation effects existed above and beyond the effects of the individual

predictors, i.e., if a moderation effect existed after accounting for variance explained by individual predictors, and (b) if moderation effects explained away main effects, i.e. individual predictors that were significant in the initial model were non-significant in the second model when interactions were present. The following levels were set as contrast groups: traditional interface, presentation order A, teacher role, no post-graduate education, and goal to earn a course certificate.

Persistence

The proportion of learners persisting week-to-week was plotted by interface type and broken down by learner characteristic to visualize persistence patterns (Figure 7). Consistent with prior literature, persistence declined over time, and just under half (49%) of learners who showed up to the course were active in by the sixth week when the last unit was released (Reich, 2014). However, persistence declined at different rates depending on the course structure and learner characteristics. Across all learners who showed up to the course, persistence was slightly higher each week in the flexible course structure than in the traditional course structure (4% higher on average). The magnitude of that difference was much larger for teachers and learners with a goal to earn a certificate, increasing each week such that persistence to the sixth week was 17% higher for teachers in flexible interface conditions and 21% higher for learners with a goal to earn in the flexible interface conditions, relative to those given the traditional interface. Learners without a post-graduate education had slightly better persistence with the flexible interface (8% higher on average), while leaders and support roles tended to have slightly better persistence in the traditional interface (4% and 5% higher on average, respectively). Persistence was very similar between interfaces for learners with a goal to collect or learn (1% difference on average) and learners with post-graduate degrees (2% difference on average).

Visually apparent differences in persistence between interface types for learners with different goals led to the inclusion of an interface-by-goal interaction in subsequent persistence analyses, even though the interaction was not initially hypothesized.

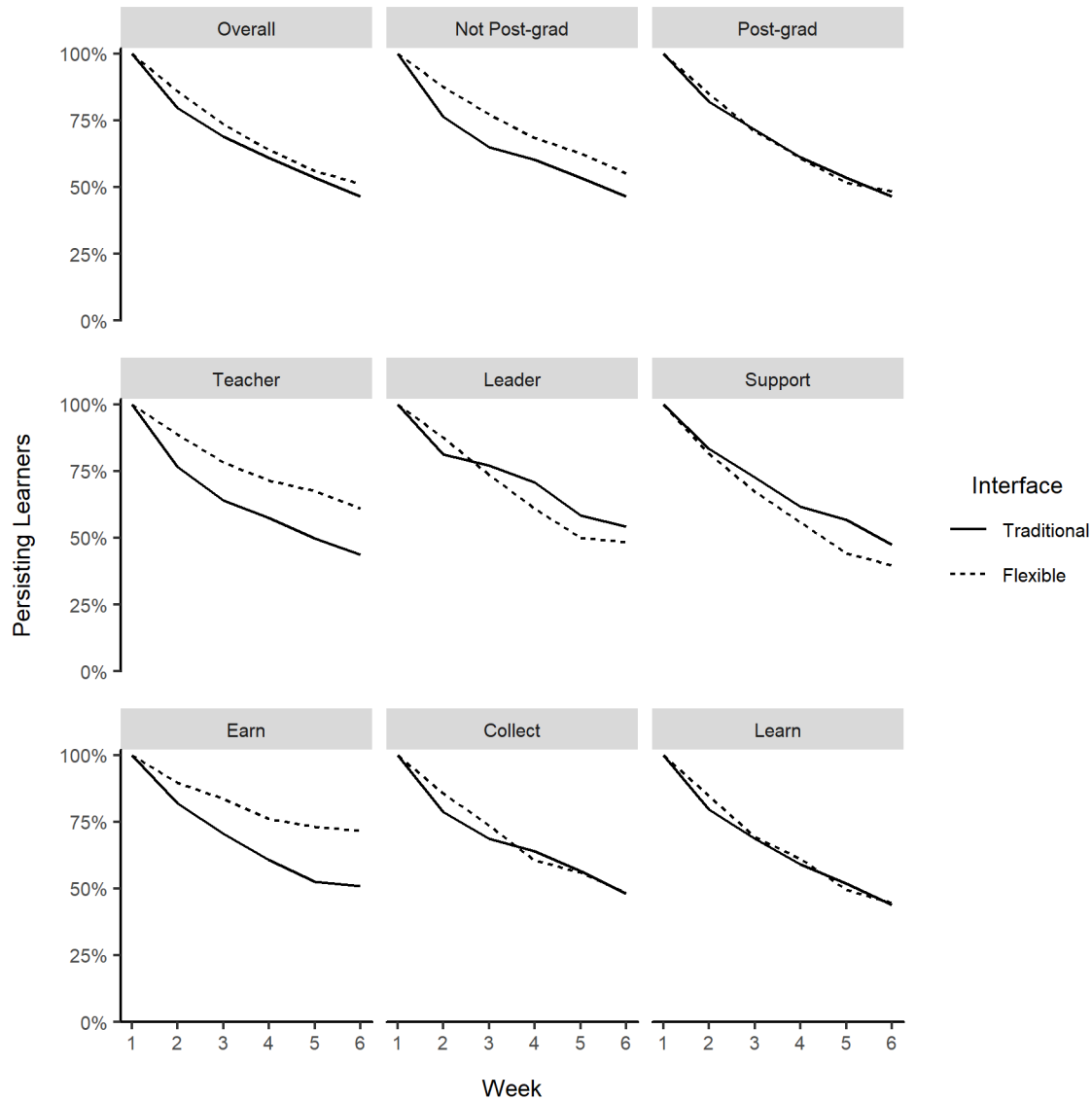


Figure 7. Persistence over time. Each panel represents a different subset of learners who showed up to the course ($n = 663$), as indicated by the learner characteristic in the title of each panel. The top left panel includes all learners who showed up to the course. The top right two panels subset by prior education. The middle row subsets by role. The bottom row subsets by goal. Percentages represent the proportion of learners with a given panel characteristic who persisted out of those who showed up to the course with the given characteristic.

Predictors of persistence to the second week of the course, when modular units were released, were analyzed via hierarchical logistic regression (see Table 5). All learners who showed up to the course were included, i.e. learners who registered for the course but never engaged with a resource after the course opened were excluded. A significant main effect was observed for the flexible interface type whereby the odds of learners given the flexible interface persisting to the second week were 1.57 times the odds of learners given the traditional interface, holding other predictors constant. A significant interaction effect was also observed between role and interface type such that the effect of interface was larger among teachers than support roles. Other main effects and interactions between learner characteristics and interface were non-significant.

Post-hoc logistic regressions were performed to analyze differences in persistence to the second week between interface types among learners with a teacher role and support role. Among teachers ($n = 318$), a significant main effect was observed for the flexible interface ($B = 0.87, p = .008, OR = 2.38, 95\% CI = [1.20, 6.22]$). Among support roles ($n = 233$), all main effects were non-significant after controlling for other the other predictors.

Table 5. Predictors of persistence to week two.

Predictor	Main Effect Model				Interaction Model			
	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI
Intercept	1.38 ***	0.33	3.96	[2.10, 7.79]	1.08 **	0.40	2.93	[1.37, 6.72]
Flexible interface	0.45 *	0.21	1.57	[1.04, 2.40]	1.13	0.59	3.09	[0.99, 10.26]
Pres. order B	-0.23	0.33	0.79	[0.42, 1.54]	-0.26	0.34	0.77	[0.40, 1.50]
Pres. order C	0.25	0.38	1.28	[0.63, 2.81]	0.28	0.38	1.32	[0.64, 2.91]
Pres. order D	0.25	0.39	1.28	[0.61, 2.90]	0.21	0.40	1.24	[0.59, 2.82]
Pres. order E	-0.28	0.33	0.75	[0.40, 1.46]	-0.25	0.33	0.78	[0.41, 1.52]
Pres. order F	0.64 *	0.30	1.89	[1.06, 3.46]	0.66 *	0.30	1.93	[1.07, 3.54]
Leadership role	0.17	0.31	1.19	[0.66, 2.23]	0.24	0.43	1.27	[0.57, 3.07]
Support role	0.02	0.23	1.02	[0.65, 1.62]	0.44	0.32	1.56	[0.85, 2.94]
Post-grad edu.	0.16	0.22	1.18	[0.77, 1.79]	0.41	0.29	1.50	[0.86, 2.64]
Collect goal	-0.31	0.32	0.74	[0.38, 1.37]	-0.35	0.42	0.71	[0.30, 1.59]
Learn goal	-0.35	0.30	0.71	[0.38, 1.25]	-0.32	0.39	0.73	[0.32, 1.53]
Flexible * Leader					-0.28	0.63	0.76	[0.22, 2.64]
Flexible * Support					-0.97 *	0.48	0.38	[0.15, 0.97]
Flexible * Post-grad					-0.53	0.44	0.59	[0.25, 1.39]
Flexible * Collect					0.12	0.66	1.13	[0.30, 4.13]
Flexible * Learn					0.01	0.61	1.01	[0.30, 3.29]
R^2_N	.04				.05			
<i>n</i>	663				663			

Note. Pres. = presentation. Edu. = education.

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

Predictors of persistence to the fifth week of the course, the week after all modular units had been released, were analyzed via hierarchical logistic regression (see Table 6). All learners who showed up to the course were included, i.e. learners who registered for the course but never engaged with a resource after the course opened were excluded. A significant main effect was observed for goal such that the odds of learners with a goal to learn persisting to the fifth week were 0.59 times the odds of learners with a goal to earn, holding other predictors constant. Significant interaction effects were also observed between role and interface type such that the effect of interface was larger among teachers than either leaders or support roles. Other main effects and interactions between learner characteristics and interface were non-significant.

Post-hoc logistic regressions were performed to analyze differences in persistence to the fifth week between interface types among learners with teacher, leadership, and support roles. Among teachers ($n = 318$), a significant main effect was observed for the flexible interface ($B = 0.74, p = .002, OR = 2.09, 95\% CI = [1.31, 3.35]$) after controlling for the other predictors. Among leaders ($n = 112$), a significant main effect was observed for a goal of learning ($B = -1.49, p = .03, OR = 0.22, 95\% CI = [0.05, 0.83]$) after controlling for other predictors. Among support roles ($n = 233$), all main effects were non-significant after controlling for other the other predictors.

Table 6. Predictors of persistence to week five.

Predictor	Main Effect Model				Interaction Model			
	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI
Intercept	0.59 *	0.25	1.81	[1.10, 3.00]	-0.03	0.32	0.97	[0.51, 1.82]
Flexible interface	0.12	0.16	1.12	[0.82, 1.54]	1.43 **	0.44	4.19	[1.78, 10.13]
Pres. order B	-0.06	0.27	0.94	[0.55, 1.61]	-0.08	0.28	0.92	[0.54, 1.60]
Pres. order C	-0.17	0.28	0.84	[0.48, 1.46]	-0.16	0.29	0.85	[0.48, 1.50]
Pres. order D	0.33	0.29	1.39	[0.78, 2.48]	0.29	0.30	1.34	[0.75, 2.42]
Pres. order E	-0.32	0.28	0.72	[0.42, 1.24]	-0.29	0.28	0.75	[0.43, 1.29]
Pres. order F	0.43 *	0.22	1.54	[1.01, 2.36]	0.43 *	0.22	1.54	[1.01, 2.37]
Leadership role	-0.12	0.23	0.89	[0.57, 1.39]	0.38	0.34	1.46	[0.75, 2.89]
Support role	-0.26	0.18	0.77	[0.54, 1.09]	0.24	0.25	1.28	[0.78, 2.08]
Post-grad edu.	-0.17	0.17	0.84	[0.61, 1.16]	0.00	0.23	1.00	[0.64, 1.58]
Collect goal	-0.20	0.24	0.82	[0.51, 1.30]	0.07	0.33	1.08	[0.56, 2.07]
Learn goal	-0.52 *	0.22	0.59	[0.38, 0.91]	-0.17	0.31	0.84	[0.46, 1.54]
Flexible * Leader					-1.02 *	0.46	0.36	[0.14, 0.90]
Flexible * Support					-1.07 **	0.36	0.34	[0.17, 0.70]
Flexible * Post-grad					-0.34	0.33	0.71	[0.37, 1.36]
Flexible * Collect					-0.60	0.49	0.55	[0.21, 1.43]
Flexible * Learn					-0.71	0.45	0.49	[0.20, 1.17]
R^2_N	.04				.08			
<i>n</i>	663				663			

Note. Pres. = presentation. Edu. = education.

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

Predictors of persistence to the sixth week of the course, when the last unit was released, were analyzed via hierarchical logistic regression (see Table 7). All learners who showed up to the course were included, i.e. learners who registered for the course but never engaged with a resource after the course opened were excluded. Significant main effects were observed for goals. The odds of learners with a goal to learn persisting to the sixth week were 0.49 times the odds of learners with a goal to earn, holding other predictors constant. The odds of learners with a goal to collect persisting to the sixth week were 0.62 times that of learners with a goal to earn, holding other predictors constant. A significant interaction effect was also observed between role and interface type such that the effect of interface was larger among teachers than support

roles. Other main effects and interactions between learner characteristics and interface were non-significant.

Post-hoc logistic regressions were performed to analyze differences in persistence to the sixth week between interface types among learners with teacher and support roles. Among teachers ($n = 318$), significant main effects were observed for the flexible interface ($B = 0.71, p = .003, OR = 2.03, 95\% CI = [1.28, 3.24]$), a goal to collect ($B = -0.77, p = .02, OR = 0.46, 95\% CI = [0.24, 0.88]$), and a goal to learn ($B = -0.61, p = .03, OR = 0.54, 95\% CI = [0.30, 0.95]$) after controlling for the other predictors. Among support roles ($n = 233$), all main effects were non-significant after controlling for other the other predictors.

Table 7. Predictors of persistence to week six.

