# Temporal flexibility, gender, and online learning completion

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**Abstract**

Flexible learning removes barriers relating to time, place, and pace. While time management skills have been identified as necessary for learners to take advantage of flexible learning, relatively little is known about the temporal dimensions of flexible learning and how gender might relate to temporal flexibility and its perceived benefits. To address this gap, we analyze data from 380,000 students participating in two massive open online courses to create a model that predicts course completion likelihood from learner time management behaviors and gender. Results supported most a priori assumptions. Successful course completers log in frequently, devote longer amounts of time to each session, move quickly through course materials, and complete coursework early. However, consistent study was associated with lower course completion likelihood, and women benefited more from reduced consistency. These findings suggest that temporal flexibility may especially benefit women.

**Keywords:** flexible learning; time management; gender; MOOC

Individuals today can enroll in online courses from many public, private, non-profit, and for-profit educational institutions and credential providers. Prior to the COVID-19 pandemic, which forced the majority of universities worldwide to shift teaching and learning from in-person to online and distance education formats, overall enrolments in online courses in the United States of America had been increasing steadily since 2002, and around 30% of university-level students were taking at least one online course (Seaman, Allen & Seaman, 2018). In Canada, it is estimated that in any given semester, there are more than 1.3 million online course registrations, and these have been growing in recent years (Bates, 2018; Jean-Louis, 2015). At the time of writing (October, 2020), these numbers pale in comparison to the numbers of students who are currently participating in remote and online education.

One of the proposed advantages of online learning is the spatial and temporal flexibility it offers students (Houlden & Veletsianos, 2019; Veletsianos & Houlden, 2019). Optimism surrounding the flexibility of online learning is reflected in the recurring claim that this mode of education provides people with the possibility of learning from *anywhere* at *anytime* (e.g., Carey, 2016; Horton, 2000). In this paper, we interrogate the claim that online learning supports individuals' ability to learn at any time by investigating potential relationships between success and temporal patterns of participation in two massive open online courses (MOOCs). Further, we examine whether course completion outcomes are associated with gender in order to add to emerging literature that suggests that the opportunities for flexible education are unevenly distributed, meaning that flexible learning may benefit some populations more than others (e.g., Houlden & Veletsianos, 2019). Specifically, we ask the following research question: In an asynchronous MOOC setting, how did time management behaviors influence completion, and how was this mediated by learner gender? We answer this question using Bayesian regression to create a model that predicts MOOC course completion likelihood from learner time management behaviors and gender. Following a review of relevant literature, we describe the methodology used to answer this question, which employed deidentified activity-level and course-completion data for two MOOCs offered by Stanford University between 2014 and 2019. Next, we describe the study's findings and implications for research and practice.

**Review of relevant literature**

Flexible learning is often described in the distance education literature as a modality or as an aspect of distance and online teaching and learning that enables learners to pursue educational endeavors without the limitations of time, place, and pace. Significantly, some researchers have recently argued that flexibility is more than just a modality but, in fact, represents an ethos that can be applied to any educational endeavor. Naidu (2017, p. 269), for instance, has argued that "it is a value principle, like diversity or equality are in education and society more broadly" because any number of taken-for-granted aspects of education—admissions, assessment, learning activities—can be made more flexible, and, as such, flexibility "is relevant in any mode of study including campus-based face-to-face education."

However, little is known about the temporal dimensions of online and flexible learning, and the degree to which temporality impacts success. Kahu and colleagues (2014) noted that few researchers have problematized the notion of time in distance education, and a systematic analysis of literature dealing with educational technology noted that even though temporal factors are significant to teaching and learning, they have been insufficiently and poorly investigated (Barbera et al., 2015). Questions that we believe are significant include the following: Do successful learners actually participate in online courses at anytime from anywhere as much of the literature suggests, or do they (intentionally or as a result of environmental variables) restrict flexibility in their studies? Who is and who is not able to take advantage of the flexibility inherent in these courses? Online and distance learners report that they value the flexibility of their studies (e.g., Tricker et al., 2001); yet the themes arising in the literature in which learners were interviewed suggest that students deal with spatial and temporal constraints and restrictions that they either faced or were imposed upon them as restricting flexibility and that, at a minimum, claims of anytime and anyplace are not wholly accurate.

