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Computational thinking and assignment resubmission predict persistence in a computer science MOOC

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Abstract

Massive open online course (MOOC) studies have shown that precourse skills (such as precomputational thinking) and course engagement measures (such as making multiple submission attempts with assignments when the initial submission is incorrect) predict students' grade performance, yet little is known about whether these factors predict students' course retention. In applying survival analysis to a sample of more than 20,000 participants from one popular computer science MOOC, we found that students' precomputational thinking skills and their perseverance in assignment submission strongly predict their persistence in the MOOC. Moreover, we discovered that precomputational thinking skills, programming experience, and gender, which were previously considered to be constant predictors of students' retention, have effects that attenuate over the course milestones. This finding suggests that MOOC educators should take a growth perspective towards students' persistence: As students overcome the initial hurdles, their resilience grows stronger.

1 | INTRODUCTION

The massive open online course (MOOC) was formally introduced to the internet in 2011 (Ng & Widom, 2012). By the year 2017, more than 9,000 MOOCs have come into existence, hosted by more than 800 higher education institutions, serving more than 80 million learners (Shah, 2018). MOOCs have no entry requirements and are easy to access (Kop, 2011; Lee, 2017), have huge numbers of participants (Cohen & Soffer, 2015; Sharples et al., 2012), often partner with prestigious higher educational institutions (Cusumano, 2014), and charge a low or no fee for a wide range of materials, such as lecture videos, online discussion forums, and assessments (Thompson, 2011). Since their advent, MOOCs have been heavily discussed in academia and the public (Anderson, 2013; Gaebel, 2013; Kovanović, Joksimović, Gasević, Siemens, & Hatala, 2015; Shen & Kuo, 2015). Advocates of MOOCs contend that MOOCs are transformative (Brahimi & Sarirete, 2015), offering an affordable pathway towards the democratization of higher education (Haggard et al., 2013; Jacobs, 2013; Belanger & Thornton, 2013; Rice, 2014; Stich & Reeves, 2017). Researchers and practitioners also anticipated that MOOCs would create a personalized environment in which students can develop their own knowledge, self-regulate learning pace (Cheng & Chau, 2013; Littlejohn, Hood, Milligan, & Mustain, 2016; Milligan & Littlejohn, 2014), and social network (Khalil & Ebner, 2014; Siemens, 2010; Shah, 2015). However, because of its unsupervised teaching structure and its low cost to enter and exit, students in an MOOC often form dispersed communities (Gillani & Eynon, 2014), have highly irregular learning trajectories (Fini, 2009; Guo & Reinecke, 2014; Milligan, Littlejohn & Margaryan, 2013) and low retention (Balsh, 2013; Jordan, 2014; Rovai, 2003).

The two general principles of improving MOOC retention, as suggested by many researchers, are to (a) know and accommodate students' background (e.g., their knowledge, experience, and motivation) before they start the course and to (b) promote students' engagement (e.g., in assignments, viewing of video components, and discussion) after they start the course (Adamopoulus, 2013; Breakwell & Cassidy, 2013; Khalil & Ebner, 2014). This study specifically investigates two factors (one associated with each of the two principles, respectively) whose effects on MOOC retention have not been systematically studied before. In terms of student background, we ask if precomputational thinking skills are associated with student retention in an introduction to computer science (CS) MOOC. By precomputational thinking skills, we do not mean prior computer programming or coding skills because students are not expected to have learned about coding before the course. Rather, we mean a problem-solving style that emphasizes algorithmic thinking. Could it be this computational mindset, or is it the actual prior CS experience, that plays a bigger role in novice learners' persistence in CS MOOC? In terms of engagement, we ask if multiple assignment submissions (enabled by the advancement in automatic and adaptive feedback feature that is widely adopted by computer science MOOCs to help students incrementally improve their codes) are associated with student retention in the same MOOC. Is multiple assignment submission a sign of engagement that would promote persistence, or a sign of a difficult experience that would increase frustration and expedite dropout? Empirical answers to such questions can inform strategies to help novices persist on MOOCs.

These questions are not only important within the MOOC framework, but may also shed some light on issues that typically remain under the surface in regular CS education. In traditional classroom settings, the cost of dropout is high (losing tuition, credits, or a degree). Dropping out because of a novice's cognitive dissonance with the computational mindset may be considered ill-advised in light of these costs, and the impulse to dropout may thus be inhibited. However, because, in the MOOC setting, the cost of dropout is minimal, MOOC dropout may be sensitive to a brief moment of frustration, the same frustration that might be experienced by students in traditional classrooms, but not manifested in terms of dropout behaviour.

2 | LITERATURE REVIEW

Several studies have looked into the factors predicting retention in an MOOC. Kizilces and Halawa (2015) found that the primary obstacle to completion was the participants' time management and that the key predictors for persistence were motivation, prior education level, and prior experience in the subject field. Multiple studies have shown that proxies of course engagement, such as video watching (He, Bailey, Rubinstein, & Zhang, 2015), pageview, clickstreams (Kloft, Stiehler, Zheng, & Pinkwart, 2014), peer interaction (Jiang, Williams, Schenke, Warschauer, & O'Dowd, 2014), and teacher–student interaction (Gregori, Zhang, Galván-Fernández, & Asís Fernández-Navarro, 2018) can be used to predict dropout. Moreover, researchers have shown that students' motivation (Xiong et al., 2015) and self-efficacy (Jung & Lee, 2018) predicted their engagement or satisfaction (Joo, So & Kim, 2018), which in turn predicted course persistence.