Predictor	Main Effect Model				Interaction Model			
	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI
Intercept	0.42	0.25	1.52	[0.93, 2.50]	-0.09	0.32	0.91	[0.49, 1.71]
Flexible interface	0.19	0.16	1.20	[0.88, 1.65]	1.24 **	0.43	3.46	[1.49, 8.20]
Pres. order B	0.19	0.28	1.21	[0.71, 2.09]	0.19	0.28	1.21	[0.70, 2.09]
Pres. order C	-0.26	0.29	0.77	[0.44, 1.35]	-0.24	0.29	0.78	[0.44, 1.38]
Pres. order D	0.26	0.29	1.29	[0.73, 2.29]	0.23	0.29	1.26	[0.71, 2.25]
Pres. order E	-0.17	0.28	0.84	[0.49, 1.45]	-0.14	0.28	0.87	[0.50, 1.51]
Pres. order F	0.39	0.21	1.48	[0.97, 2.25]	0.39	0.22	1.47	[0.97, 2.25]
Leadership role	0.04	0.23	1.04	[0.67, 1.63]	0.49	0.34	1.63	[0.84, 3.19]
Support role	-0.26	0.18	0.77	[0.54, 1.09]	0.14	0.25	1.15	[0.71, 1.88]
Post-grad edu.	-0.11	0.16	0.90	[0.65, 1.24]	-0.04	0.23	0.96	[0.61, 1.51]
Collect goal	-0.48 *	0.24	0.62	[0.39, 0.98]	-0.18	0.33	0.84	[0.44, 1.60]
Learn goal	-0.72 ***	0.22	0.49	[0.32, 0.74]	-0.41	0.31	0.67	[0.36, 1.22]
Flexible * Leader					-0.88	0.46	0.41	[0.17, 1.02]
Flexible * Support					-0.86 *	0.36	0.42	[0.21, 0.86]
Flexible * Post-grad					-0.12	0.33	0.89	[0.46, 1.70]
Flexible * Collect					-0.66	0.48	0.52	[0.20, 1.32]
Flexible * Learn					-0.64	0.44	0.53	[0.22, 1.25]
R^2_N	.05				.07			
<i>n</i>	663				663			

Note. Pres. = presentation. Edu. = education.

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

Engagement

A principal axis exploratory factor analysis (EFA) was conducted on course frequency, variety, and duration measures without rotation to investigate the underlying latent structure of engagement among learners who showed up to the course, i.e. learners who registered for the course but never engaged with a resource after the course opened were excluded. Correlations between items are reported in Table 8. Bartlett's test of sphericity, $\chi^2(3) = 1385.43$, $p < .001$, indicated correlations between items were sufficiently large for an EFA, and the determinant of the item correlation matrix, $\det = 0.12$, indicated multicollinearity was not extreme. Scree plot inflection (Figure 8), parallel analysis, and the Kaiser criterion of eigen values greater than one

all favored a single factor solution upon initial analysis. Table 9 shows the factor loadings for the single resulting factor representing engagement.

Table 8. Correlation between course engagement measures.

Measure	1	2	3
1. Course frequency	-		
2. Course variety	.65***	-	
3. Course duration	.88***	.66***	-

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

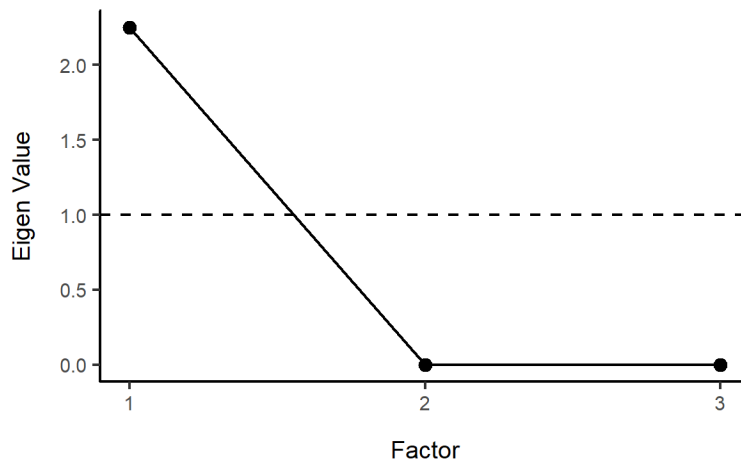


Figure 8. Scree plot for course engagement. The eigen value of the first factor was well above the Kaiser criterion of 1, but subsequent factors had near-zero eigenvalues. A point of inflexion at the second potential factor supported a single-factor solution.

Table 9. Factor loadings for course engagement.

Item	Factor
	Engagement
Course frequency	.93
Course variety	.70
Course duration	.94
Eigen value	2.25
Variance explained	75%

Note. Factor loadings greater than .40 are shown in boldface.
 * $p < .05$. ** $p < .01$. *** $p < .001$.

Given that duration correlated very strongly with the latent engagement factor (.94), duration was selected as the representative criterion for outcome analyses. The distribution of course engagement duration for learners who showed up to the course was positively skewed ($M = 5.73$, $SD = 6.66$) and significantly different from the normal distribution according to the Shapiro-Wilk test, $W = 0.79$, $p < .001$, so a base-ten log transformation was applied prior to further analyses ($M' = 0.36$, $SD' = 0.74$). Here forth, log-transformed values are reported, as indicated by the prime symbol (e.g. M' and SD').

To understand engagement patterns for the course overall, log transformed course engagement duration was plotted by interface type and broken down by learner characteristic to visualize engagement across the entire course for all learners who showed up to the course (see Figure 9). Log engagement was similar between levels of prior education, but teachers and learners with a goal to earn had higher log engagement than other roles and goals, respectively on average. Log engagement was slightly higher in the flexible interface conditions than the traditional interface conditions on average, and this trend held for every characteristic subset, except learners with a support role. The largest differences between interface types were observed for teachers, leaders, and learners with a goal to earn a certificate.

Visually apparent differences in log course engagement duration between interface types for learners with different goals led to the inclusion of an interface-by-goal interaction in subsequent engagement analyses, even though the interaction was not initially hypothesized.

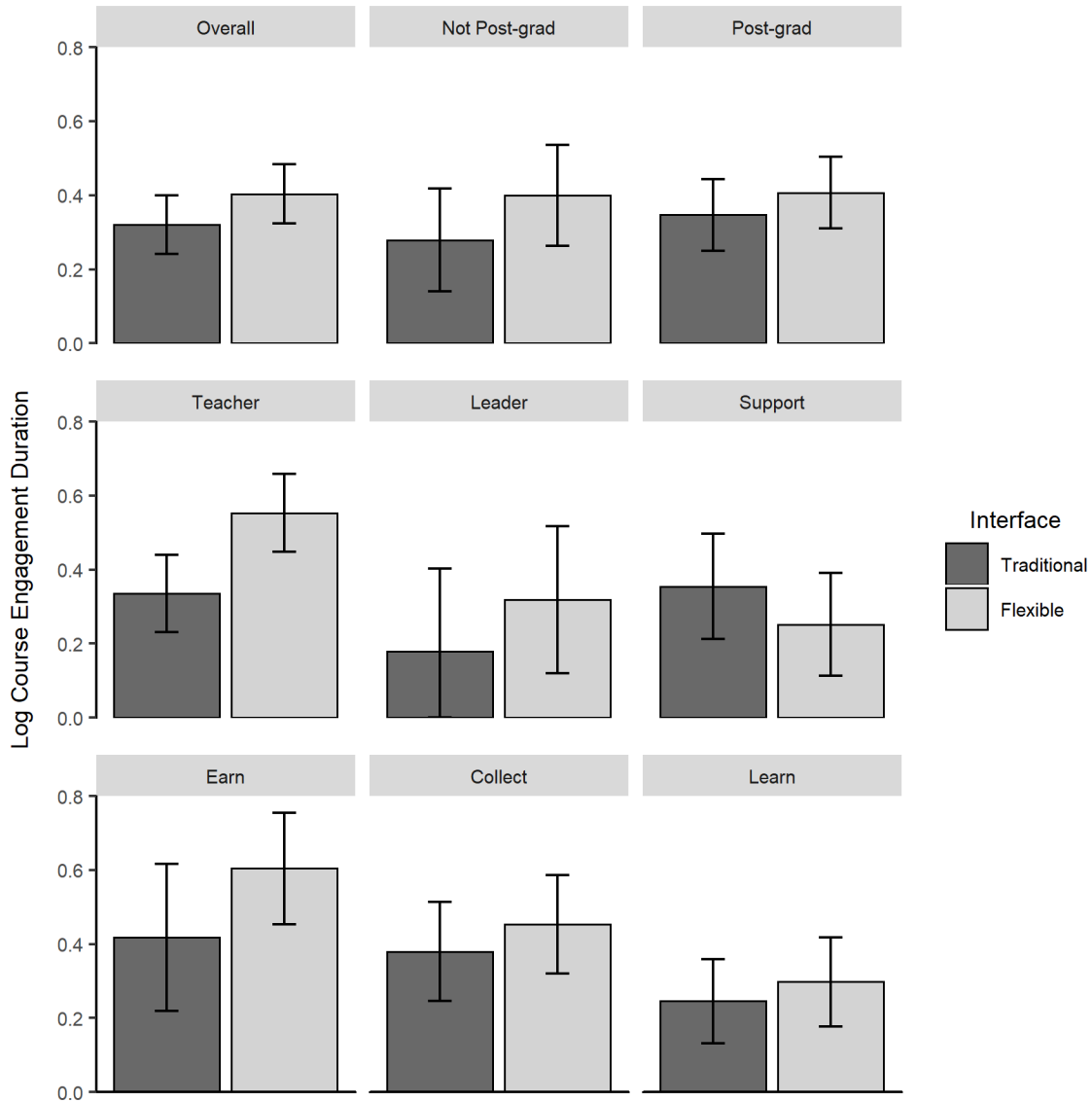


Figure 9. Log transformed course engagement duration. Each panel represents a different subset of learners who showed up to the course ($n = 663$), as indicated by the learner characteristic in the title of each panel. The top left panel includes all learners who showed up to the course. The top right two panels subset by prior education. The middle row subsets by role. The bottom row subsets by goal. Error bars are 95% confidence intervals.

Predictors of log-transformed course engagement duration were analyzed via hierarchical multiple regression (Table 10). All learners who showed up to the course were included, i.e. learners who registered for the course but never engaged with a resource after the course opened were excluded. Significant main effects were observed for role and goal. Leaders ($M' = 0.26$, $SD' = 0.80$) and support roles ($M' = 0.30$, $SD' = 0.78$) both spent significantly less time engaging with resources than teachers ($M' = 0.44$, $SD' = 0.68$) across the entire course while holding other predictors constant. Learners with a goal to learn ($M' = 0.27$, $SD' = 0.77$) spent significantly less time engaging with resources than learners with a goal to earn ($M' = 0.52$, $SD' = 0.72$) across the entire course, holding other predictors constant. A significant interaction effect was also observed between role and interface type where teachers shown the flexible interface ($M' = 0.55$, $SD' = 0.66$) engaged for longer durations than teachers shown the traditional interface ($M' = 0.34$, $SD' = 0.69$), whereas support roles shown the flexible interface ($M' = 0.25$, $SD' = 0.75$) engaged for shorter durations than support roles shown the traditional interface ($M' = 0.35$, $SD' = 0.80$). Other main effects and interactions between learner characteristics and interface were non-significant.

Post-hoc multiple regressions were performed to analyze differences in log course engagement duration between interface types among learners with teacher roles and support roles. Among teachers ($n = 318$), a significant main effect was observed for the flexible interface ($B = 0.21$, $p = .007$) after controlling for the other predictors. Among support roles ($n = 233$), all main effects were non-significant after controlling for other the other predictors.

Table 10. Predictors of log transformed course engagement duration.

Predictor	Main Effect Model		Interaction Model	
	<i>B</i>	<i>SE</i>	<i>B</i>	<i>SE</i>
Intercept	0.39 ***	0.09	0.28 *	0.12
Flexible interface	0.09	0.06	0.29 *	0.15
Pres. order B	0.22 *	0.10	0.22 *	0.10
Pres. order C	0.12	0.10	0.14	0.10
Pres. order D	0.15	0.10	0.14	0.10
Pres. order E	0.08	0.10	0.09	0.10
Pres. order F	0.14	0.08	0.14	0.08
Leadership role	-0.19 *	0.08	-0.18	0.12
Support role	-0.14 *	0.06	0.00	0.09
Post-grad edu.	0.05	0.06	0.08	0.08
Collect goal	-0.06	0.08	-0.01	0.12
Learn goal	-0.22 **	0.08	-0.17	0.11
Flexible * Leader			-0.04	0.16
Flexible * Support			-0.29 *	0.13
Flexible * Post-grad			-0.03	0.12
Flexible * Collect			-0.09	0.17
Flexible * Learn			-0.10	0.15
<i>R</i> ²	.04		.05	
<i>n</i>	663		663	

Note. Pres. = presentation. Edu. = education.

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

A second engagement analysis was performed on engagement during the modular units to understand engagement patterns specifically where the experimental treatment was applied. Log transformed modular engagement duration was plotted by interface type and broken down by learner characteristic to visualize engagement, for learners who showed up to the modular units (see Figure 10), i.e. only learners who used at least one resource in the modular units were included. As with log course engagement, average log modular engagement was similar between levels of prior education. However, average log modular engagement was more similar across different roles and goals than seen with log course engagement. Average log modular engagement was also very similar between interface types overall. A large difference was

observed between interface types for teachers and support roles in the same directions as with log course engagement but more exaggerated.