For instance, Du and colleagues (2019) suggested that the facet of location-based entropy is negatively affecting performance—where students working in multiple locations and times on multiple projects experience greater difficulty maintaining coursework. As a result, students with high variability in time and location scored lower than comparative peers and had the least success of all students even when compared to students who changed only the time they studied or changed only their location. The most successful students from this study relied on established and scheduled patterns of study that worked for them. While all students had the same access to resources, it was the students who imposed self-managed commitments, who were most successful. This was particularly the case with female students as they generally were more likely to study at fixed times and locations, which—in this instance—resulted in higher overall grades. This study suggests that time-based consistency in study behaviors may influence performance and that gender may be an important variable to consider.

Studies of student study behavior to forecast completion or achievement have been used for course design and retention by examining student learning events, activities, and behavior in connection with their academic performance (e.g., Richardson et al., 1999; Richardson & Price, 2003; Schraw et al., 2007; Tempelaar et al., 2015). Barbera et al. (2015) suggested temporal analyses examine student behavior at the individual activity level (e.g., studying, seeking assistance) rather than aggregating these activities to the student level. An example of using a more fine-grained approach is seen in research on homework and its relationship to student performance noting the need to analyze the separate effects of homework accuracy and homework completion (Englander et al., 2015). While accuracy and completion had statistically significant impacts on student performance in that study, homework accuracy was the most important variable explaining student performance on the midterm and final exams. Researchers also found that the impact of variables that students have control over (e.g., completion of homework assignments, average scores on homework assignments, procrastination, and class attendance) were substantially more influential in explaining variations in student performance than those variables considered beyond a student's control (Englander et al., 2015).

Previous research examining students' engagement in learning activities and study practices has reported mixed findings with regard to student achievement in investigations of spaced study versus procrastination and last-minute cramming (Pychyl et al., 2001; Romano et al., 2005; Zuriff, 2003). Despite the increased opportunity for self-management offered by online courses where students may have more control over whether, when, and how they will study, there are concerns that increased freedom may lead to study procrastination, which in turn could result in cramming. Moreover, the potential for distraction may be greater where all class activities are online and students are on their own to manage their time and efforts, making motivation even more critical (Artino & Stephens, 2009; Sansone et al., 2012). Romano and colleagues (2005) found students in blended courses tended to procrastinate more than students participating completely at a distance, suggesting self-selection, where more independent learners opt for the total distance sections, might be one explanation. In other studies examining procrastination behaviours in postsecondary education, Adams and Blair (2019) reported that students tend to procrastinate on tasks they do not like but must be done; while Pyc and Dunlosky (2010) found a general preference for students to space practice for both easy and more difficult tasks and reserve mass practice for more difficult tasks.

Another study investigating temporal and instructional conditions in blended or hybrid courses found that regular patterns of below-average activity led to worse performance while steady, above-average activity was beneficial for course performance, noting that as students gain experience with blended models they may come to see the advantages of preparation (van Leeuwen et al., 2017). This led researchers to suggest possible benefits of monitoring students' activity early in a course to promote regular study patterns later on. Furthermore, findings reported in a study by Adams and Blair (2019) suggest that students find the mechanics of time management challenging as they perceive limited control over their own time. Those researchers found that participants with higher scores for both setting goals and priorities, and perceived concepts of time, had on average significantly greater cumulative grade point averages. This finding was partially corroborated in an earlier study where students in online courses were not found to differ from students in an on-campus section in their use of goal-defined motivational strategies. While such strategies (such as reminding oneself about the importance of good grades and working to see the usefulness of learning the topic for real life) were not correlated with grades, results did show that experience-defined motivational strategies such as persuading oneself to work hard to learn course content and applying learning to real life were positively correlated with a greater interest in the class and topic. Stronger engagement, especially early in the course, involved trade-offs, which had indirect positive impacts on students' abilities to sustain interested engagement while learning on their own, mitigating negative effects on grades (Sansone et al., 2012).

Regarding learner differences, Adams and Blair (2019) found that regardless of gender, age bracket, entry qualification, or time in the program, students typically want to be organized, but they may struggle to develop needed strategies to do so. As a result, interventions aimed at promoting self-efficacy and engagement in online settings may be an effective means of reducing procrastination and promoting student interest in course topics (Artino & Stephens, 2009; Sansone et al., 2012). These studies draw attention to evidence around how effective time management behaviors may lead to improvements in students' cumulative grade point average and increased engagement with topics, which may lead to greater time spent with course materials and learning activities. They also suggest the importance of scaffolding student time-management behaviors to help students better organize their time and set priorities.