Research that examines pre-MOOC predictors for dropout has been limited to drawing on information that is easy to obtain (Zhu, Sari & Lee, 2018), such as demographic information (van de Oudeweetering & Agirdag, 2018), course viewing, and activity history (Cohen, 2017; Evans, Baker & Dee, 2016; Kahan, Soffer & Nachmias, 2017; Soffer & Cohen, 2018), general knowledge levels (Breslow et al., 2013), self-reported motivation (Watted & Barak, 2018), or other self-reported attitudes towards the course (Shapiro et al., 2017). The only prior research, to the best of our knowledge, that looked into the effect of pre-MOOC knowledge on MOOC persistence was conducted by Chen et al. (2019) who showed that prior misconceptions in astronomy negatively affected students' retention in the initial stages of an astronomy MOOC, but not in the later stages. One reason for the scarcity of research on the impact of prior knowledge on course persistence is that it is difficult to measure or obtain students' knowledge before they have learned the subject, especially for introductory level courses.

Previous research has linked learners' precomputational thinking skills to their success in formally learning introductory computer programming (Kazimoglu, Kiernan, Bacon, & Mackinnon, 2012). Precomputational thinking skills do not require a learner to have any programming knowledge, rather they are skills to "seek algorithmic approaches to problem domains; [and show] a readiness to move between differing levels of abstraction and representation; familiarity with decomposition; separation of concerns; and modularity" (Barr & Stephenson, 2011, p. 49). Research has shown that students often acquire precomputational thinking skills in modelling and simulation, as well as in gaming or other out-of-school activities (Kazimoglu et al., 2012; Lee et al., 2011; Levy & Murnane, 2004; Seehorn et al., 2011). We hypothesized that precomputational thinking skills would also have a positive effect on students' persistence in an introductory CS MOOC. If students in an MOOC setting, where interpersonal relationships are distant and social belonging takes a longer time to stabilize (Knox, 2014; Oleksandra & Shane, 2016), find a new language or a new problem-solving framework to be counter-intuitive and hard to adapt to, they may quickly identify themselves as not belonging to the community and drop out in the initial stages. This hypothesis further predicts that pre-existing computational thinking intuition would only have an effect on dropout in early stages, not in later stages. As students acquire core knowledge in the course and adapt to the new language and way of thinking, we expect the mismatch between initial intuition and the subject-specific framework to diminish and social belonging to increase.

In addition to providing the opportunity to examine the effect of computational thinking intuition on persistence in an MOOC, introductory CS MOOCs are a suitable testing ground for advancements in the automatization of immediate feedback or hints (Gerdes, Heeren, Jeuring, & van Binsbergen, 2017; Rivers & Koedinger, 2013; Rivers & Koedinger, 2014; Vihavainen, Luukkainen & Kurhila, 2012). In a CS MOOC, assignments can be easily designed not solely for assessment and grading, but also for providing timely scaffolding so that students can test their code interactively until it is correct (code is arguably never "perfect"). Even if students' codes yield the desired result, they can still receive adaptive feedback to improve the elegance and efficiency of their code and algorithm. The "smart" (automatic, immediate, and unsupervised) feedback gives students individual attention while affording them the freedom to explore other possible solutions, which is a key element that MOOC educators anticipated to deliver technology-enhanced learning environment for effective self-regulated learning and transform higher education (Bernacki, Aguilar & Byrnes, 2011). Indeed, it has been well documented in MOOCs literature that students' increased engagement to be associated with positive learning outcomes (Hew, 2016; Soffer & Nachmias, 2018). In particular, research has shown that students who make multiple attempts to solve problems and improve their solutions in assignments have higher grades in MOOCs (DeBoer & Breslow, 2014). Yet, little is known about whether multiple attempts on assignments protect against future dropout. On the one hand, it is possible that multiple attempts lead to frustration that expedites dropout. On the other, they may be a sign of engagement or resilience that counteracts dropout.

For this study, we used data about students' characteristics, activities, and performance in a popular CS MOOC, to examine the predictors of dropout. Besides a list of variables that have been examined by previous research, such as demographic information, motivation, general academic aptitude, and prior experience, we are particularly interested in whether the students' precomputational thinking level (a time-constant variable) and students' number of attempts on assignments (a time-varying variable) that were technology enhanced by smart feedback predict students' dropout behaviour and whether the effects of these predictors change over time.

We hypothesized that (H1) students with higher precomputational thinking score would be more likely to persist through the initial milestones of the course, but that this effect would diminish over milestones (interaction effect). We also hypothesized that (H2) multiple attempts on an assignment would correlate with dropout rates. However, we did not specify the direction of this effect. If completion of multiple assignments mainly indicated a high level of engagement, students who made more attempts would more likely to persist; alternatively, if multiple attempts indicated a high level of frustration, those who made more attempts would be more likely to drop out. Lastly, we hypothesized that, as in earlier studies, (H3) students with higher motivation and more prior experience would be more likely to persist in the course.