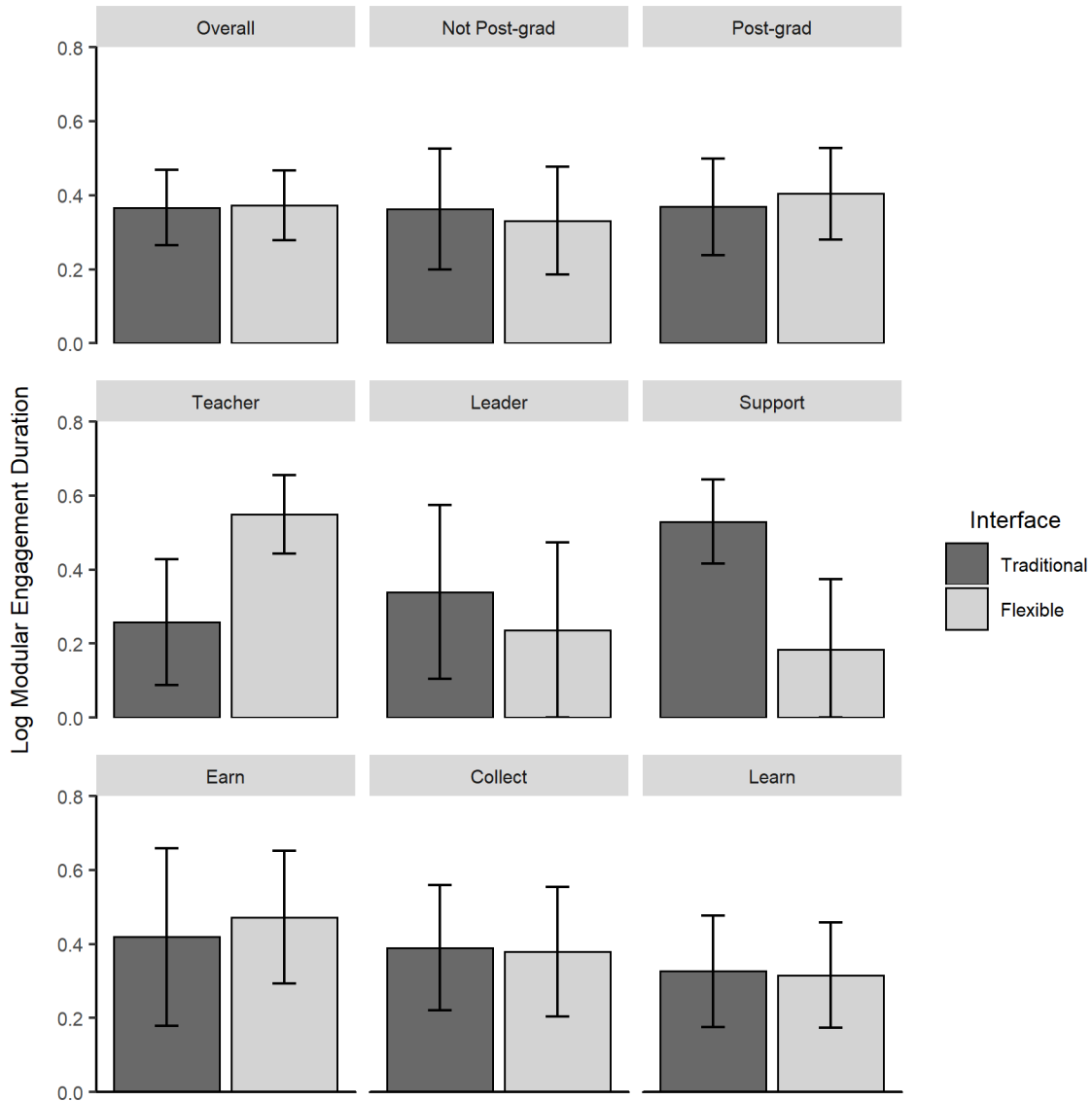


Figure 10. Log transformed modular engagement duration. Each panel represents a different subset of learners who showed up to the modular units ($n = 411$), as indicated by the learner characteristic in the title of each panel. The top left panel includes all learners who showed up to the modular units. The top right two panels subset by prior education. The middle row subsets by role. The bottom row subsets by goal. Error bars are 95% confidence intervals.

Predictors of log-transformed modular engagement duration were analyzed via hierarchical multiple regression (Table 11). Only learners who showed up to the modular units were included in the models, i.e. learners who never experienced the modular units where the treatment focused were excluded. All main effects were non-significant, but significant interactions were observed between role and interface type. Teachers shown the flexible interface ($M' = 0.55$, $SD' = 0.55$) engaged for longer durations than teachers shown the traditional interface ($M' = 0.26$, $SD' = 0.86$), while support roles shown the flexible interface ($M' = 0.28$, $SD' = 0.82$) engaged for shorter durations than support roles shown the traditional interface ($M' = 0.53$, $SD' = 0.49$). A crossover interaction was also observed between teachers and leaders, who engaged for shorter durations with the flexible interface ($M' = 0.24$, $SD' = 0.79$) than the traditional interface ($M' = 0.34$, $SD' = 0.61$). Other interactions between learner characteristics and interface were non-significant.

Post-hoc multiple regressions were performed to analyze differences in log modular engagement duration between interface types among each professional role. Among teachers ($n = 204$), a significant main effect was observed for the flexible interface ($B = 0.27$, $p = .009$) after controlling for the other predictors. Among leaders ($n = 68$), a significant main effect was observed for a goal to learn ($B = -0.54$, $p = .03$) after controlling for the other predictors. Among support roles ($n = 233$), significant main effect was observed for the flexible interface ($B = -0.31$, $p = .009$) after controlling for the other predictors

Table 11. Predictors of log transformed modular unit engagement duration.

Predictor	Main Effect Model		Interaction Model	
	<i>B</i>	<i>SE</i>	<i>B</i>	<i>SE</i>
Intercept	0.47 ***	0.11	0.35 *	0.15
Flexible interface	0.01	0.07	0.19	0.17
Pres. order B	0.23	0.13	0.23	0.13
Pres. order C	-0.12	0.12	-0.10	0.12
Pres. order D	0.07	0.13	0.07	0.13
Pres. order E	-0.14	0.13	-0.09	0.12
Pres. order F	-0.05	0.10	-0.03	0.10
Leadership role	-0.15	0.10	0.09	0.16
Support role	-0.06	0.08	0.25 *	0.11
Post-grad edu.	0.04	0.07	-0.01	0.10
Collect goal	-0.02	0.10	-0.08	0.14
Learn goal	-0.12	0.09	-0.12	0.14
Flexible * Leader			-0.43 *	0.20
Flexible * Support			-0.62 ***	0.16
Flexible * Post-grad			0.12	0.14
Flexible * Collect			0.09	0.20
Flexible * Learn			-0.01	0.18
<i>R</i> ²	.03		.07	
<i>n</i>	411		411	

Note. Pres. = presentation. Edu. = education.

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

Achievement

Achievement was analyzed at the course level in terms of earning a course certificate and at the modular unit level in terms of whether or not a micro-credential was earned during the units where the experimental treatment was applied. First, the percentage of learners who earned a course certificate was plotted by interface type and broken down by learner characteristic for all learners who showed up to the course (Figure 11). Certificate achievement was similar between levels of prior education, but a greater percentage of teachers and learners with a goal to earn actually earned course certificates relative to other roles and goals, respectively, on average. Certificate achievement was slightly higher in the flexible interface conditions than the

traditional interface conditions on average, and this trend held for every characteristic subset, except learners with a support role. The largest differences between interface types were observed for teachers and learners with a goal to earn a certificate.

Visually apparent differences in certificate achievement between interface types for learners with different goals led to the inclusion of an interface-by-goal interaction in subsequent achievement analyses, even though the interaction was not initially hypothesized.

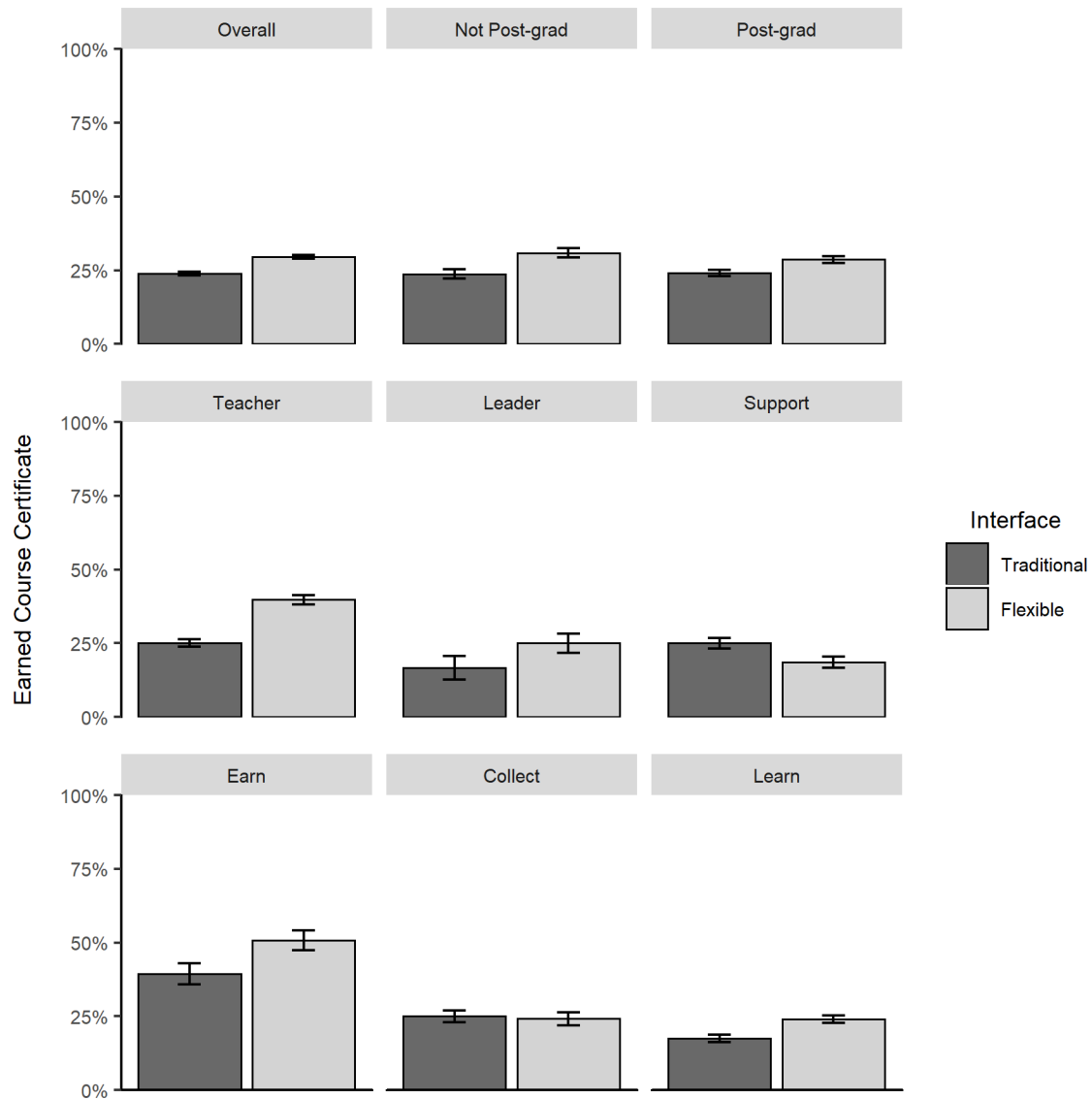


Figure 11. Percentage of learners who earned a course certificate. Each panel represents a different subset of learners who showed up to the course ($n = 663$), as indicated by the learner characteristic in the title of each panel. The top left panel includes all learners who showed up to the course. The top right two panels subset by prior education. The middle row subsets by role. The bottom row subsets by goal. Error bars are 95% confidence intervals.

Predictors of earning a course certificate were analyzed via hierarchical logistic regression (see Table 12). All learners who showed up to the course were included, i.e. learners who registered for the course but never engaged with a resource after the course opened were

excluded. Significant main effects were observed for role and goal. The odds of learners in a support role earning a course certificate were 0.63 times that of teachers, holding other predictors constant. The odds of learners with a goal to collect and goal to learn earning a course certificate were 0.44 and 0.32 times, respectively, the odds of learners with a goal to earn a certificate, holding other predictors constant. Significant interaction effects were also observed between role and interface type such that the effect of interface was larger among teachers than support roles. Other main effects and interactions between learner characteristics and interface were non-significant.

Post-hoc logistic regressions were performed to analyze differences in certificate achievement between interface types among learners with teacher and support roles. Among teachers ($n = 318$), significant main effects were observed for the flexible interface ($B = 0.69, p = .007, OR = 2.00, 95\% CI = [1.21, 3.33]$), a goal to collect ($B = -1.21, p < .001, OR = 0.30, 95\% CI = [0.13, 0.60]$), and a goal to learn ($B = -1.06, p < .001, OR = 0.34, 95\% CI = [0.19, 0.62]$) when controlling for the other predictors. Among support roles ($n = 233$), all main effects were non-significant when controlling for other the other predictors.

Table 12. Predictors of earning a course certificate.

Predictor	Main Effect Model				Interaction Model			
	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI
Intercept	-0.49	0.27	0.61	[0.36, 1.05]	-0.73 *	0.35	0.48	[0.24, 0.95]
Flexible interface	0.32	0.18	1.37	[0.96, 1.97]	0.74	0.44	2.10	[0.90, 5.00]
Pres. order B	0.86 **	0.31	2.35	[1.28, 4.32]	0.86 **	0.31	2.37	[1.28, 4.37]
Pres. order C	-0.02	0.35	0.98	[0.48, 1.93]	0.03	0.35	1.03	[0.50, 2.04]
Pres. order D	0.35	0.33	1.41	[0.73, 2.70]	0.33	0.34	1.39	[0.71, 2.68]
Pres. order E	0.60	0.31	1.81	[0.98, 3.34]	0.65 *	0.32	1.92	[1.03, 3.57]
Pres. order F	0.43	0.25	1.53	[0.93, 2.53]	0.45	0.26	1.56	[0.95, 2.59]
Leadership role	-0.49	0.27	0.61	[0.35, 1.03]	-0.44	0.44	0.64	[0.25, 1.47]
Support role	-0.46 *	0.21	0.63	[0.42, 0.95]	0.02	0.29	1.02	[0.57, 1.81]
Post-grad edu.	-0.02	0.19	0.98	[0.68, 1.43]	-0.03	0.28	0.98	[0.57, 1.68]
Collect goal	-0.83 **	0.25	0.44	[0.27, 0.71]	-0.63	0.36	0.53	[0.26, 1.08]
Learn goal	-1.13 ***	0.23	0.32	[0.21, 0.51]	-1.14 ***	0.34	0.32	[0.16, 0.63]
Flexible * Leader					-0.15	0.56	0.86	[0.29, 2.68]
Flexible * Support					-1.00 *	0.42	0.37	[0.16, 0.84]
Flexible * Post-grad					0.08	0.38	1.08	[0.51, 2.27]
Flexible * Collect					-0.47	0.51	0.63	[0.23, 1.69]
Flexible * Learn					0.02	0.46	1.02	[0.41, 2.53]
R^2_N	.10				.11			
<i>n</i>	663				663			

Note. Pres. = presentation. Edu. = education.