Similar results have been found in research with MOOCs. In a study by Rizvi et al. (2018), two student groups were examined: completers and non-completers. Techniques with an emphasis on extracting process-related data from event logs were applied to reveal how students divided their time between various participatory requirements. Namely, on a per-hour basis, student behavior was noted regarding how they engaged with videos, articles, audio, discussions, quizzes, and tests. While both groups demonstrated an increase in time to the course requirements, the non-completers engaged more sporadically, with distinct and dramatic spikes and dips in their activity. They also spent less time immersed in preparation material and spent slightly more time completing the assessments. In comparison, the completers of the course maintained a connection with the course materials in between spikes of additional study. The resulting inference is that steadiness of schedule and consistency prevailed over irregular attempts at assignment completion and preparation. A study by Tang et al. (2018) corroborates these findings. Examining the patterns of success relating to temporal forum activity in MOOCs, Tang and colleagues found that students who were participating in forums in an ongoing and persistent manner outperformed other learners.

Overall, these findings suggest that student success in MOOCs seems to be strongly connected to students' abilities and dispositions to manage themselves (Nawrot & Doucet, 2014). Undergirding our common understandings of flexibility and time management, however, is an implicit assumption that all learners benefit from educational innovations in similar ways (Veletsianos & Houlden, 2019) or that any differences between learners in this regard stem from cognitive differences (e.g., brain-based differences between men and women in Du et al., 2019). However, some studies have suggested that women in particular face significant environmental obstacles to taking advantage of flexible learning opportunities. For instance, some women's studies are interrupted by caregiving responsibilities (e.g., child-rearing or looking after the elderly)—that remain unchanged when women commence or continue studies—or by bearing the responsibility for unpaid household work (e.g., Castles, 2004; Horne et al., 2018; Selwyn, 2011). Such obstacles suggest that temporally flexible learning opportunities may yield different benefits and outcomes for women versus men.

As MOOCs are predominantly self-paced, self-imposed scheduling is necessary to succeed in such a high-freedom learning environment. However, the time available to a student to study (and to do so in a structured manner) seems to also be a fundamental component of success. Studying this topic in the context of MOOCs is further problematized by the fact that men and women might enroll and participate in these courses at different rates and for different reasons (e.g., Bayeck, 2016; Jiang et al., 2018; Zafras, Kostas, Sofos, 2020) due to a variety of factors such as motivational differences, gender dynamics, or subtle environmental cues (Brooks et al., 2018; Crues et al., 2018; Gokool-Ramdoo, 2006; ).

Given this background, it seems clear that understanding temporal factors in online courses is essential for course designers and researchers alike. Such an understanding may lead to interventions, both at the course and institutional level, to improve participation, completion rates, and success. Toward this goal, researchers also need to better understand the degree to which temporal flexibility is valuable and how the benefits and constraints of such flexibility may vary by individual learner characteristics, such as gender. In this study, we focus on self-paced MOOCs because they allow for large-scale investigation of temporal flexibility. In particular, we focus our efforts on a dataset of about 380,000 students from two MOOCs to better understand how time-based factors (such as consistency) influenced course completion and how findings regarding such factors might be connected to student gender.

**Methodology**

This study used Bayesian regression to create a model that predicts MOOC course completion likelihood from learner time-management behaviors and gender by asking the following research question: In an asynchronous MOOC setting, how did time-management behaviors influence certificate completion, and how was this mediated by learner gender? By time-management behaviors, we mean behaviors like chunking time, focusing engagement, scheduling consistency, and early emphasis (described below), which represent either externally or internally imposed time-structuring behaviors for managing learning. Null and alternative hypotheses we proposed for this question were as follows:

- $H_0$: Learners' time-management behaviors did not affect MOOC completion.

- $H_1$: Learners' time-management behaviors positively affected MOOC completion.
- $H_2$: Learners' time-management behaviors negatively affected MOOC completion.

Stanford University's Center for Advanced Research through Online Learning (CAROL) provided open course data for this study. At the time of writing, one of the Center's practices involved providing data for analysis to third-party researchers. The data for this study consisted of deidentified activity-level and course-completion data for two MOOCs offered on an instance of the OpenEdX platform: How to Learn Math and Computer Science 101. The courses cover the 2014–2019 time period, beginning from the date the courses were launched to the date we received the data. We are not affiliated with the research center providing the data and have had no involvement or relationship in the design, development, or teaching of these courses.