3 | DATA AND METHODS

3.1 | Sample

A total of 422,799 individuals registered for the MOOC "Introduction to Computer Science" (CS50x) (from HarvardX on the EdX platform) from January 2013 to December 2014; however, only 28,350 of those who registered filled in the presurvey, and 20,134 of them finished the presurvey, which was a prerequisite to gain access to the course material. In this study, we consider those who finished the presurvey as formal enrollees and only applied statistical analysis to those formal enrollees. Not all participants followed the sequence designated by the MOOC teaching team. Around 6% of the participants were samplers, meaning they skipped at least one milestone in their sequence (e.g., someone could complete problem sets [psets]1, 2, and 5 and then drop out, skipping pset 3 and pset 4). This irregular pattern is not suitable for a survival analysis framework and is investigated in a separate study. In the analysis of this article, we excluded the irregular participants, which reduced our sample size to 18,925.

The pretest (see Appendix A) included a 12-item precomputational thinking skill test developed from a number of online sources by first assembling 31 unique items thought particularly relevant to success a CS course. These items were administered to 911 subjects using the Amazon Mechanical Turk platform to estimate item parameters (item difficulty and discrimination) and employing item response theory to build a shorter, unidimensional test (Sadler et al., 2016). Of all items, 12 appeared to offer high vales of discrimination and a range of difficulty. When administered as pretest in this study, the test performed well with a Cronbach's alpha of .843. The average precomputational skill test score was 0.75 (9 out of 12 questions, *SD* = 0.19).

Table 1 shows a brief course syllabus including the milestones and their corresponding tests and course content.

Among the 18,925 individuals in the analytic sample, 78.2% were male and 12.8% were female. The average age was 28.8 years (*SD* = 9.9, ranging from 10 to 69), and 42.3% were living in a country outside of the United States. 48.7% could speak more than one language. 43.5% had a college degree as their highest educational level, and 3.1% had an advanced degree. 38.4% of the enrollees were concurrently going to school. The enrollees spent 6 hr/week, on average, playing digital games (unrelated to the MOOC). 58.3% had some computer programming experience prior to the MOOC. On average, enrollees (including those with no prior knowledge) had some experience (more than none) with three programming languages. 43.3% of the enrollees rated their familiarity with computer programming to be *not familiar at all* or *slightly familiar* (rating 0 or 1 on a scale ranging from 0 to 4), and 19.9% rated themselves to be *very familiar* or *extremely familiar* (rating 3 or 4). 47.1% answered that they did not have friends or family members who could give them programming help. 67.2% predicted that they were very likely or extremely likely to finish the course in order to attain a certificate.

3.2 | Outcome variables

On average, participants completed 1.5 psets; 966 (4.8% of all) participants finished all 8 psets. A total of 1,130 (5.6% of all) participants submitted their final exam, and 200 of them passed the final exam. If we define completion of the MOOC as finishing all 8 psets as well as passing the final exam, then 152 (0.7% of all) had completed the MOOC. If we relax the definition of completion to include anyone who omitted pset 8, which was an optional pset, and submitted the final exam (not necessarily passed the final exam), then 1.3% of the full sample had completed the MOOC. Among all psets for the whole sample, 69.7% were submitted only once, 15.8% submitted twice, and 3.1% submitted five times, which was the maximum number of submissions.

Table 2 presents each of the outcome variables broken down by key predictive variables. We also carried out hypothesis tests (*t* test or chi-squared test) to determine if the two subcategories within each predictor were significantly different from each other on each of the outcome variables (boldness indicates $p < .05$). Hypothesis tests showed that male students, students who have higher education, students who have higher pretest scores, students who consider the

TABLE 1 A brief course syllabus showing the milestones and their corresponding tests and course content

Release week	Milestone	Test	Content
0	NA	Pretest	NA
1	1	Pset-1	Data type; operators; conditional statement; loops
2	2	Pset-2	Functions; arrays; search; sort; algorithms summary
3	3	Pset-3	Recursion; hexadecimal; pointers, call stacks, dynamic memory allocation
4	4	Pset-4	Data structure; defining custom types; singly-linked lists; hash tables; tries
5	5	Pset-5	IP; TCP; HTTP; HTML; CSS
6	6	Pset-6	Python; Flask
7	7	Pset-7	Flask; MVC; SQL
8	8	Pset-9	JavaScript; DOM; AJAX
9	9	Final project	Individual project and presentation

completion of MOOC to be important (higher motivation), and students who had more prior programming experience tended to finish more psets, compared with their counterparts.

3.3 | Survival analysis

To model the dropout rate at a given milestone (milestones are psets and the final project) as a function of predictors (prior experience, motivation, etc.), we adopted a survival analysis approach. A survival analysis has three important elements: event, time, and censoring. In our case, *event* is student dropout (1 = dropout; 0 = completion) at a given milestone, *time* is measured in milestones, and *censoring* occurs when a subject does not experience dropout during the entire MOOC period (in other words, the student completes all milestones). Survival analysis is analogous to logistic regression: The dropout event is a binary outcome variable, milestone and other covariates are predictors, and the model parameters can be interrelated in the fashion of a logistic regression.