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

The second achievement analysis focused on whether or not a micro-credential was earned in the modular units. The percentage of learners who earned a modular micro-credential was plotted by interface type and broken down by learner characteristic for only learners who showed up to the modular units (Figure 12). As with certificate achievement, micro-credential achievement was similar between levels of prior education, but a greater percentage of teachers and learners with a goal to earn actually earned micro-credentials relative to other roles and goals, respectively, on average. Certificate achievement was slightly higher in the flexible interface conditions than the traditional interface conditions on average, and this trend held for every characteristic subset, except learners without post-graduate degrees and learners with a

support role. The largest differences between interface types were observed for teachers and learners with a goal to earn a certificate.

Visually apparent differences in micro-credential achievement between interface types for learners with different goals led to the inclusion of an interface-by-goal interaction in subsequent achievement analyses, even though the interaction was not initially hypothesized.

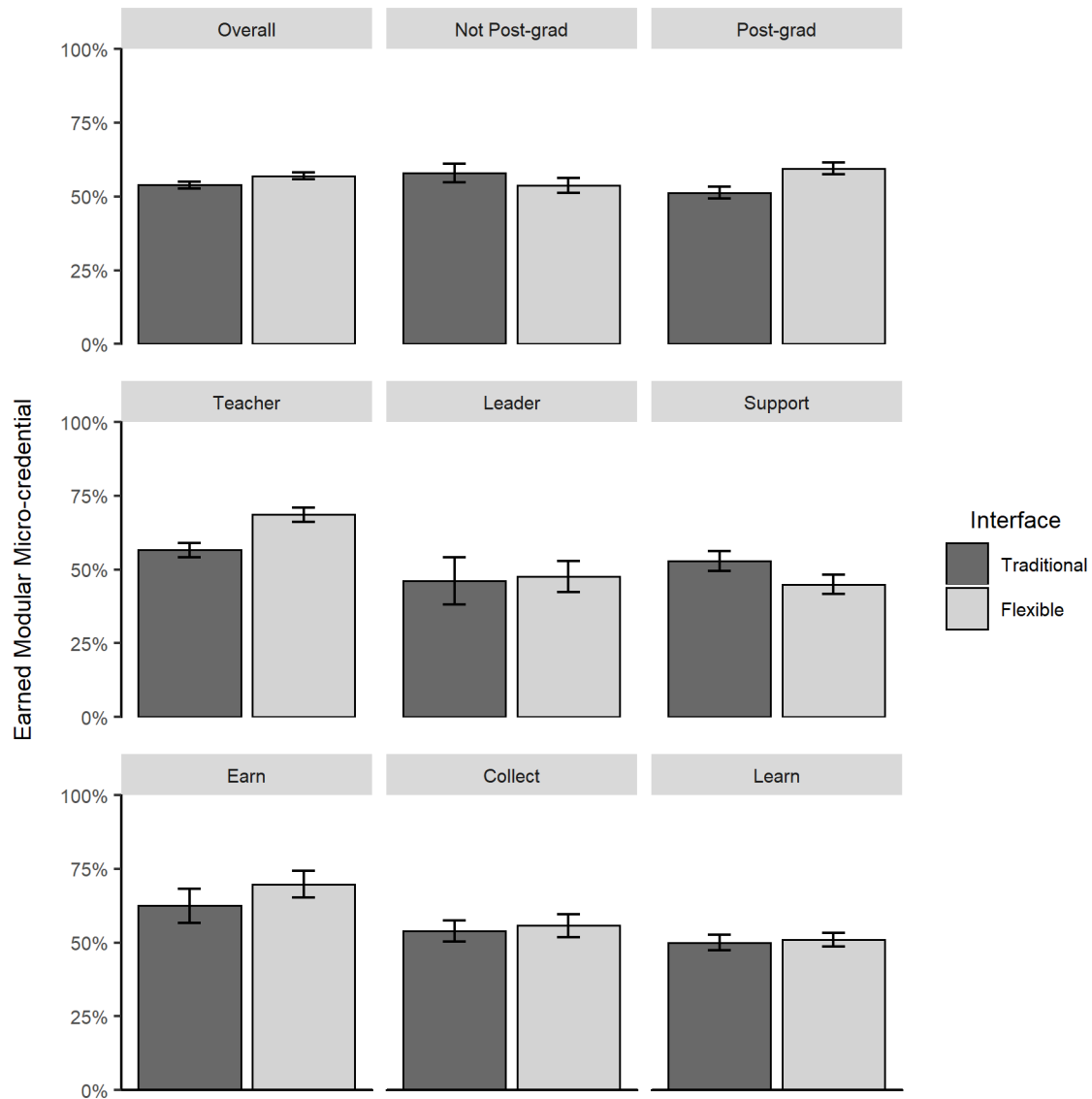


Figure 12. Percentage of learners who earned a modular micro-credential. Each panel represents a different subset of learners who showed up to the modular units ($n = 411$), as indicated by the learner characteristic in the title of each panel. The top left panel includes all learners who showed up to the modular units. The top right two panels subset by prior education. The middle row subsets by role. The bottom row subsets by goal. Error bars are 95% confidence intervals.

Predictors of earning a modular micro-credential were analyzed via hierarchical logistic regression (Table 13). Only learners who showed up to the modular units were included in the models, i.e. learners who never experienced the modular units where the treatment focused were

excluded. Significant main effects were observed for role and goal. The odds of learners in a leadership or support role earning a modular unit micro-credential were 0.50 times or 0.55 times, respectively, the odds of teachers earning a modular unit micro-credential, holding other predictors constant. The odds of learners with a goal to learn earning a modular unit micro-credential were 0.54 times that of learners with a goal to earn a certificate, holding other predictors constant. Other main effects and interactions between learner characteristics and interface were non-significant.

Table 13. Predictors of earning at least one modular micro-credential.

Predictor	Main Effect Model				Interaction Model			
	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI
Intercept	0.85 *	0.34	2.34	[1.22, 4.57]	0.76	0.43	2.14	[0.93, 5.11]
Flexible interface	0.13	0.21	1.13	[0.75, 1.70]	0.32	0.53	1.37	[0.48, 3.92]
Pres. order B	0.73	0.39	2.07	[0.98, 4.52]	0.74	0.39	2.09	[0.99, 4.59]
Pres. order C	-0.23	0.36	0.79	[0.39, 1.60]	-0.18	0.36	0.83	[0.41, 1.70]
Pres. order D	0.07	0.37	1.07	[0.52, 2.25]	0.06	0.38	1.06	[0.50, 2.24]
Pres. order E	0.05	0.36	1.05	[0.52, 2.15]	0.12	0.37	1.13	[0.55, 2.33]
Pres. order F	-0.21	0.28	0.81	[0.47, 1.40]	-0.21	0.28	0.81	[0.46, 1.42]
Leadership role	-0.69 *	0.29	0.50	[0.28, 0.89]	-0.37	0.45	0.69	[0.28, 1.68]
Support role	-0.60 *	0.23	0.55	[0.35, 0.87]	-0.22	0.33	0.80	[0.42, 1.53]
Post-grad edu.	0.02	0.21	1.02	[0.67, 1.55]	-0.33	0.30	0.72	[0.40, 1.30]
Collect goal	-0.32	0.30	0.73	[0.41, 1.29]	-0.26	0.43	0.77	[0.33, 1.77]
Learn goal	-0.61 *	0.27	0.54	[0.32, 0.92]	-0.42	0.40	0.65	[0.30, 1.42]
Flexible * Leader					-0.62	0.60	0.54	[0.17, 1.76]
Flexible * Support					-0.81	0.47	0.44	[0.18, 1.12]
Flexible * Post-grad					0.73	0.42	2.07	[0.91, 4.80]
Flexible * Collect					-0.17	0.59	0.84	[0.26, 2.71]
Flexible * Learn					-0.37	0.55	0.69	[0.23, 2.02]
R^2_N	.07				.09			
<i>n</i>	411				411			

Note. Pres. = presentation. Edu. = education.

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

Relationship between Role and Goal

The relationship between role and goal was analyzed due to similar emergent patterns across outcomes for learners with a teacher role and learners with a goal to earn a course certificate. A breakdown of role by goal in the sample (Table 14) shows a greater proportion of teachers had the goal of earning a certificate, relative to other roles, and the distribution of goals was similar between learners with leadership and support roles.

Table 14. Counts and percentages of goals by role.

Role	Goal		
	Learn	Collect	Earn
Teacher	157 (49%)	78 (25%)	83 (26%)
Leader	59 (53%)	38 (34%)	15 (13%)
Support	120 (52%)	83 (36%)	30 (13%)

Note. Only participants who showed up to the course are included. Percentages reflect the proportion of the row total. Some row percentages may not sum to 100% due to rounding.

A *post-hoc* multinomial logistic regression analysis was performed to examine the causal relationship between professional role and primary goal while controlling for education (see results in Table 15), and significant relationships were found between role and goal. All learners who showed up to the course were included, i.e. learners who registered for the course but never engaged with a resource after the course opened were excluded. The odds of learners with leadership and support roles having a goal of collecting were 2.64 and 2.90 times, respectively, the odds of teachers, relative to a goal of earning a certificate. Similarly, the odds of learners with leadership and support roles having a goal of learning were 2.05 and 2.09 times, respectively, the odds of teachers having a goal of learning, relative to a goal of earning a certificate.

Table 15. Predictors of primary goal.

Criterion	Predictor	<i>B</i>	<i>SE</i>	<i>OR</i>	95% CI
Collect goal	Intercept	-0.13	0.20	0.87	[0.59, 1.30]
	Post-grad edu.	0.14	0.24	1.14	[0.72, 1.82]
	Leadership role	0.97 **	0.35	2.64	[1.34, 5.19]
	Support role	1.07 ***	0.27	2.90	[1.72, 4.89]
Learn goal	Intercept	0.58 ***	0.18	1.79	[1.27, 2.53]
	Post-grad edu.	0.10	0.21	1.11	[0.73, 1.68]
	Leadership role	0.72 *	0.32	2.05	[1.09, 3.84]
	Support role	0.74 **	0.25	2.09	[1.29, 3.39]
R^2_N		.04			
<i>n</i>		663			

Note. Pres. = presentation. Edu. = education.

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

Flexible Navigation Behaviors

In an effort to understand how the flexible course structure was utilized, descriptive metrics of pace change, inter-unit transitions, and divergent unit use were explored for learners in flexible interface conditions who showed up to the modular units ($n = 216$), i.e. learners in the traditional interface conditions were excluded and learners in the flexible interface conditions who never experienced the flexible modular units were excluded.

The distribution of pace change, or duration differential between weeks modular units were released, had a slightly positive skew and was leptokurtic ($M = 1.03$, $SD = 1$) as shown in Figure 13. Average pace broken down by role is shown in Figure 14. Teachers had marginally higher pace change scores than the other roles.

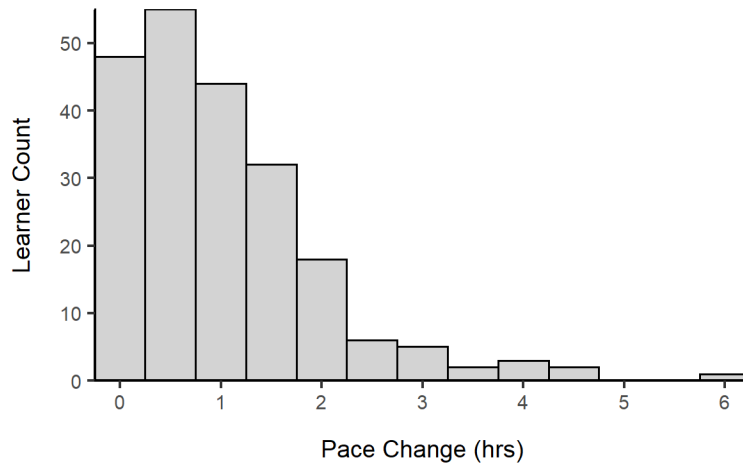


Figure 13. Histogram of pace change. Bins are half-hour increments. Graph includes learners in flexible interface conditions who showed up to at least one modular unit ($n = 216$).

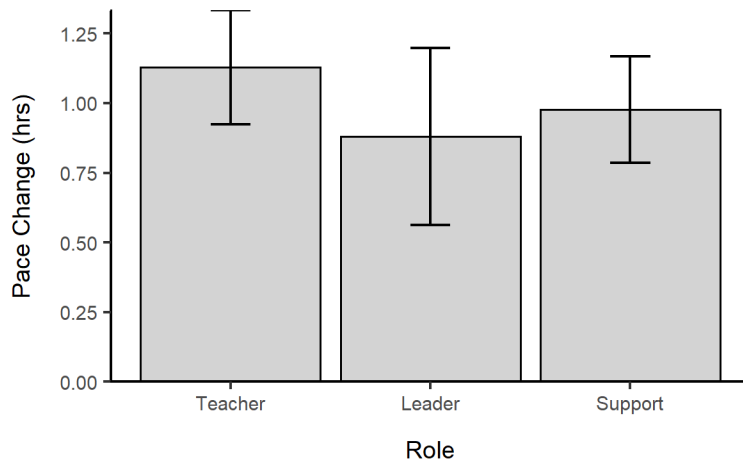


Figure 14. Average pace change by role. Graph includes learners in flexible interface conditions who showed up to at least one modular unit ($n = 216$). Error bars are 95% confidence intervals.

The distribution of transition frequency between modular units also had a heavy positive skew and was leptokurtic ($M = 3.36$, $SD = 4.19$) as shown in Figure 15. Average transitions

broken down by role is shown in Figure 16. Teachers had a higher transition count than the other roles, particularly compared to support roles.