Previous research has found that MOOCs have a notoriously low completion rate, due to observers, drop-ins, and lurkers (Rivard, 2013). The two courses followed this same pattern with only 20.7% of the 227,126 learners for whom we had data in How to Learn Math and 25.3% of the 155,814 learners in Computer Science 101 receiving a certificate. In response, our research question required us to exclude learners in the dataset whose activity patterns suggested that they were not certificate-seeking. Assuming that the best way for determining this would be by focusing on learner time in the course, we excluded all learners whose total time was below the median time exhibited by those who completed the course. This enabled us to compare completers to other learners who should have been expected to complete the course, due to the amount of time and concomitant effort, but did not. Even with this exclusion criterion, we had a very large number of learners to compare for each course—$n$ = 165,961 in How to

Learn Math (26.9% exclusion) and $n$ = 108,041 in Computer Science 101 (30.7% exclusion). As a result of this exclusion the certificate completion rate went up slightly to 26.7% and 28.1% (see Table 1). Certificate completion consisted of a single, binary variable and served as the dependent variable for the study.

[INSERT TABLE 1 ABOUT HERE]

### ***Data coding***

We cleaned, collated, recalculated, and recoded activity data for each included learner to match six desired theoretical constructs relating to time-structuring behaviors. We will now explain each of these six activity variables, which were used as the independent variables for the study.

*Login frequency* was the total or the raw number of times each student logged in to the course. This basic variable was used to determine how generally active the student was in the course with the expectation that greater activity would yield a greater likelihood of certificate completion. The average time and number of sessions among studied learners in each course varied, with learners spending an average of 1.7 hr across 3.5 sessions in How to Learn Math and 3.44 hr across 5.38 sessions in Computer Science 101 (see Table 1).

*Time chunking* was the average amount of time that each student devoted to each session. For instance, if the student logged in three times—for 0.25, 0.5, and 0.75 hr—their time chunking value would be 0.5 ($M$ = 0.51 hr for the math course; $M$ = 0.54 hr for the computer science course). This variable was used to determine how consistently the student devoted a reasonable amount of time to each session (rather than just logging in briefly) and was expected to yield a greater likelihood of certificate completion.

*Activity speed* was the number of activities or interactions each student completed per minute of being logged in. For instance, if the student logged in for 10 min and engaged in 15 system activities and/or events, such as watching a video, then their activity speed would be 1.5 (*M* = 1.96 for math; *M* = 1.39 for computer science). This variable was used to determine the engagement or focus of the student during their time in the course and was expected to yield a greater likelihood of certificate completion.

*Login consistency (hr)* was the percentage of each student's logins that occurred during their most common hour of logging in. For instance, if the student logged in twice in the 9am hour, twice in the 10am hour, and six times in the 11am hour, then their login consistency (hr) would be 60%, representing six logins for the 11am hour divided by 10 total logins (*M* = .68 for math; *M* = .62 for computer science). This variable was used to determine student consistency to a daily schedule and was expected to yield a greater likelihood of certificate completion. Notably, this method of operationalizing login consistency varied from that employed by Du et al. (2019) in that ours (a) was more granular at the hourly level (whereas theirs focused on segments of the day: morning, afternoon, and evening), (b) treated hourly and daily consistency as separate variables (whereas theirs collapsed the two and only differentiated between workdays and weekdays), and (c) allowed for time zone, cultural, and other individual differences between learners by resisting generalist labeling of time increments (e.g., 5pm might have differential significance and norms to learners according to culture, life situation, or work schedule, which defies the afternoon/evening dichotomy).

*Login consistency (d)* was the percentage of each student's logins that occurred during their most common day of the week of logging in. For instance, if the student logged in once on Monday, twice on Tuesday, and seven times on Wednesday, then their login consistency would be 70%, representing seven logins for Wednesday divided by 10 total logins (*M* = .73 for math; *M* = .7 for computer science). This variable was used to determine student consistency to a weekly schedule and was expected to yield a greater likelihood of certificate completion.