As basic steps for survival analysis (see Singer & Willett, 2003), we first calculated the hazard of dropout at each milestone. The hazard function represents the proportion of the sample in each milestone interval that dropped out during that interval:

$$h(m_j) = Pr[M = j | M_i \geq j],$$

where $h(m_{ij})$ is known as the population discrete-time hazard, and M_i represents the milestone period j when individual i experiences the dropout event (e.g., for a student who drops out at the third milestone, M_i = 3). The hazard function denotes that the probability that the dropout event will occur at a certain milestone j for student i is conditional on student i not having experienced the dropout event at any time prior to j.

Next, we used a logit link function to link between the hazard and a linear specification of predictors, similar to a logistic regression:

$$\text{logit}\, h(m_{ij}) = \alpha_1 M_{ij} + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \ldots + \beta_p X_{pij} + \gamma_1 U_{ij} + [\text{interactions}].$$

In this function, M is the main effect of milestone. There are multiple possible specifications of the main effect of a milestone, such as treating milestones as dummies (completely discrete time function), as a linear main effect, or as nonlinear effect, such as quadratic function, which would add the term $\alpha_2 M_{ij}^2$ to the equation above.

Figure 1 shows the predicted logit hazard at each milestone based on the completely discrete time model without any covariates. In essence, this model has each milestone as a dummy variable to predict the logit hazard. This model will serve to diagnose the linear or nonlinear trend of the logit hazard over time, so that we can justify a more succinct specification of the effect of time. As shown in Figure 1, a linear specification can successfully summarize the decreasing trend through the seventh milestone. The logit hazard increases at the eighth and ninth milestone. One option to model this overall trajectory is to specify a quadratic (or even higher order) model; however, because the eighth milestone was an optional pset and the ninth milestone was the final exam, both of which were conceptually different from the first seven milestones, we chose to model them as separate events. Hence, we specified a partial linear and partial discrete model in which the first seven milestones were specified as linear and the eighth and ninth milestones were specified as dummy variables, such as

$$\begin{aligned}\text{logit}\, h(m_{ij}) = \log\frac{h(m_{ij})}{1-h(m_{ij})} = [&\alpha_1 \text{Milestone\_First\_Seventh}_j \\ &+ \alpha_2 \text{Milestone\_Eighth} + \alpha_3 \text{Milestone\_Ninth}] + \beta_1 X_{1i} \\ &+ \ldots + \beta_p X_{pi} + \gamma_1 U_i + [\text{interactions}],\end{aligned}$$

where for each individual i at time j, when $0 < j < 8$, then Milestone_First_Seventh (hereafter MS) = j, Milestone_Eighth (hereafter M8) = 0, and Milestone_Ninth (hereafter M9) = 0; when j = 8, then MS = 0 and M8 = 1, M9 = 0; and when j = 9, then MS = 0, M8 = 0, and M9 = 1.

Predictors of interest in this model are the X variables and U. X variables are time invariant variables, and they include age, gender, education level, self-reported motivation to complete, prior experience, pretest (precomputation readiness test score), English fluency, foreign status, extrovert personality, game hours, number of MOOC completed previously, and the availability of extra help from friends or at home. Such variables were only measured in the initial questionnaire (Milestone 1). They reflected students' initial status and were considered time-invariant variables.

U is a time-varying predictor. In our case, there was only one time-varying predictor, the number of submission attempts (hereafter

TABLE 2 The description of outcome variables (by row) broken down by key predictors (by column)

	Full sample	Gender		Education		Precomputation readiness test score		Importance of completion		Prior experience	
		Male	Female	Above HS	HS or below	Average or above	Below average	Very important	Not very important	Basic or above	Never program
Num of psets	1.5	**1.64**	**1.12**	**1.59**	**1.42**	**1.37**	**0.98**	**1.58**	**1.39**	**1.91**	**1.14**
Finish all psets	4.8%	**5.3%**	**3.1%**	5.0%	4.5%	**5.5%**	**3.1%**	**5.2%**	**3.8%**	**6.5%**	**3.20%**
Submit final	5.6%	**6.0%**	**4.4%**	5.5%	5.7%	5.6%	5.5%	**5.9%**	**4.8%**	5.9%	5.30%
Pass final	17.7%	18.0%	16.4%	16.7%	19.4%	18.6%	15.4%	17.9%	15.7%	18.7%	16.60%
Complete MOOC	0.7%	**0.8%**	**0.5%**	0.8%	0.7%	0.8%	0.6%	0.8%	0.6%	0.9%	0.60%
Sample size	20,134	15,672	4,412	9,841	8,426	14,504	5,630	11,929	5,875	10,217	9,917

Notes: Bolded numbers indicate that the two numbers in the respective category are significantly significant at the level of .05. The sample size of specific categories may not match the full sample size on the left column, due to missing data.
Abbreviation: MOOC, massive open online course.