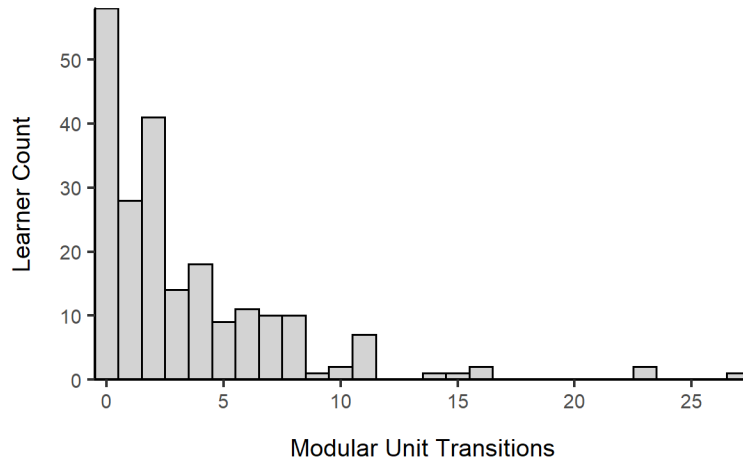


Figure 15. Histogram of modular transition frequency. Bins are 1 transition increments. Graph includes learners in flexible interface conditions who showed up to at least one modular unit ($n = 216$).

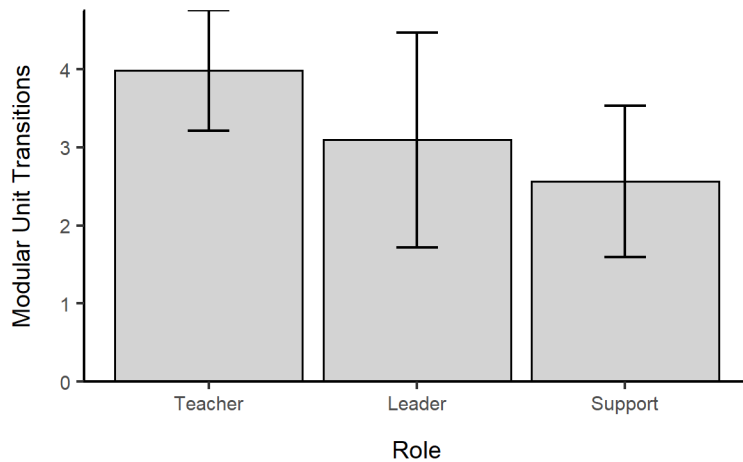


Figure 16. Average modular transition frequency by role. Graph includes learners in flexible interface conditions who showed up to at least one modular unit ($n = 216$). Error bars are 95% confidence intervals.

Twenty-one percent of learners who were given the flexible interface and showed up to modular units followed a pathway through the modular units that was different from the presentation order. A graph of this divergence broken down by role is shown in Figure 17. A greater proportion of teachers and leaders followed divergent pathways than learners in support roles.

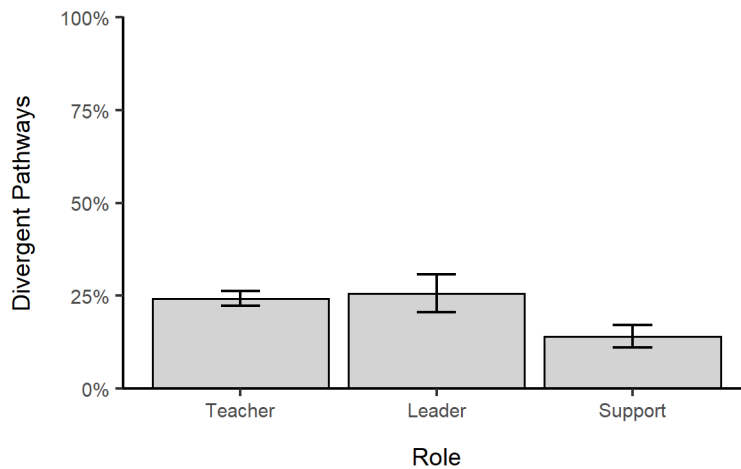


Figure 17. Percentage of learners with divergent pathways by role. Graph includes learners in flexible interface conditions who showed up to at least one modular unit for at least five minutes ($n = 206$). Error bars are 95% confidence intervals.

Discussion

Persistence

Persistence was analyzed at three points in time to understand effects leading up to the experimental treatment of the flexible units, through the release of the flexible units when the treatment was applied, and to the release of the last unit of the course. The most consistent pattern that emerged was the flexible course design provided a benefit for learners who were classroom teachers without significant detriment to learners with leadership and support roles. Teachers given the flexible interface had higher odds of persisting to each point in time than

teachers given the traditional interface. This was true even of persistence to the second week when the flexible units were introduced, suggesting an anticipatory effect. In addition, teachers had the greatest odds among the roles of seeing an increase in persistence from the flexible interface, as indicated by interaction effects. Although graphs indicated persistence later in the course was slightly higher in the traditional interface conditions for leaders and support roles, relative to the flexible conditions, those differences were found to be non-significant.

Interestingly, the interaction between role and interface type seemed to dominate the interaction between goal and interface type. Graphs indicated learners with a goal to earn had the largest gains in persistence from the flexible interface, compared to other goals. However, graphs also suggested a similar pattern for teachers relative to other roles. When both interactions were entered into the statistical models, the interaction between interface and role was consistently significant, whereas the interaction between interface and goal was non-significant.

Interface by role interaction effects were accompanied by main effects at each point in time. Interface type had a main effect on persistence to the second week, largely due to teachers and learners with a goal to earn. Goal-related main effects were then observed for persistence to weeks five and six, whereby the group of learners with a goal to earn a course certificate had more persisting learners than learners with goals of learning and collecting. This was consistent with trends prior MOOC literature connecting learners with a certificate-earning goal to greater persistence (Kizilcec & Halawa, 2015; Kizilcec & Schneider, 2015; Phan et al., 2016; Wang et al., 2017)

Engagement

Engagement was analyzed as a construct and as an outcome which provided insight into the relationships between engagement measures themselves, as well as effects of course structure and learner characteristics on engagement. Although measures of frequency, variety, and duration captured unique aspects of engagement, they were highly correlated and loaded onto a single latent factor of behavioral engagement. Duration and frequency, in particular, were very representative of the latent factor which suggested both a combined engagement score and a single measure were reasonable criterion for analysis.

As an outcome, different predictive relationships were observed at different levels of scope for engagement. For the course overall, observed effects of engagement were similar to those of persistence. Once again, teachers had the greatest increase of engagement from the flexible interface compared to other roles, and that effect dominated interaction effects between interface and goal. In addition, the flexible course design led to improved engagement for classroom teachers without significant detriment to learners with leadership and support roles. Staying consistent with prior literature, learners with a goal to earn had the highest engagement of learners with different goals. One distinction that emerged was the addition of role as a significant predictor. Across the interface conditions, teachers had the highest engagement of the different roles.

Within the modular units where flexible features were experimentally manipulated, teachers continued to have the most improvements in engagement due to the flexible interface and they had the highest engagement overall among the different roles. However, engagement in the modular units was more balanced between interface types and goals, and differences were exaggerated for roles compared to the course overall. Within the modular units, learners with

support roles had significantly lower engagement in the flexible interface condition than in the traditional interface conditions.

One potential explanation for balance of engagement duration across goals in the modular units yet differences across goals in the course overall was a difference in motivation that did not emerge until later in the course. The goal to earn a certificate was a distal goal that may have motivated learners continuously over time, whereas proximal goals of learning and collecting may have only sustained motivation for part of the course. An alternative, though not mutually exclusive, explanation was goal completion. The course curriculum was designed so that summative and project-based material came after the modular units. It seems possible that learners with learning and collecting goals could have achieved their initial goals during the modular units, but learners with a goal to earn a certificate needed to continue engaging to meet their goal. Both of these explanations are consistent with the earlier persistence findings. Learners with a goal to earn a certificate had the highest persistence to the weeks after the modular units, but there was notably no effect of goal on persistence going into the modular units.

A potential explanation for the exaggeration of role effects in the modular units was a role-specific interest in the modular unit resources. Teachers may have found value in the majority of resources provided, and the flexible conditions motivated and enabled them to structure their participation in a way that allowed them to engage more. On the other hand, learners with support roles may have had job-relevant interest in a smaller subset of the modular unit resources, since some of the course materials were directed at application in the context of classroom teaching (Bonk & Lee, 2017; Milligan & Littlejohn, 2014). Promotion of freedom of choice in the flexible interface condition might have made learners in support roles more

comfortable skipping resources that they found to be less valuable, whereas they may have felt as though they had to use all resources in the traditional version of the course in order to continue. Support for this explanation comes from the observation that learners in support roles tended to persist, even though they engaged less in the modular units. An alternative explanation could be related to self-regulated learning skills (Zimmerman, 2002). Previous research has demonstrated that some learners struggle to structure their own learning due to a lack of skills related to regulating the learning process (Bernacki, Aguilar, & Byrnes, 2011; Kop & Fournier, 2010; Littlejohn et al., 2016) so it is possible that support staff in the flexible conditions struggled to choose their learning path and participation schedule, even though a default order and standard pace were provided in the course. However, this explanation seems less likely due to 63% of support staff having post-graduate degrees (Kizilcec et al., 2017).

Achievement

Similar to the engagement analyses, achievement was analyzed at two levels of scope. First, predictors of earning a course certificate for the course overall were similar to those of course engagement and persistence. Teachers continued to receive the greatest benefit from being in the flexible interface conditions, and they also had the highest certification rate among different roles. The effects of interface were again non-significant (i.e., neither beneficial nor detrimental) for learners with leadership and support roles, but learners with a goal to earn a course certificate had the highest certification rate, as expected from prior literature (Kizilcec & Schneider, 2015; Phan et al., 2016).

At the scope of the modular units, some of the same predictors observed for certificate achievement also applied to earning micro-credentials, but some predictors were different. Learners with a goal to earn and teachers continued to have the highest achievement with a

greater percentage of learners earning modular micro-credentials relative to other roles and goals. However, the interaction effect between interface and role was non-significant. The flexible interface notably did not seem to have an effect (main or interaction) on modular achievement.

A notable contrast is that the effect of goal was absent for modular engagement but present for modular achievement. A likely explanation is that earning micro-credentials was required for earning a course certificate. It follows that learners aiming to earn a course certificate would be more likely to earn micro-credentials. Teachers would have been affected by this as well, since teachers had the largest proportion of certificate-seekers relative to other roles.

Relationship between Role and Goal

Graphical evidence suggested similar patterns for roles and goals in most of the studied outcomes. Specifically, teachers and learners with a goal of earning a certificate tended to have the best outcomes and receive the most benefits from the flexible interface, whereas other roles and goals tended to have similar outcomes across and between interface conditions. Analyses between the demographics of role and goal confirmed a predictive relationship existed. Teachers had the highest proportion of learners with the goal of earning a certificate, relative to other roles, and the positive relationship between teachers and certificate-seekers was significantly greater than that of other roles. This finding offered explanation for the observation that interface-by-role interactions dominated interface-by-goal interactions in the outcome analyses. In other words, the effects of the flexible treatment were more a factor of role than goal.

Flexible Navigation Behaviors

The flexible interface introduced in the present study promoted new navigation behaviors with respect to the pace and order of participation in modular units. Learners in the flexible interface condition had the opportunity to work ahead and/or catch-up during the weeks in which modular units were released. They also had the opportunities to jump back and forth between units and choose their path through the modular unit content. An exploratory look into new metrics that could capture these flexible behaviors showed some learners do take advantage of course flexibility.

Descriptive behavioral evidence supported the idea that learners in the flexible interface conditions would exercise their freedom of pace by participating different amounts each week. Considering the instructor-estimated time to complete the course was ~25 hours, each unit was designed to take a little over four hours to complete on average. Comparing this to actual engagement duration, week-to-week duration fluctuated by over an hour, or over 25% of the estimated completion time, as modular units were released. Teachers notably had slightly more variation in pace than other roles on average, which could contribute to their greater outcome benefits from the flexible interface.

Descriptive behavioral evidence also supported the idea that learners in the flexible interface conditions would exercise their freedom of pathway by jumping back and forth between modular units. Two transitions would be required between modular units to progress through all three modular units in a perfectly linear order. Despite the fact that many learners did not persist through the modular units, the average number of modular inter-unit transitions was over three, suggesting many learners jumped between modular units more than necessary. The number of transitions was also greatest for teachers – again potentially contributing to their

greater outcome benefits from the flexible interface relative to other roles. The reason for these jumps is unknown (perhaps to explore and gather information to make a decision), but the flexibility was utilized regardless.

Some evidence, albeit weaker, also supported the idea that learners would choose to complete units in the order that was best for them. There were six possible permutations of modular units. Each learner was presented only one of those orders, so there was a one-in-six chance that a learner would receive their preferred order by default. Over 20% of learners in the flexible interface conditions completed the modular units in an order that was different from presented, but 20% was a small fraction of the five-sixths of learners who would have not been shown their preferred order by chance. There are many possible explanations for the disparity. For example, learners may not have known enough about the different units to make a decision about order, or perhaps they were simply indifferent to the topics and defaulted to the presented order. Regardless, a noteworthy percentage of learners did have a preference and were able to learn in their preferred way due to the flexibility to diverge from the default order.

Although pace, transitions, and divergence metrics highlighted some ways learners take advantage of flexible course structures, the metrics seem unlikely explain the full extent of the observed effects of interface type on outcomes. Future research could explore alternative behavioral metrics, as well as subjective metrics, such as feelings of autonomy and empowerment. For example, it is possible that giving learners flexibility improves motivation, even though learners may not exercise their rights to flexibility.

Summary

Support was found for many of the relationships included in the initially proposed model of course flexibility and learner characteristics. In particular, significant direct relationships

were observed between primary goal and course outcomes (H2d), as well as between professional role and course outcomes in most of the examined outcomes. Though, teachers received the most benefits from the flexible interface, instead of leaders or support roles as originally hypothesized (H2a and H2b). Professional role also consistently moderated the effect of the flexible course structure on course outcomes, but the interaction was greatest for teachers – a different direction from initially hypothesized (H3a and H3b).

Consistent supporting evidence was not found for the remaining initially proposed relationships. An adjusted model is presented in Figure 18, which takes into account patterns observed in the present study. Most notably, effects of prior education (H2c and H3c) and the main effect of course flexibility (H1) were removed due to a lack of observed significant relationships with most of the examined outcomes (with the exception of persistence to week two), and a relationship was added between professional role and course goal.