*Early emphasis* was the percentage of each student's activity that occurred within the first 3 weeks of their activity in the course. For instance, if the student began the course on April 1 and logged in eight times before April 21 and two times after April 21, then their early emphasis would be .8, representing eight logins before the 3-week cutoff divided by 10 total logins (*M* = .87 for math; *M* = .89 for computer science). This variable was used to determine the student's initial excitement, prioritization, and commitment to the course and was expected to yield a greater likelihood of certificate completion. We selected 3 weeks as the cutoff because earlier literature shows a high level of dropout in Weeks 1 and 2 (e.g., Kloft et al., 2014). *Gender* of each student was also included as a covariate to determine whether this played a significant role in certificate completion. Gender distribution varied between the two courses. In How to Learn Math, 56% of learners identified as female, 43% as male, and 2% as other. In Computer Science 101, 29% identified as female, 70% as male, and 1% as other.

### *Data analysis*

Bayesian regression, similar to linear regression, attempts to make a model that predicts and explains the causal relations between a set of covariates and certain outcomes. Bayesian regression is superior to linear regression as all normality assumptions are unnecessary: Bayesian regression creates a posterior distribution for each of the parameter estimates, which is close in concept to a sampling distribution in frequentist statistics. This posterior distribution can be used to create credibility intervals, which are flexible alternatives to traditional confidence intervals that allow for asymmetric and non-normal-looking distributions in creating the plausible set of values for the parameter. The other assumptions of traditional linear regression (linearity, independence, multicollinearity, and equality of variance) still apply, and we checked them via looking at residual plots, variance inflation factors. Because course structure, context, population, and expectations were anticipated to be at least somewhat unique between the two courses, we analyzed each course separately and then compared the results.

### *Limitations*

This study was limited to data from two large MOOCs across 5 years. Large sample sizes allowed for sufficient variability and predictive power in user data to model results, but special attention should be paid to the strength of effects for interpreting results. Furthermore, to ensure privacy and confidentiality, the deidentified data available via CAROL exclude sensitive data, and as such prevent a more detailed reporting of learner characteristics (e.g., learners' geographic location) or the development of more complex models or analyses that could have taken into account such important variables as prior knowledge, motivation, and intent behind enrolment.

## Results

The relevant assumptions for linear regression were checked and were found to be met. Results for the Bayesian regression with 6 covariates indicated that identified time-management behaviors had a large, statistically significant effect on certificate completion, with the overall model accounting for 30% of completion variance in How to Learn Math and 43% in Computer Science 101. Furthermore, all individual covariates exhibited statistically significant effects. However, given the size of the dataset, statistical significance for any of these covariates should not be surprising. Our attention should focus on the size and direction of effects for determining meaningful significance. Absolute values for each estimated effect ranged from weak (.01) to very strong (1.32). These values are shown in Table 2.

For both courses, half of the modeled covariates—*login frequency*, *time chunking*, and *activity speed*—exhibited anticipated positive effects on certificate completion (ranging from .01 to .33), revealing that as learners logged in more, devoted more time to each session, and were more active while logged in, they were more likely to complete the course. However, the other three covariates—*login consistency (hr)*, *login consistency (d)*, and *early emphasis*—each exhibited unanticipated negative effects. What is more, the two *login consistency* variables were the strongest of all predictors in both courses (ranging from -.32 to -1.32), revealing that as learners persisted in schedules of only logging in on particular hours or particular days, their likelihood of completing the course decreased dramatically.

[INSERT TABLE 2 ABOUT HERE]

Effects of *gender* were also statistically significant for both courses, but the sizes of the estimated effects were relatively small (.08 and .03). We also added interaction terms of (a) gender*hourly consistency and (b) gender*daily consistency. Both interaction terms were significant ($p < .01$). As the terms themselves are difficult to interpret, we graphed them in Figures 1 and 2. Both effects were small but indicated that male and female certificate completion differed little in cases of high hourly consistency and also in cases of low daily consistency. However, exhibiting low hourly consistency provided a greater benefit to women than to men for earning a certificate.