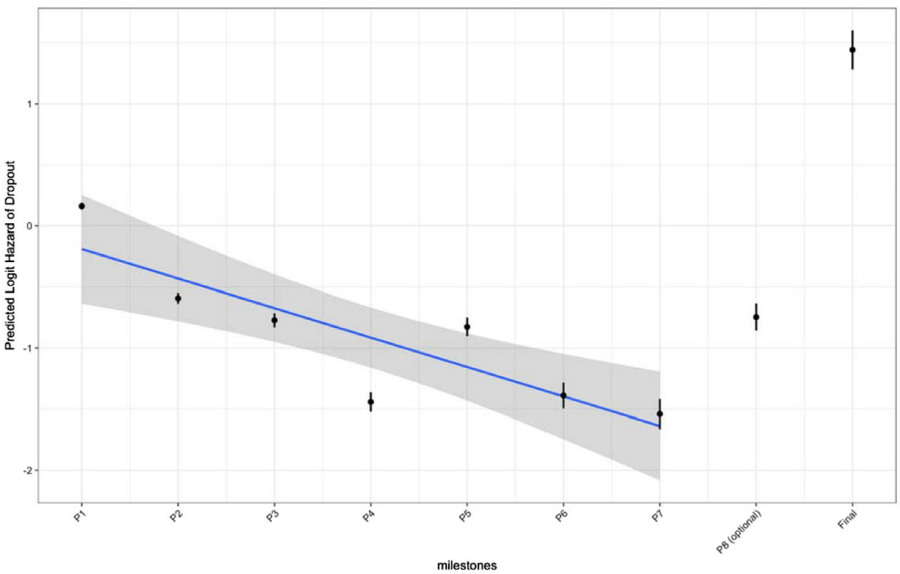

FIGURE 1 Fitting the logit hazard of dropout using a discrete time model, in which each milestone is treated as a dummy variable. As is apparent from this graph, the first seven psets can be modelled using a linear specification (see regression line with a 95% confidence interval), whereas the pset 8 and final exam should be treated as distinct events

submit-attempts) made in the previous pset. For example, at Milestone 7, the value of submit-attempts is the number of submissions one made for pset 6. This variable is only applicable starting from Milestone 2, because, obviously, there was no prior pset before pset 1. Therefore, we specified two separate types of models. One type, comprising two models (M1 and M2), excludes U so that we can model the full range of time from Milestone 1 to Milestone 9. We will rely on this model type to obtain a more accurate estimation of the time invariant predictors. In the other type of models (M3 and M4), we added U, while keeping all other terms from M1 or M2. However, this model type ignored Milestone 1 and only included Milestones 2 to 9. We are only interested in the estimated effect of the time-varying predictor in this model type. Although all other covariates are controlled for in M3 and M4 as well, we will not delve into the parameters of these covariates, because the estimations of such parameters in M3 and M4, when Milestone 1 information is omitted, are less accurate than the estimations from M1 and M2.

The parameters (βs and γ) associated with the Xs and U stand for the shift in the baseline logit hazard function (as depicted by the main effect of a milestone), corresponding to unit differences in the associated predictors. We also considered interaction terms between predictors and milestones. This would allow different students to have different shapes of the logit hazard function depending on their Xs and U. When two groups (categorized by a predictor of interest, such as gender) have converging logit hazard curves, it means that the two groups have larger differences in dropout rates at earlier milestones and smaller differences at later milestones (i.e., the effect of the predictor attenuates over time). If the logit hazard curves diverge between two groups, it means that the group differences increase over time. We can use a post generalized linear model (GLM) test to examine if and at which milestone the two logit hazard curves converge or diverge. The primary quantities of interest to us are the parameters associated with *X*s, *U*, and interaction terms, because these would determine the outcome of our hypothesis testing.

Last, we re-express the logits as odds ratios and then as probabilities for easier interpretation, based on the formulas: Odds = e^{logit} and probability $= \frac{1}{1+e^{-\text{logit}}}$. For example, when logit = 0, the odds ratio is 1:1, which means the odds of dropping out are the same as the odds of remaining and, consequently, the probability of dropping out is .5.

4 | RESULTS

Table 3 presents the parameters for two fitted models. The baseline model (M1) included the main effects of time invariant predictors. We converted the estimated parameters of the discrete model to odds ratios and marginal probabilities (the change of the probability of dropping out corresponding to one unit change in a specific covariate, provided the other covariates are held constant at the mean, and the milestone is held at the first milestone). We included education level, self-reported English fluency, number of MOOCs completed previously, and availability of extra help in our model but did not present these variables in the table because their effects were not statistically significant. The second model (M2) included the interaction effects of milestone with four predictors: pretest, CS experience, gender, and age, respectively. We explored other interaction effect, but none of them were statistically significant.

The last two models (M3 for main effects only and M4 adding interaction terms) included the time-varying predictor, submit-attempts, in addition to the same terms as in M1 and M2. Submit-attempts did not have an interaction effect with any variable. For reasons explained above, M3 and M4 omit Milestone 1 information, which renders their estimation of time invariant covariates less accurate. Therefore, we did not report the full M3 and M4 models in the table but inserted the estimated submit-attempts coefficients from M3 and M4 into the columns of M1 and M2 in Table 3 for a tidy presentation.

The continuous variables—pretest, CS experience, computer game hours, motivation, extrovert personality, and age—were standardized. MS and submit-attempts were not standardized, for ease of interpretation.