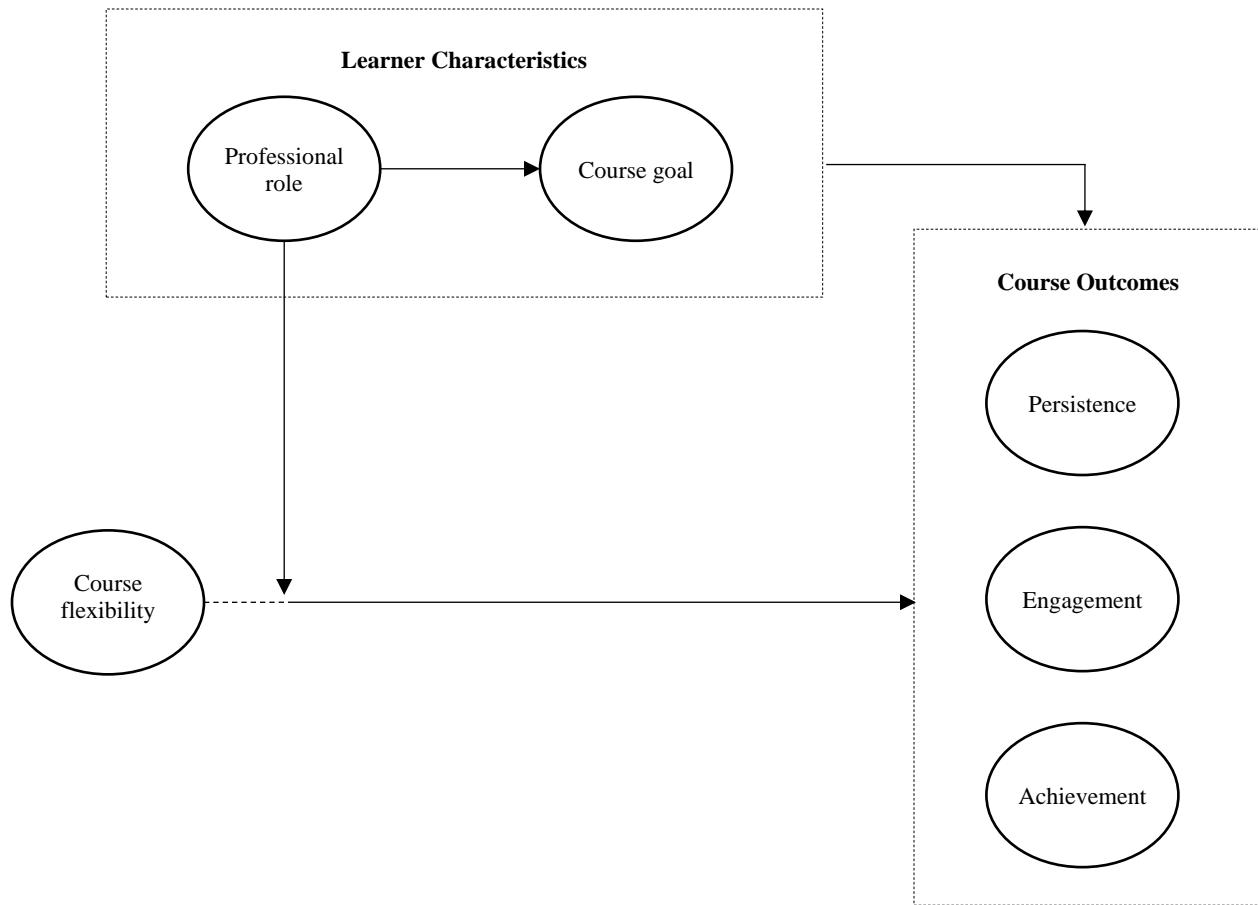


Figure 18. Adjusted model of course flexibility, learner characteristics, & course outcomes. This updated model reflects patterns of findings from the present study. The professional role learners have influences the goals they set for a course. Both professional role and course goals have a direct effect on course outcomes. Additionally, professional role moderates the effect of course flexibility on course outcomes. Prior education is excluded from the model due to a lack of observed effects for that characteristic. Also, the main effect of course flexibility is excluded due to a lack of observed effects, except for persistence to the second week, as indicated by the initially dotted line from course flexibility.

Conclusion

The results of this study suggest course flexibility is an influential factor of course outcomes. A common pattern was observed where teachers experienced benefits from a flexible course structure, while negligible differences were typically observed between course structures

for educational leaders and support roles. Improved persistence, engagement, and achievement were achieved with a relatively small and unobtrusive treatment.

Professional role unexpectedly emerged as the most influential learner characteristic deserves future study. Professional role was not only predictive of course goal, but also the interaction of interface and role had more explanatory power than the interaction interface and goal. The MOOC literature has heavily focused on the implications of the goals learners bring to a course, and much less attention has been given to learners' professional roles, despite research demonstrating relationships between professional needs, course decisions, and motivation as suggested in self-directed learning theory (Milligan & Littlejohn, 2014). Future research could expand our understanding of what factors in a professional role relate to course behaviors. For example, one potential explanation for the differences in role in the present study was an intention to master course concepts. Recent unpublished evidence from the Friday Institute suggests many leaders and support roles attend education professional development MOOCs to get a rough overview of what teachers are learning about, rather than to master all of the material themselves, but teachers are much more invested in mastering course content. One of the challenges with this type of research will be finding participants with roles desired for study, as seen with the small sample of leaders which was a limitation of the present study.

The generalizability of the present findings is limited by the fact that this study explored only one type of flexible course design in only one course. Alternative flexible course designs may not produce the same results, especially if the flexibility is not accompanied by sufficient supports to prevent lostness and confusion when navigating unfamiliar content. In addition, not all courses have curricula that allow reordering of units as implemented in this study. Some courses have learning paths with more dependencies, such as foundational mathematics concepts

that build on one another throughout a statistics course, and changing the order of their units could lead to more detriment than benefit.

Moving forward, MOOC researchers and course designers may find it beneficial to experiment with alternative ways of increasing course flexibility, particularly in courses where units should be completed in a fixed order. For example, learners could be allowed to designate their own unit release schedule, extension periods could be integrated to provide extra time to complete coursework, and additional micro-credentials could provide supplemental opportunities for exploration and mastery of specific topics and skills relevant to individual learners (Acree, 2016; Ifenthaler, Bellin-Mularski, & Mah, 2016). A greater understanding of how learners utilize flexibility would also be beneficial. For example, flexibility could encourage learners to explore a course before diving in, and flexibility could allow for deeper dives into the most relevant learning resources. Moreover, future research could continue to explore the relationships between engagement measures. A confirmatory factor analysis could validate the single factor solution that emerged in the present study. Lastly, additional measures of engagement could also be explored, including subjective engagement measures and measures of depth into specific topics.

References

- Acree, L. (2016). *Seven Lessons Learned From Implementing Micro-credentials*. Retrieved from The Friday Institute for Educational Innovation website: <https://place.fi.ncsu.edu/local/catalog/section.php?id=1>
- Acree, L., Creager, J. H., Wiebe, E. N., & Wolf, M. A. (2018, April). *The impact of micro-credentials on professional learning in a massive open online course for educators*. Paper presented at the 2018 Annual Meeting of the American Education Research Association. Retrieved June 2018, from the AERA Online Paper Repository.
- Admiraal, W., Huisman, B., & Pilli, O. (2015). Assessment in massive open online courses. *The Electronic Journal of E-Learning*, 13, 207–216.
- Anderson, T., & Dron, J. (2011). Three generations of distance education pedagogy. *The International Review of Research in Open and Distributed Learning*, 12(3), 80–97.
- Belanger, Y., & Thornton, J. (2013). *Bioelectricity: A quantitative approach*. Retrieved from Duke University website: <https://dukespace.lib.duke.edu/dspace/handle/10161/6216?show=full>
- Bergner, Y., Kerr, D., & Pritchard, D. E. (2015). Methodological challenges in the analysis of MOOC data for exploring the relationship between discussion forum views and learning outcomes. In O. C. Santos, J. G. Boticario, C. Romero, M. Pechenizkiy, A. Merceron, P. Mitros, J. M. Luna, C. Mihaescu, P. Moreno, A. Hershkovitz, S. Ventura, & M. Desmarais (Eds.), *Proceedings of the 8th International Conference on Educational Data Mining* (pp. 234-241).
- Bernacki, M. L., Aguilar, A. C., & Byrnes, J. P. (2011). Self-regulated learning and technology-enhanced learning environments: An opportunity-propensity analysis. In G. Dettori & D. Persico (Eds.), *Fostering Self-Regulated Learning through ICT* (pp. 1–26). Hershey, PA, USA: IGI Global.
- Blackmore, K. (2014). Measures of success: Varying intention and participation in MOOCs. In B. Hegarty, J. McDonald, & S.-K. Loke (Eds.), *Rhetoric and Reality: Critical perspectives on educational technology. Proceedings ascilite Dunedin 2014* (pp. 549-553).
- Bond, P. (2015). Information literacy in MOOCs. *Current Issues in Emerging eLearning*, 2(1).
- Bonk, C. J., & Lee, M. M. (2017). Motivations, achievements, and challenges of self-directed informal learners in open educational environments and MOOCs. *Journal of Learning for Development - JLAD*, 4, 36-57.
- Bouchard, P. (2009a). Pedagogy without a teacher: What are the limits. *International Journal of Self-Directed Learning*, 6(2), 13–22.
- Bouchard, P. (2009b). Some factors to consider when designing semi-autonomous learning environments. *Electronic Journal of E-Learning*, 7, 93–100.

- Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom: Research into edX's first MOOC. *Research & Practice in Assessment*, 8, 13-25.
- Brooks, C., & Gibson, S. (2012). Professional learning in a digital age. *Canadian Journal of Learning and Technology*, 38(2), 1-17.
- Chen, K.-C., & Jang, S.-J. (2010). Motivation in online learning: Testing a model of self-determination theory. *Computers in Human Behavior*, 26, 741–752.
- Clow, D. (2013). MOOCs and the funnel of participation. In D. Suthers, K. Verbert, E. Duval, & X. Ochoa (Eds.), *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 185–189). New York, NY, USA: ACM.
- Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (Third Edition). Mahwah, NJ: Lawrence Erlbaum Associates.
- Collins, J. (2004). Education techniques for lifelong learning: Principles of adult learning. *Radiographics*, 24, 1483–1489.
- Couros, A. (2010). Developing personal learning networks for open and social learning. In G. Veletsianos (Ed.), *Emerging technologies in distance education* (pp. 109–128). Edmonton, AB: AU Press.
- Coursera. (2015). *Impact revealed: Learner outcomes in open online courses* [PowerPoint slides]. Retrieved from https://d396qusza40orc.cloudfront.net/learninghubs/LOS_final_9-21-.pdf
- Creager, J. H., Wiebe, E. N., & Kellogg, S. B. (2018, April). *Time to shine: Extending certificate deadlines to support open online teacher professional development*. Paper presented at the 2018 Annual Meeting of the American Education Research Association. Retrieved June 2018, from the AERA Online Paper Repository.
- Creager, J. H., Wiebe, E., Thompson, I. B., & Behrend, T. (2019). *Impartial engagement trajectories in open online courses*. Manuscript in preparation.
- Crosslin, M. (2016). From instructivism to connectivism: Theoretical underpinnings of MOOCs. *Current Issues in Emerging eLearning*, 3, 84–102.
- Crosslin, M., Dellinger, J. T., Joksimovic, S., Kovanovic, V., & Gasevic, D. (2018). Customizable modalities for individualized learning: Examining patterns of engagement in dual-layer MOOCs. *Online Learning*, 22(1), 19–38.
- Darling-Hammond, L., Wei, R. C., Andree, A., Richardson, N., & Orphanos, S. (2009). *Professional learning in the learning profession: A status report on teacher development in the United States and abroad*. Retrieved from ERIC database. (ED536383)

Davis, D., Chen, G., van der Zee, T., Hauff, C., & Houben, G.-J. (2016). Retrieval practice and study planning in MOOCs: Exploring classroom-based self-regulated learning strategies at scale. In K. Verbert, M. Sharples, & T. Klobučar (Eds.), *Lecture Notes in Computer Science: Vol. 9891. Adaptive and Adaptable Learning. EC-TEL 2016*. (pp. 57–71). Cham, Switzerland: Springer International Publishing.

Dawson, S., Joksimović, S., Kovanović, V., Gašević, D., & Siemens, G. (2015). Recognising learner autonomy: Lessons and reflections from a joint x/c MOOC. In T. Thomas, E. Levin, P. Dawson, K. Fraser, & R. Hadgraft (Eds.), *Research and Development in Higher Education: Vol. 38. Learning for Life and Work in a Complex World* (pp. 117–129). Milperra, AU: Higher Education Research and Development Society of Australasia, Inc.

DeBoer, J., Ho, A. D., Stump, G. S., & Breslow, L. (2014). Changing “course” reconceptualizing educational variables for massive open online courses. *Educational Researcher*, 43, 77–84.

DiStefano, D. (2018). *How pre-service teachers' engagement and affect informs instructional format of an introductory methods course* (Doctoral dissertation). Available from ProQuest Dissertations and Theses database. (UMI No. 10823350)

Downes, S. (2008). Places to go: Connectivism & connective knowledge. *Innovate: Journal of Online Education*, 5(1), 1-6.

Duignan, P. (2007). Key challenges for educational leaders. In *Educational leadership: Key challenges and ethical tensions* (pp. 21–41). Cambridge, NY, USA: Cambridge University Press.

Evans, B. J., Baker, R. B., & Dee, T. S. (2016). Persistence patterns in massive open online courses (MOOCs). *The Journal of Higher Education*, 87, 206–242.

Ferguson, R., & Clow, D. (2016). Consistent commitment: Patterns of engagement across time in massive open online courses (MOOCs). *Journal of Learning Analytics*, 2(3), 55–80.

Ferguson, R., & Sharples, M. (2014). Innovative pedagogy at massive scale: Teaching and learning in MOOCs. In C. Rensing, S. de Freitas, T. Ley, & P. J. Muñoz-Merino (Eds.), *Lecture Notes in Computer Science: Vol. 8719. Open Learning and Teaching in Educational Communities. EC-TEL 2014* (pp. 98–111). Cham, Switzerland: Springer International.

Flynn, J. T. (2013). MOOCs: Disruptive innovation and the future of higher education. *Christian Education Journal*, 10, 149–162.