[INSERT FIGURE 1 ABOUT HERE]

[INSERT FIGURE 2 ABOUT HERE]

## Discussion

Some results of this study were unsurprising and expected. These supported a priori assumptions about time-structuring behaviors, as students' likelihood of completing each course improved by logging in to the course more frequently, devoting longer time intervals to working while logged in, and spending their logged-in time more actively interacting with course content. These findings are widely supported in prior literature (e.g., Adams & Blair, 2019; DeBoer et al., 2014; Rizvi et al., 2018; Tang et al., 2018). Though not surprising, these results affirm practices that support frequent and sustained engagement as essential to support learning. Thus, making the content temporally flexible and available at any time may be valuable on its own, but for students to be most successful with flexible courses, they also need realistic understandings of time commitments required to be successful. Practical suggestions to support such efforts may include human-led or algorithmic-led participation reminders, encouragements to develop scheduled and structured time for study, or the delivery of messaging that highlights the outcomes associated with such study habits. The development and future study of such interventions and support structures would be worthwhile in the context of both MOOCs and online courses generally. Without such supports, poor time-management skills may prevent students from completing coursework that they are otherwise capable and motivated to complete (Sansone et al., 2012). Time-management skills should be considered essential elements of learning—not only in MOOC design but also any learning design as the development of such skills is rarely an intended learning outcome of any given course. This is especially important when underdeveloped time-management skills run the risk of being misinterpreted as lack of interest, lack of motivation, or lack of ability.

Results, however, also suggest that less-classically-structured approaches to logging in throughout the week and throughout any given day improved certificate completion. Results also showed that taking longer than the initial 3 weeks enabled learners to revisit courses, potentially completing them when such courses fit better into learner schedules. One potential explanation for this revolves around the context of these two MOOCs, which were asynchronous and self-paced, meaning that they afforded wide flexibility to learners. It is possible that temporal flexibility was more important for completion than was study consistency because the greatest barriers for completion among the diverse group of learners participating may have been more external in nature (e.g., life events, work schedules, professional deadlines) than internal (e.g., lack of motivation, lack of time-management skills). In other words, while time management may be one of the guiding predictors of success in some environments and for some learners, this study suggests that in some contexts, such as MOOCs, time management may be less important than other variables that demand learners' attention, such as available time. To this end, participation reminders, as we suggested above, may do little to address limitations and inflexibilities that learners face in their broader life, such as having limited time available to study due to other responsibilities. There is a potential tension evident here between an individual's course-level participation and their life beyond the course, that hints at negotiation. In other words, if we are to view learners as individuals who have responsibilities, needs, desires, and so on, beyond their online courses (Veletsianos, 2020; Veletsianos, Reich, & Pasquini 2016), then we come to recognize course-level participation as negotiated, and learners as negotiating competing demands and attending to them based on everchanging circumstances. It may be worthwhile therefore, for future research to attend more to the forces that shape learner participation beyond course-level practices.

In other words, what are the takeaways for researchers and practitioners in cases where learners have well-honed time-management skills, but lack time or lack neat chunks of time, as may be the case with some learner populations? In this study, we noted that some women may face such obstacles as lack of neat chunks of time due to other responsibilities and argued that variations in participation may be the result of structural and systemic influences on learners' time or lack thereof. We found that gender exerted a significant (but weak) influence on course completion. This is noteworthy for a number of reasons. Significantly, the subject areas of both courses—math and computer science—have historically been critiqued for under-serving women (Cheryan et al., 2013) and even encompassing inherently sexist pedagogical or design strategies (Brooks et al., 2018; Gokool-Ramdoo, 2006). Self-selection of women out of such coursework may play some role in explaining disparities, but the demographics of these two courses are interesting: though the computer science course highly favored male self-selection and the math course favored female self-selection, both exhibited greater completion likelihood among males. It could be that the design of both courses exhibits subtle biases toward male students that implicitly supports their performance above that of their female peers, though in this study we were not able to control for motivational differences as in Crues et al. (2018). Yet, the fact that women with low hourly consistency were actually the most likely to receive a completion certificate of any group (i.e., men or women at any consistency) also suggests that women may need and benefit more from flexible course designs than men. The implications are significant. For instance, encouraging women to have more consistent study schedules (e.g., an hourly schedule) may not be a viable solution if those women face challenges and environments that prevent such time allocation. A typical example may be a person whose time to study is the time that is available after family responsibilities are met. In such cases, solutions at the micro level (e.g., individual) may be less successful than solutions at the meso or macro levels (e.g., institutional supports, cultural shifts).