The interpretation of the parameters is similar to the interpretation of a logistic model: β shows the amount of change in logit hazard associated with one unit of change in the predictor, and the logit hazard can be converted to an odds ratio. For example, in M1, β_{male} = −0.423, which shows that the logit hazard for males was smaller than the logit hazard for females by 0.423, controlling for other covariates. This could further translate to an odds ratio of 0.655 ($e^{-0.423}$ = 0.655), which means the odds of dropping out for a male were 0.655 times those of the odds of dropping out for a female. In other words, male students were less likely to drop out than female students.

Similarly, students who reported to have higher motivation to complete the MOOC had lower odds of dropout at each milestone, compared with their counterparts. Students from outside of the United States, students who self-describe as extroverted, and students who spent more time playing computer games, had higher odds of dropout at each milestone, compared with their counterparts. These predictors did not have an interaction effect with milestones, which means that changes in these predictors shifted the fitted line of the logit hazard over milestones up or down, but did not change the slope of the line.

M2 also contained four interaction terms. The main effect for males was −0.423, the negative number showing that male students had lower odds of dropout than did female students; however, the interaction term was 0.064, a positive number that counteracted the effect of maleness. Moreover, because the interaction term was multiplied by the milestones, the effect of maleness should be increasingly offset as milestones increase. This led to different fitted line of logit hazard over milestones for male and female students, with the female starting off with a higher logit hazard (i.e., larger odds for dropping out) than male students, and gradually converging towards the curve of the male students, as the milestones increased. As shown by a post GLM test, the logit hazards of the two groups were no longer significantly different from each other by Milestone 5. Thus, gender was a key predictor to predict drop out in the beginning of the MOOC, but had no effect at all in the later part of the MOOC. Figure 2 illustrates this interaction effect on the probability scale. The *y* axis in Figure 2 is the *probability* of dropout rather than *logit hazard* of dropout for easier interpretation. On a logit scale, the trajectory from Milestone 1 to Milestone 7 was a linear trend; however, when converted to the probability scale (with covariates held at the mean), the trajectory becomes curvy.

Other interaction terms (milestones with pretest, prior CS experience, and age) should be interpreted similarly. Figure 3 plots the probability of dropping out over milestones by above and below average pretest scores.

A post GLM test showed that participants with above and below average precomputational skill test scores converged at Milestone 5, and interestingly, participants with a lower pretest were more likely to finish the final exam; participants with above and below average prior CS experience converged by milestone 6; participants of different age groups (below 18, 18–30, 30–45, 45–60, above 60) converged at Milestone 4 (the younger cohorts had higher initial retention).

Focusing on the time-varying predictor in M3, we found that submit-attempts had a negative effect on the logit hazard of dropout, meaning that the more attempts students made on a pset, the less likely they were to drop out at the following milestone. Submit-attempts did not have an interaction with milestone, which means that, on a logit scale, groups with different submit-attempts had linear and parallel trends of logit hazard over milestones. Figure 4 converted logit to the probability scale and illustrated the predicted probability of dropout over milestones by three groups with different submit-attempts.

TABLE 3 Survival analysis predicting logit hazard of dropout

	Parameter estimates		Odds ratio	Marginal change in probability
	M1	M2	M1	M1
MS	−0.210***	−0.291***	0.81	−0.069
	0.009	0.026		
M8	−0.479***	−0.713***	0.619	−0.039
	0.084	0.242		
M9	1.927***	1.097***	6.868	0.277
	0.123	0.381		
Male	−0.281***	−0.423***	0.755	−0.017
	0.042	0.076		
Foreign status	0.272***	0.259***	1.312	0.059
	0.032	0.032		
Pretest	−0.208***	−0.432***	0.812	−0.027
	0.017	0.032		
CS experience	−0.244***	−0.244***	0.783	−0.058
	0.029	0.029		
Computer game hour	0.050***	0.048***	1.051	0.011
	0.015	0.016		
Motivation	−0.095***	−0.094***	0.909	−0.022
	0.016	0.016		
Extrovert	0.095***	0.096***	1.099	0.022
	0.017	0.017		
Age	−0.044*	−0.101***	0.956	−0.025
	0.017	0.029		
Submit-attempts[a] (for M3 and M4)	*−0.164****	*−0.166****	*0.848*	*−0.041*
	0.022	*0.022*		
MS × pretest		0.090***		
		−0.012		
MS × CS-experience		0.023**		
		0.010		
MS × male		0.064**		
		0.028		
MS × age		0.022**		
		0.009		
Constant	0.021	0.192***		
	0.049	0.073		
N (invariant/varying)	17792/13732	17792/13732		
Pseudo R^2 (invariance/varying)	0.65/0.54	0.67/0.55		

Abbreviation: CS, computer science.
[a]Submit-attempts was only applicable to the time varying models, which omitted Milestone 1.
***$p < .001$; **$p < .01$; *$p < .05$.