Gilson, T. (2008). Educational leadership: Are we busy yet? *American Secondary Education*, 36(3), 84–97.

Gray, J., Corley, J., & Eddy, B. P. (2016). An experience report assessing a professional development MOOC for CS principles. In *Proceedings of the 47th ACM Technical Symposium on Computing Science Education* (pp. 455–460). New York, NY, USA: ACM.

Gütl, C., Rizzardini, R. H., Chang, V., & Morales, M. (2014). Attrition in MOOC: Lessons learned from drop-out students. In L. Uden, J. Sinclair, Y.-H. Tao, & D. Liberona (Eds.),

Communications in Computer and Information Science: Vol 446. Learning Technology for Education in Cloud. MOOC and Big Data. LTEC 2014. (pp. 37–48). Cham, Switzerland: Springer.

Haggard, S. (2013). *The maturing of the MOOC: Literature review of massive open online courses and other forms of online distance learning* (Report No. 130). Retrieved from https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/240193/13-1173-maturing-of-the-mooc.pdf

Hew, K. F., & Cheung, W. S. (2014). Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges. *Educational Research Review*, 12, 45–58.

Ho, A. D., Chuang, I., Reich, J., Coleman, C., Whitehill, J., Northcutt, C., Williams, J. J., Hansen, J., Lopez, G., & Petersen, R. (2015). *HarvardX and MITx: Two years of open online courses* (HarvardX Working Paper No. 10). Retrieved from MIT website: <https://dspace.mit.edu/bitstream/handle/1721.1/96825/SSRN-id2586847.pdf?sequence=1>

Ho, A. D., Reich, J., Nesterko, S. O., Seaton, D. T., Mullaney, T., Waldo, J., & Chuang, I. (2014). *HarvardX and MITx: The first year of open online courses, Fall 2012-Summer 2013* (HarvardX and MITx Working Paper No. 1). Retrieved from Harvard website: <http://harvardx.harvard.edu/multiple-course-report>

Hodges, C., Lowenthal, P., & Grant, M. (2016). Teacher professional development in the digital age: Design considerations for MOOCs for teachers. In G. Chamblee & L. Langub (Eds.), *Proceedings of Society for Information Technology & Teacher Education International Conference* (pp. 2075–2081). Savannah, GA, USA: Association for the Advancement of Computing in Education (AACE).

Hollands, F. M., & Tirthali, D. (2014). *MOOCs: Expectations and reality. Full report*. Retrieved from ERIC database. (ED547237)

Hood, N., Littlejohn, A., & Milligan, C. (2015). Context counts: How learners' contexts influence learning in a MOOC. *Computers & Education*, 91, 83–91.

Ifenthaler, D., Bellin-Mularski, N., & Mah, D.-K. (2016). *Foundations of digital badges and micro-credentials: Demonstrating and recognizing knowledge and competencies*. Switzerland: Springer International.

Jo, Y., Tomar, G., Ferschke, O., Rosé, C. P., & Gašević, D. (2016). Expediting support for social learning with behavior modeling. In T. Barnes, M. Chi, & M. Feng (Eds.), *Proceedings of the 9th International Conference on Educational Data Mining* (pp. 400–405).

Jordan, K. (2014). Initial trends in enrolment and completion of massive open online courses. *The International Review of Research in Open and Distributed Learning*, 15(1), 133–160.

Kellogg, S. B. (2018). MOOC-Ed Dashboard [Tableau dashboard]. Retrieved from <https://tableau.fi.ncsu.edu/views/MOOC->

EdDashboardMaster/Dashboard?:embed=y&:showShareOptions=true&:display_count=no&:showVizHome=no#1

Kellogg, S., & Kleiman, G. (2018). *MOOC-Ed evaluation summative report*. Raleigh, NC: The Friday Institute for Educational Innovation.

Khalil, M., & Ebner, M. (2016). When learning analytics meets MOOCs - a review on iMooX case studies. In G. Fahrnberger, G. Eichler, & C. Erfurth (Eds.), *Communications in Computer and Information Science: Vol. 648. Innovations for Community Services. I4CS 2016* (pp. 3–19). Cham, Switzerland: Springer International.

Kizilcec, R. F., & Halawa, S. (2015). Attrition and achievement gaps in online learning. In *Proceedings of the Second (2015) ACM Conference on Learning @ Scale* (pp. 57–66). New York, NY: ACM.

Kizilcec, R. F., Pérez-Sanagustín, M., & Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education, 104*, 18–33.

Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: Analyzing learner subpopulations in massive open online courses. In D. Suthers, K. Verbert, E. Duval, & X. Ochoa (Eds.), *Proceedings of the Third International Conference on Learning Analytics and Knowledge* (pp. 170–179). New York, NY: ACM.

Kizilcec, R. F., & Schneider, E. (2015). Motivation as a lens to understand online learners: Toward data-driven design with the OLEI scale. *ACM Transactions on Computer-Human Interaction (TOCHI), 22*(2), 1-24.

Kleiman, G., Kellogg, S., & Booth, S. (2015). *MOOC-Ed evaluation final report*. Retrieved from The Friday Institute for Educational Innovation website:
<https://place.fi.ncsu.edu/local/catalog/section.php?id=1>

Kleiman, G. M., & Wolf, M. A. (2016). Going to scale with online professional development: The Friday Institute MOOCs for Educators (MOOC-Ed) initiative. In C. Dede, A. Eisenkraft, K. Frumin, & A. Hartley (Eds.), *Teacher learning in the digital age: Online professional development in STEM education* (pp. 49–68). Cambridge, MA: Harvard Education Press.

Kleiman, G. M., Wolf, M. A., & Frye, D. (2013). *The digital learning transition MOOC for educators: Exploring a scalable approach to professional development*. Retrieved from The Friday Institute for Educational Innovation website:
<https://place.fi.ncsu.edu/local/courseblog/view.php?post=3&category=2>

Koller, D., Ng, A., Do, C., & Chen, Z. (2013). *Retention and intention in Massive Open Online Courses: In depth*. Retrieved from EDUCAUSE Review website:
<http://er.educause.edu/articles/2013/6/retention-and-intention-in-massive-open-online-courses-in-depth>

Kolowich, S. (2013, April 8). Coursera takes a nuanced view of MOOC dropout rates [Web log message]. Retrieved from <http://chronicle.com/blogs/wiredcampus/coursera-takes-a-nuanced-view-of-mooc-dropout-rates/43341>

Kop, R. (2011). The challenges to connectivist learning on open online networks: Learning experiences during a massive open online course. *The International Review Of Research In Open And Distributed Learning*, 12(3), 19–38.

Kop, R., & Fournier, H. (2010). New dimensions to self-directed learning in an open networked learning environment. *International Journal of Self-Directed Learning*, 7(2), 1–18.

Kroll, C., & Reed, A. (2017). Towards optimizing MOOC pedagogy: Learner self-control study. In J. Johnston (Ed.), *Proceedings of EdMedia 2017* (pp. 650–656). Washington, DC: Association for the Advancement of Computing in Education (AACE).

Laurillard, D. (2016). The educational problem that MOOCs could solve: Professional development for teachers of disadvantaged students. *Research in Learning Technology*, 24.

Lavigne, H. J., Shakman, K., Zweig, J., & Greller, S. L. (2016). *Principals' time, tasks, and professional development: An analysis of schools and staffing survey data*. Retrieved from ERIC database. (ED569168)

Lee, Y. (2018). Effect of uninterrupted time-on-task on students' success in Massive Open Online Courses (MOOCs). *Computers in Human Behavior*, 86, 174–180.

Littlejohn, A., Hood, N., Milligan, C., & Mustain, P. (2016). Learning in MOOCs: Motivations and self-regulated learning in MOOCs. *The Internet and Higher Education*, 29, 40–48.

Littlejohn, A., & Milligan, C. (2015). Designing MOOCs for professional learners: Tools and patterns to encourage self-regulated learning. *eLearning Papers*, 42, 38–47.

Liu, M., Kang, J., Cao, M., Lim, M., Ko, Y., Myers, R., & Schmitz Weiss, A. (2014). Understanding MOOCs as an emerging online learning tool: Perspectives from the students. *American Journal of Distance Education*, 28(3), 147–159.

Loizzo, J., Ertmer, P. A., Watson, W. R., & Watson, S. L. (2017). Adult MOOC learners as self-directed: Perceptions of motivation, success, and completion. *Online Learning*, 21(2).

Margaryan, A., Bianco, M., & Littlejohn, A. (2015). Instructional quality of Massive Open Online Courses (MOOCs). *Computers & Education*, 80, 77–83.

Merriam, S. B. (2001). Andragogy and self-directed learning: Pillars of adult learning theory. *New Directions for Adult and Continuing Education*, 2001(89), 3–14.

Milligan, C., & Littlejohn, A. (2014). Supporting professional learning in a massive open online course. *The International Review of Research in Open and Distributed Learning*, 15(5), 197–213.

- Milligan, C., & Littlejohn, A. (2016). How health professionals regulate their learning in massive open online courses. *The Internet and Higher Education*, 31, 113–121.
- Milligan, C., & Littlejohn, A. (2017). Why study on a MOOC? The motives of students and professionals. *The International Review of Research in Open and Distributed Learning*, 18(2), 92–102.
- Milligan, C., Littlejohn, A., & Margaryan, A. (2013). Patterns of engagement in connectivist MOOCs. *MERLOT Journal of Online Learning and Teaching*, 9(2), 149–159.
- Moe, R. (2015). The brief & expansive history (and future) of the MOOC: Why two divergent models share the same name. *Current Issues in Emerging eLearning*, 2.
- Mohamed, M. H., & Hammond, M. (2018). MOOCs: A differentiation by pedagogy, content and assessment. *The International Journal of Information and Learning Technology*, 35, 2–11.
- Morris, N. P., Hotchkiss, S., & Swinnerton, B. (2015). Can demographic information predict MOOC learner outcomes. *Proceedings of the EMOOCs Stakeholder Summit*, 199–207.
- Mullaney, T., & Reich, J. (2015). Staggered versus all-at-once content release in massive open online courses: Evaluating a natural experiment. In *Proceedings of the Second (2015) ACM Conference on Learning @ Scale* (pp. 185–194). New York, NY: ACM.
- National Center for Education Statistics. (2018). Teacher trends. Retrieved from <https://nces.ed.gov/fastfacts/display.asp?id=28>
- Nawrot, I., & Doucet, A. (2014). Building engagement for MOOC students: Introducing support for time management on online learning platforms. In *Proceedings of the 23rd International Conference on World Wide Web* (pp. 1077–1082). New York, NY: ACM.
- Onah, D. F. O., Sinclair, J., & Boyatt, R. (2014). Dropout rates of massive open online courses: Behavioural patterns. In L. G. Chova, A. L. Martínez, & I. C. Torres (Eds.), *EDULEARN14 Proceedings* (pp. 5825–5834). Barcelona, Spain: IATED Academy.
- Park, J.-H., & Choi, H. J. (2009). Factors influencing adult learners' decision to drop out or persist in online learning. *Educational Technology & Society*, 12(4), 207–217.
- Phan, T., McNeil, S. G., & Robin, B. R. (2016). Students' patterns of engagement and course performance in a Massive Open Online Course. *Computers & Education*, 95, 36–44.
- Reich, J. (2014). *MOOC completion and retention in the context of student intent*. Retrieved from EDUCAUSE Review website: <http://er.educause.edu/articles/2014/12/mooc-completion-and-retention-in-the-context-of-student-intent>
- Rieber, L. P. (2016). Participation patterns in a massive open online course (MOOC) about statistics. *British Journal of Educational Technology*, 48, 1295–1304.

Rodriguez, C. O. (2012). MOOCs and the AI-Stanford like courses: Two successful and distinct course formats for massive open online courses. *European Journal of Open, Distance and E-Learning*, 2012(2), 1–13.

Saks, K., & Leijen, Ä. (2014). Distinguishing self-directed and self-regulated learning and measuring them in the e-learning context. *Procedia - Social and Behavioral Sciences*, 112, 190–198.

Salmon, G., Gregory, J., Dona, K. L., & Ross, B. (2015). Experiential online development for educators: The example of the Carpe Diem MOOC. *British Journal of Educational Technology*, 46, 542–556.

Salmon, G., Pechenkina, E., Chase, A.-M., & Ross, B. (2017). Designing Massive Open Online Courses to take account of participant motivations and expectations. *British Journal of Educational Technology*, 48, 1284–1294.

Scholastic, & Bill & Melinda Gates Foundation. (2012). *Primary sources: 2012. America's teachers on the teaching profession*. Retrieved from <http://www.scholastic.com/primarysources/download.asp>

Schulze, A. S. (2014). *Massive open online courses (MOOCs) and completion rates: Are self-directed adult learners the most successful at MOOCs?* (Doctoral dissertation). Available from ProQuest Dissertations and Theses database. (UMI No. 3622996).

Shapiro, H. B., Lee, C. H., Roth, N. E. W., Li, K., Çetinkaya-Rundel, M., & Canelas, D. A. (2017). Understanding the massive open online course (MOOC) student experience: An examination of attitudes, motivations, and barriers. *Computers & Education*, 110, 35–50.

Siemens, G. (2005). Connectivism: A learning theory for the digital age. *International Journal of Instructional Technology and Distance Learning*, 2(1), 3–10.

Smith, M. K. (2002). Malcolm Knowles, informal adult education, self-direction and andragogy. In *The Encyclopedia of Informal Education*. Retrieved from www.infed.org/thinkers/et-knowl.htm

Song, L., & Hill, J. R. (2007). A conceptual model for understanding self-directed learning in online environments. *Journal of Interactive Online Learning*, 6, 27–42.

Staubitz, T., Willems, C., Hagedorn, C., & Meinel, C. (2017). The gamification of a MOOC platform. In *Proceedings of 2017 IEEE Global Engineering Education Conference (EDUCON)* (pp. 883–892).

Stubbé, H. E., & Theunissen, N. C. M. (2008). Self-directed adult learning in a ubiquitous learning environment: A meta-review. In *Proceedings of Special Track on Technology Support for Self-Organized Learners* (pp. 5–28).

Sun, N., Rau, P. P.-L., & Ma, L. (2014). Understanding lurkers in online communities: A literature review. *Computers in Human Behavior*, 38, 110–117.