As we have mentioned before, the reason for certain people benefiting more than others from flexibility may be varied, but the environmental and social factors influencing women's academic opportunities may be a culprit here, as women in North America and globally have historically borne more responsibility for household work, childcare, and caring for the elderly (Horne et al., 2018; Kamo & Cohen, 1998). This might also suggest that if online coursework is more temporally rigid and does not allow for flexibility in daily schedules, then women might be disadvantaged more than men, and if course designers, instructors, and educational leaders want to address gender disparities in online course enrollment and completion, then increasing opportunities for temporal flexibility could be a key place to start. One practical suggestion for course instructors could be to evaluate their own course in terms of its flexibility and consider whether certain aspects to it could be made more flexible. More research into these issues, however, is necessary. Such research may help researchers and designers understand how flexibility and flexible learning operate and are enacted by different instructor and learner populations.

**Disclosure statement**

The authors report that they have no potential conflicts of interest.

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## Data availability statement

Data for this study were provided by Stanford University's Center for Advanced Research through Online Learning (CAROL). Requests for data should be directed to CAROL.

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**Table 1.** Descriptive results for targeted learners of two MOOCs.

| | How to Learn Math | | Computer Science 101 | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| Certificate completion rate | 0.267 | 0.442 | 0.281 | 0.45 |
| Total time (hr) | 1.7 | 2.06 | 3.436 | 5.036 |
| Login frequency | 3.504 | 4.4 | 5.378 | 7.155 |
| Time chunking (hr) | 0.513 | 0.475 | 0.536 | 0.495 |
| Activity speed (min) | 1.962 | 2.651 | 1.39 | 2.906 |
| Login consistency (hr) | 0.682 | 0.309 | 0.615 | 0.338 |
| Login consistency (d) | 0.729 | 0.28 | 0.7 | 0.3 |
| Early emphasis | 0.873 | 0.238 | 0.886 | 0.233 |
| Gender (Male) | 0.426 | 0.495 | 0.702 | 0.457 |

**Table 2.** Bayesian model analysis of temporal covariates on certificate completion for two MOOCs.

| | How to Learn Math | | | Computer Science 101 | | |
|---|---|---|---|---|---|---|
| | Estimate | SD | p value | Estimate | SD | p value |
| Login frequency | 0.049 | 0.001 | < .001 | 0.012 | 0.001 | < .001 |
| Time chunking | 0.159 | 0.003 | < .001 | 0.329 | 0.002 | < .001 |
| Activity speed | 0.012 | 0.001 | < .001 | 0.022 | 0.001 | < .001 |
| Login consistency (hr) | -0.397 | 0.021 | < .001 | -1.319 | 0.017 | < .001 |
| Login consistency (d) | -0.321 | 0.024 | < .001 | -0.859 | 0.018 | < .001 |
| Early emphasis | -0.082 | 0.021 | < .001 | -0.239 | 0.017 | < .001 |
| Gender (Male) | 0.08 | 0.009 | < .001 | 0.025 | 0.008 | < .001 |
| Model R-Square | 0.296 | 0.003 | < .001 | 0.429 | 0.003 | < .001 |