5 | DISCUSSION

This study confirmed our key hypotheses about precomputational thinking skills (H1) and multiple attempts in assignment submission (H2). First, to answer H1, our result showed that pre-existing precomputational thinking skills had a positive relationship with persistence and that this effect decreased as students progressed through the course milestones. Such an interaction effect with milestones suggests that a mismatch between prior intuition and the problem-solving framework in CS may pose an initial hurdle to participation, but that such a hurdle is temporary. This finding is strengthened by an analogous finding about prior CS experience. Taken together, these results support the conclusion that prior course preparedness (i.e., intuition and experience) does not determine students' perseverance constantly throughout the course. Students can adapt to the new framework as they stick with the course even if this framework may be counterintuitive in the beginning. This finding suggests two possible approaches to preventing MOOC dropout in the early stages:

1. A gradual learning curve for beginners to adapt to computational thinking styles before being exposed to the coding and problem solving using specific programming languages. In fact, the course has implemented a unit at the start of the course that introduces computer programming using a visual programming language, Scratch. Numerous studies have shown that graphical programming languages are effective introductory languages for novices in terms of computing attitudes and programming performances (Chen et al., 2019; Bau, Gray, Kelleher, Sheldon, & Turbak, 2017; Kelleher & Pausch, 2005;) by helping the students to focus more on the logic rather than the syntax (Resnick et al., 2009). A Scratch

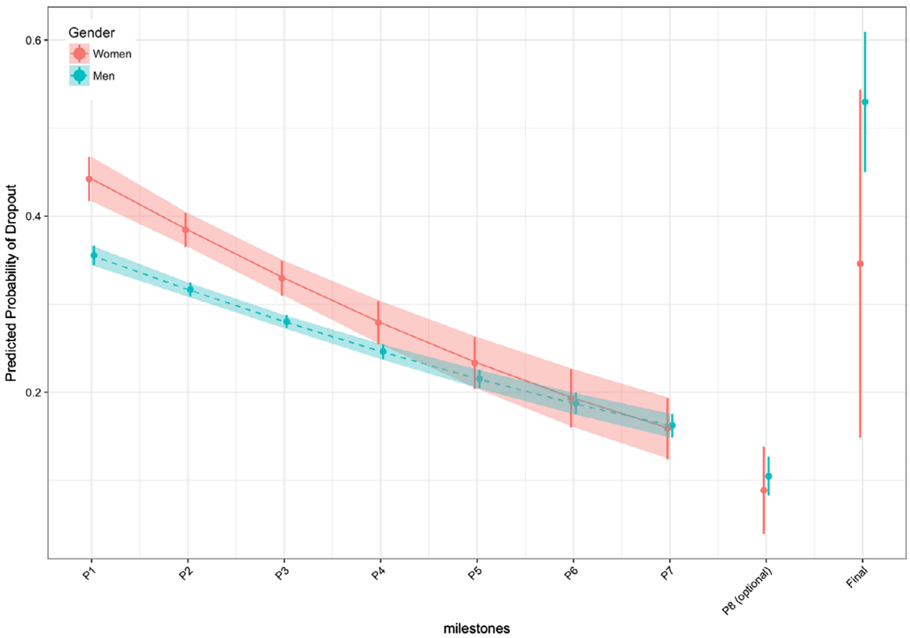

FIGURE 2 Plotting fitted probability of dropout by gender

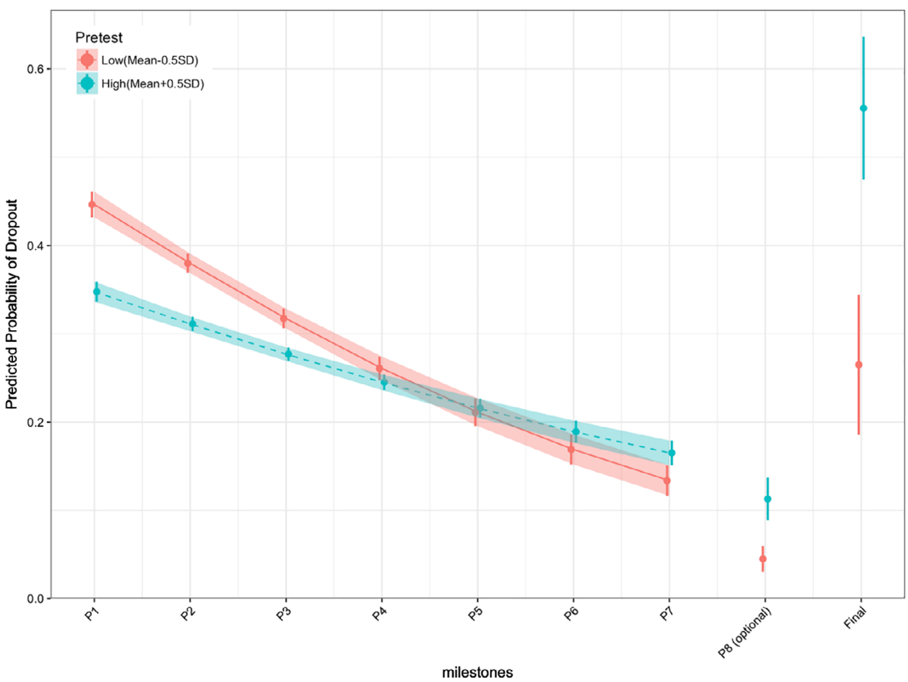

FIGURE 3 Plotting the fitted probability of dropout by precomputational skill test score