Thompson, I. B., Wiebe, E., Creager, J., & Frankosky, M. (2016, April). *Massive open online course learner subpopulations: A person-centric analysis of longitudinal course utilization classes with predicting factors*. Paper presented at the 2016 annual meeting of the American Education Research Association. Retrieved October 2016, from the AERA Online Paper Repository.

van Cooten, C. H. (2017). *Increasing MOOC completion rates through adaptive learning: A case study* (Master's thesis). Retrieved from <https://dspace.library.uu.nl/handle/1874/353202>

Vigentini, L., & Clayphan, A. (2015). Pacing through MOOCs: Course design or teaching effect? In O. C. Santos, J. G. Boticario, C. Romero, M. Pechenizkiy, A. Merceron, P. Mitros, ... M. Desmarais (Eds.), *Proceedings of the 8th International Conference on Educational Data Mining* (pp. 572–573).

Waard, I. De. (2016). *Self-Directed Learning of Experienced Adult Online Learners Enrolled in FutureLearn MOOCs* (Doctoral dissertation). Retrieved from <http://oro.open.ac.uk/49604/>

Walton, M. (2016, February 10). Welcoming 3 million people to FutureLearn [Web log message]. Retrieved from <https://about.futurelearn.com/blog/welcoming-3-million-people-to-futurelearn>

Wang, Y., Baker, R. S., & Paquette, L. (2017). Behavioral predictors of MOOC post-course development. *CEUR Workshop Proceedings, 1967*, 100–111.

Wei, R. C., Darling-Hammond, L., & Adamson, F. (2010). *Professional development in the United States: Trends and challenges*. Retrieved from The Stanford Center for Opportunity Policy in Education website: <https://edpolicy.stanford.edu/sites/default/files/publications/professional-development-united-states-trends-and-challenges.pdf>

Wen, M., Yang, D., & Rosé, C. P. (2014). Linguistic reflections of student engagement in massive open online courses. In *Proceedings of the Eighth International AAAI Conference on Weblogs and Social Media* (pp. 525–534).

Wiseman, P. J., Kennedy, G. E., & Lodge, J. M. (2016). Models for understanding student engagement in digital learning environments. In *Conference Proceedings: 33rd International Conference of Innovation, Practice and Research in the Use of Educational Technologies in Tertiary Education* (pp. 666–671).

Yang, Q. (2014). Students motivation in asynchronous online discussions with MOOC mode. *American Journal of Educational Research*, 2, 325–330.

Yeager, C., Hurley-Dasgupta, B., & Bliss, C. A. (2013). cMOOCs and global learning: An authentic alternative. *Journal of Asynchronous Learning Networks*, 17(2), 133–147.

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

Zhou, M. (2016). Chinese university students' acceptance of MOOCs: A self-determination perspective. *Computers & Education*, 92–93, 194–203.

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, 41, 64–70.

APPENDICES

Appendix A: Registration Survey

Construct	#	Item
Demographics	1	Gender (Male, Female, I do not identify)
	2	Level of education (High school; 2 year college degree; 4 year college degree; Master's degree; Doctoral degree; Professional degree, e.g. JD or MD)
	3	Organization type (School; School District; College/University; Other Organization)
	4	Primary area of responsibility (Classroom teaching; Curriculum and Instruction; Professional development; Instructional technology; Library/media; School counselor; Special education; Mentor; School-based administration; School district administration; Teach preparation – College/university; Student in college/graduate school; Student in K-12; Research; Other)
	5	Years of experience in education (free response)
	6	I specialize in the following grade levels. Select all that apply. (Pre-K; Kindergarten; Elementary; Middle grades; High school; Post-secondary; N/A)
Recruitment	7	How did you hear about this MOOC-Ed? (Professional organization; Administrator/supervisor; Colleague/peer; Conference; Digital Promise; Friday Institute, e-mail; Friday Institute, social media; Future Ready campaign; Google ad; NBPTS; NCTM; Regional Education Service Agency (RESA); Search engine (Google, Bing, etc.); State Department of Education)
Goals	8	Which of the following best describes your primary reason for enrolling in this course? (Just browsing; Deepen my knowledge of the course topic(s); Connect with peers/colleagues; Collect resources and tools for my practice; Earn a certificate of accomplishment/renewal credits)
	9	Do you plan to participate in the Coaching Modules associated with this course? (Yes; No)
Current practice	10a-f	Please indicate how often you use the following strategies in your classroom. (Never; Rarely/a few times a year; Sometimes/once a month; Often/weekly; Every day; I don't know what this strategy is)

		<ul style="list-style-type: none"> a) I use data about individual students to build a learner profile for individual students. b) I use a variety of techniques to meet individual student needs related to their learning differences. c) I have explicit conversations with students to find out what they need to be successful in my class or other contexts. d) I use information about learning science (e.g., executive function or motivation) to support my teaching practice. e) I present information/content in a variety of ways to meet different learning needs (e.g., I say directions, provide written directions, and demonstrate directions). f) I chunk information according to students' strengths and needs.
	11a-e	<p>Please indicate how comfortable you are using or addressing the following concepts in your practice. (Not at all comfortable; Slightly comfortable; Comfortable; Very comfortable; I don't know what this concept is)</p> <ul style="list-style-type: none"> a) Learner profiles b) Executive functioning skills c) Working memory d) Intrinsic and extrinsic motivation e) Growth mindset

Appendix B: Unit 1-4 Survey

Construct	#	Item
Learning and application	1a-d	To what extent do you agree with the following statements? (all 1 Strongly Agree to 5 Strongly Disagree) <ul style="list-style-type: none"> a) The information in this unit was entirely new to me. b) This unit deepened my understanding of learning differences. c) I am better able to meet my students' different learning needs as a result of this unit. d) I intend to use the resources/materials provided in this unit in my own professional practice.
Time spent	2	Approximately how many hours did you spend on this unit's activities? (1-2 hours; 3-4 hours; 5-6 hours; 7-8 hours; more than 8 hours)
Design feedback	3	Did you have any issues with navigating through this unit? (Yes; No)

Appendix C: Unit 5 Survey

Construct	#	Item
Usefulness	1	What concepts or strategies highlighted in this course do you believe will be most useful to you to better understand and support your student's unique learning differences? (free response)
Changes to professional practice	2	What changes, if any, have you made (or anticipate making) in your professional practice as a result of your participation in this MOOC-Ed so far? (E.g., Application of new knowledge, skills, or course resources) (free response)
UX feedback	3	What recommendations, if any, do you have for improving the user experience in this course (e.g., navigation, visual design, unit organization, etc.) (free response)
Time spent	4	Approximately how many hours did you spend on this unit's activities? (1-2 hours; 3-4 hours; 5-6 hours; 7-8 hours; more than 8 hours)

Appendix D: End-of-course Survey

Construct	#	Item
Learning support	1	As a whole, how effective was this MOOC-Ed in supporting your personal and/or professional learning goals? (1 Very Effective to 5 Very Ineffective)
	2	What was the most valuable aspect of this MOOC-Ed in supporting your personal or professional learning goals? (free response)
Learning gains	3a-f	<p>To what extent do you agree with the following statements? As a result of my participation in this MOOC-Ed, I have improved my knowledge and/or skills related to... (1 Strongly Agree to 5 Strongly Disagree)</p> <ul style="list-style-type: none"> a) what learning differences are and how they affect all students. b) how to foster a growth mindset or problem solving approach among educators as they work with students. c) working memory and its impact on learning and behavior in classrooms. d) student motivation and its impact on learning and behavior in classrooms. e) executive functioning skills and their impact on learning and behavior in classrooms. f) strategies or solutions to address learning differences and better support students.
Conceptual understanding	4	Based on your overall experience as a participant in this course, how would you define learning differences? (free response)
Changes to professional practice	5	Overall, how effective do you feel this MOOC-Ed was in preparing you to make positive changes in your professional practice? (1 Very Effective to 5 Very Ineffective)
Micro-credential participation	6	Did you attempt to earn a micro-credential for this MOOC-Ed? (Yes; No; I'm not sure)
	7	[If Yes to 6...] Why did you choose to pursue a micro-credential for this course? (free response)
	8	[If Yes to 6...] In what ways, if any, did the micro-credentialing process impact your professional practice? (free response)
	9	[If No to 6...] Why did you choose not to pursue a micro-credential for this course? (free response)

Micro-credential value	10a-f	<p>To what extent do you agree with the following statements? MOOC-Ed Micro-credentials are a valuable tool for... (1 Strongly Agree to 5 Strongly Disagree, with I Don't Know option coded as 0)</p> <ul style="list-style-type: none"> a) engaging in professional learning with an increased level of rigor. b) promoting significant changes to my instructional practice. c) communicating my professional competencies with others. d) personalizing my professional learning experience. e) facilitating collaboration and communication with other educators. f) motivating me to pursue additional learning opportunities within or beyond the MOOC-Ed.
Course feedback	11	<p>What recommendations do you have for making this course more valuable to future participants (e.g., other resources, additional features, activities, etc.)? Please explain. (free response)</p>
Time	12	<p>Were you able to complete all of the activities that you wanted to complete in this course? (Yes; No)</p>
	13	<p>If no, please explain (free response)</p>
	14	<p>Approximately how many hours did you spend on this unit's activities? (1-2 hours; 3-4 hours; 5-6 hours; 7-8 hours; more than 8 hours)</p>

Appendix E: Duration Calculation

Durations of the six key resource interactions studied in this project were calculated by aggregating durations of events recorded in Moodle course logs. Logs captured a variety of events, such as page loads, activation of elements within pages, and account-related actions (e.g. logging in/out) so duration calculations accounted for resource usage that spanned multiple log events. The process of computing these durations is described below, and example code snippets are provided to illustrate how the durations can be computed in the R programming language with tidyverse packages.

Given chronologically ordered Moodle log events for each learner, event durations were calculated as the time to subsequent events, capped at a maximum of 0.33 hours.

```
max_duration <- 60 * 20
logs <- logs %>%
  group_by(userid) %>%
  arrange(timecreated) %>%
  mutate(
    eventduration = lead(timecreated) - timecreated,
    eventduration = ifelse(is.na(eventduration), max_duration, eventduration),
    eventduration = ifelse(eventduration > max_duration, max_duration,
                          eventduration))
```

Three of the key resource interactions (lecture note views, external link views, and forum views) were logged as single events fired at the start of the interactions so their resource durations were equivalent to the corresponding event durations. In the following snippets, it is assumed that each log event has already been classified into an `eventgroup` category, which can be used to identify key resource interactions, such as lecture note views. This categorization must be performed on a course-by-course basis because the types of Moodle modules a course instructor uses and the way in which the course instructor uses those modules affects which event logs correspond to the higher-order interactions of interest.

```
logs <- logs %>%
  mutate(
    interactduration = case_when(
      eventgroup == "lecture note view" ~ eventduration,
      eventgroup == "external link view" ~ eventduration,
      eventgroup == "forum view" ~ eventduration) %>%
  ungroup()
```

Other resource interaction durations were more complex to compute. Multiple events were associated with video resources, such as the page load, playing of the video, pausing of the video, viewing the video transcription, etc. so durations of video resource views were computed by finding a video page load and summing durations of subsequent chronological events until an event was reached that did not correspond to the video resource. Video resource view durations included time while the video was not playing or paused because video resources included text content that accompanied video content. In the following snippets, `userid` represents a unique participant identifier, and `cmid` represents the Moodle course module id corresponding to the video resource.

```
for (i in 1:nrow(logs)) {
  if (!is.na(logs$eventgroup[i]) & logs$eventgroup[i] == "video view") {
    userid <- logs$userid[i]
    cmid <- logs$cmid[i]
    dur <- logs$eventduration[i]
    for (j in (i+1):nrow(logs)) {
      if (j > nrow(logs)) break
      if (logs$userid[j] != userid) break
      if (is.na(logs$cmid[j]) | logs$cmid[j] != cmid) break
      dur <- dur + logs$eventduration[j]
    }
    logs$interactduration[i] <- dur
  }
}
```

Forum post interactions were logged as either single events or multiple simultaneous events if attachments, such as pictures or documents, were provided with the posts. The events were logged at the time the posts were submitted, rather than when they were started so duration

of the post interaction was computed by looking chronologically backward in the event log until an event at an earlier timestamp was encountered.

```
for (i in 1:nrow(logs)) {
  if (!is.na(logs$eventgroup[i]) & logs$eventgroup[i] == "forum post") {
    userid <- logs$userid[i]
    timestamp <- logs$timecreated[i]
    dur <- 0
    for (j in (i-1):1) {
      if (j < 1) break
      if (logs$userid[j] != userid) break
      if (logs$timecreated[j] != timestamp) {
        dur <- logs$eventduration[j]
        break
      }
    }
    logs$interactduration[i] <- dur
  }
}
```

Multiple log events were associated with assessments (e.g. start, save progress, and submit) and those events could be non-sequential if an assessment was saved with partial progress and resumed at a later time. Assessment submission durations were computed by finding submit events, looking chronologically backward, and summing all prior events related to the same assessment, even if non-sequential, until either an earlier submission of that assessment or the beginning of the course was reached.

```

for (i in 1:nrow(logs)) {
  if (!is.na(logs$eventgroup[i]) &
      logs$eventgroup[i] == "assessment submit") {
    userid <- logs$userid[i]
    cmid <- logs$cmid[i]
    dur <- 0
    for (j in (i-1):1) {
      if (j < 1) break
      if (logs$userid[j] != userid) break
      if (!is.na(logs$cmid[j]) & logs$cmid[j] == cmid) {
        if (!is.na(logs$eventgroup[j]) &
            logs$eventgroup[j] == "assessment submit")
          break
        if (!is.na(logs$cmid[j]) & logs$cmid[j] == cmid) {
          dur <- dur + logs$eventduration[j]
        }
      }
    }
    logs$interactduration[i] <- dur
  }
}

```

Resource interaction durations were capped at a maximum of 0.33 hours. Then learners' course and modular resource interaction durations were calculated by summing interaction durations within the corresponding time windows, i.e. the entire course or within the weeks modular units were released.

```

logs <- logs %>%
  mutate(
    interactduration = ifelse(interactduration > max_duration, max_duration,
                              interactduration))

```