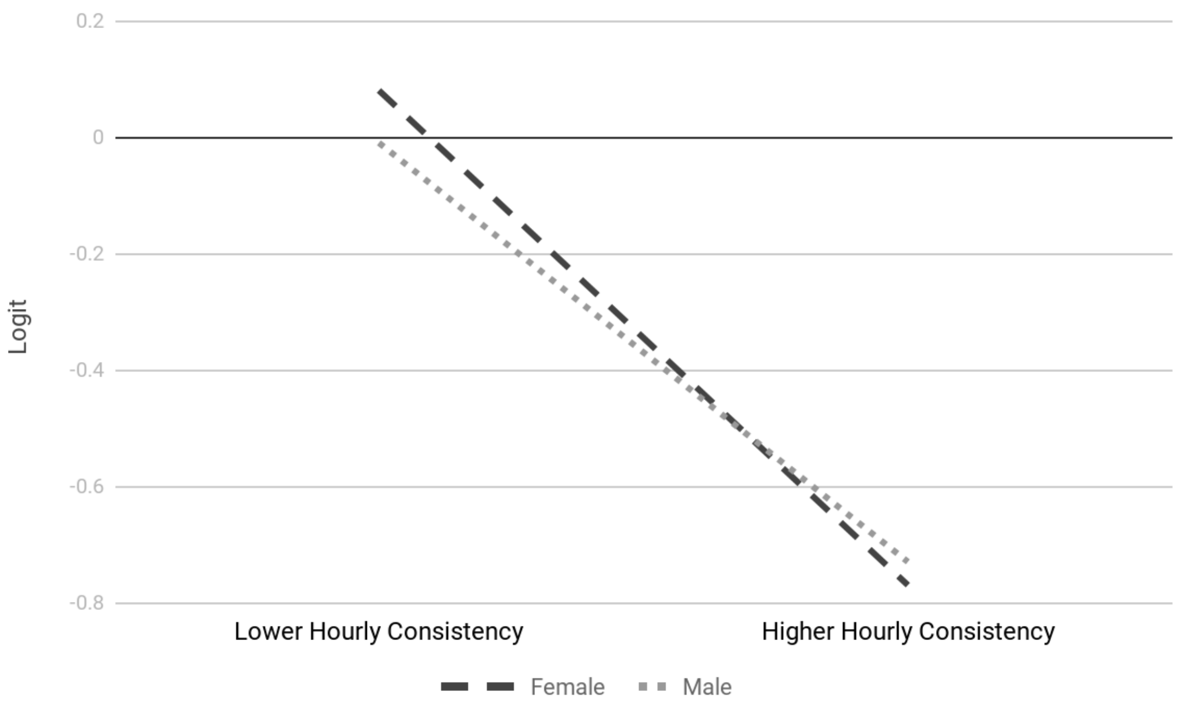


**Figure 1.** Interaction of gender and hourly consistency on course completion.

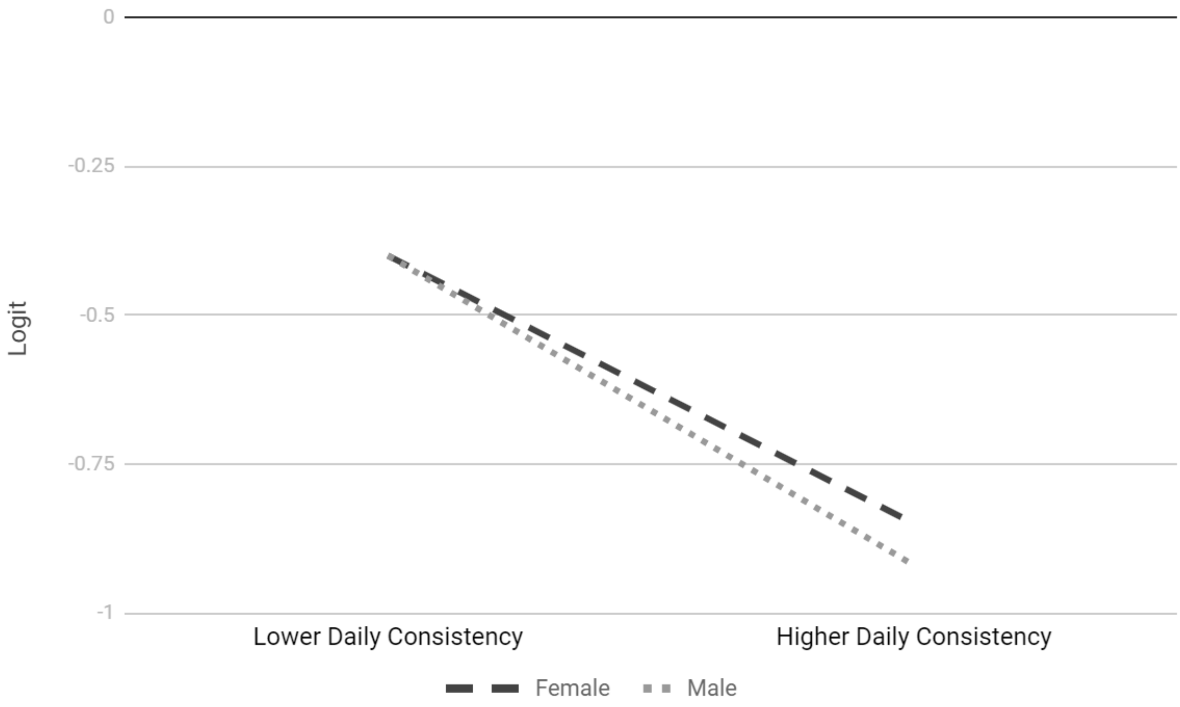


**Figure 2.** Interaction of gender and daily consistency on course completion.