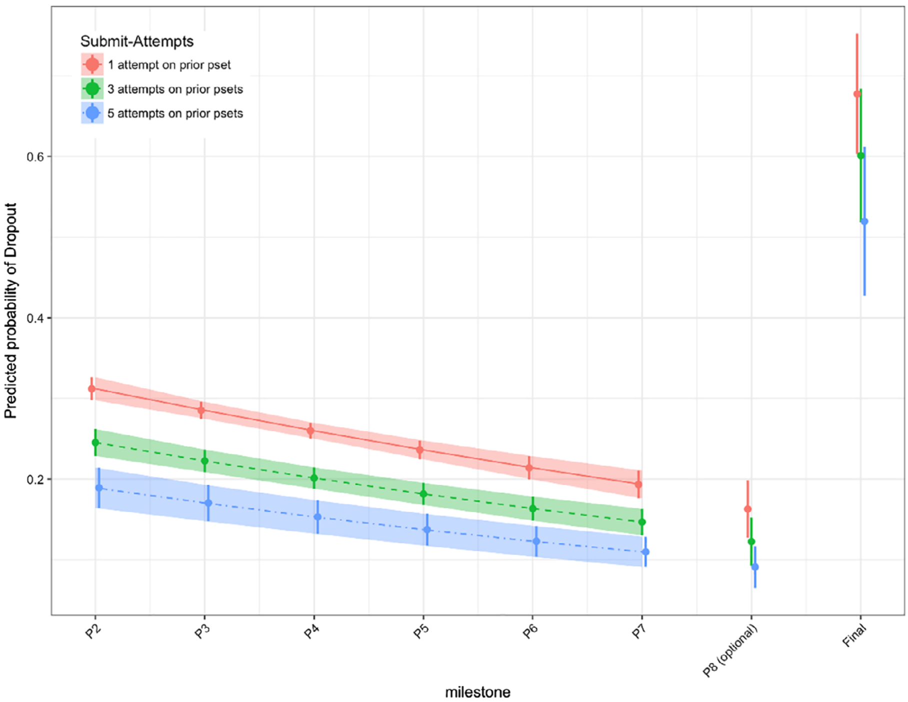

FIGURE 4 Plotting the fitted probability of dropout by the number of submission attempts in the previous one pset

session can potentially be used to target the precomputing intuition about logic and algorithmic thinking to solidify students' programming readiness. Future study should examine the effectiveness of such a targeted pedagogical intervention on dropout prevention.

2. To explicitly encourage students to stay in the course even if they find the content to be counterintuitive and to assure students that they will adapt to the new framework and that their (lack of) background knowledge will not define their future experience and performance as they progress. We expect such an approach to be applicable to other factors that interact with time, such as prior CS experience (new experience will overcome the lack of prior experience), age, and gender (may relate to self-ascribed stereotypes).

Second, to answer H2, we found that students who submit psets multiple times were more likely to persist. In other words, multiple submission is an indicator of engagement or resilience, and it does not frustrate students or presage dropout. Automated and immediate feedback is an important smart and special feature of online courses. It has the potential to revolutionize assessment in higher education, changing it from an evaluation and grading procedure to an experimental exercise in which students are allowed to make mistakes, make incremental improvements, and try out different scenarios. Prior research has shown that students who take advantage of such features earn higher grades (DeBoer & Breslow, 2014). Our study additionally shows that such features engage students to be more persistent.

Based on this finding, we expect that pedagogical approaches that explicitly encourage students to use a trial-and-error strategy, testing different scenarios and experimenting with different solutions, while being afforded adaptive and immediate scaffolding, will make assessment not only more personalized and flexible, but also more engaging and rewarding. Schophuizen, Kreijns, Stoyanov, and Kalz (2018) highlighted eight key challenges that a successful MOOC must address: online teaching, support, assessment, external target groups, flexibility, quality, reputation, and efficiency. Schopheizen et al. (2017) also called for a more centrally organized support from the MOOC team to engage these challenges. Notwithstanding the importance of centralized support, we are hopeful that decentralized approaches, such as smart feedback, if combined with the proper pedagogy, have the potential to successfully address some of the challenges, such as support, assessment, flexibility, and efficiency.

However, we also anticipate a potential downside: It is possible that students start to rely on the automated check tools provided by the MOOC as an alternative to actually running appropriate compilers themselves, and thus, they may end up lacking hands-on skills with the latter. It is possible that students who heavily rely on adaptive feedback and hints tend not to take the time (and the pains) to solve a problem completely and independently. By frequently seeking hints, students effectively reduce the difficulty level and/or the workload of a course, and students who perceive the difficulty or workload of a course to be low are more likely to remain in the course (Adamopoulous, 2013).

This study also confirmed (H3) the conclusion from prior studies (Kizilces & Halawa, 2015; Watted & Barak, 2018; Wen, Yang & Rosé, 2014; Xiong et al., 2015) that students with stronger motivation to complete are more likely to persist. One might speculate optimistically that students who were less motivated in the beginning would gain interest in the subject as they learn more about the content and that the disadvantage of low motivation would diminish over milestones. However, our finding did not support such a speculation, because we did not find motivation to interact with milestones.

We did, nevertheless, find an interaction effect between prior programming experience and milestones, which suggests that prior knowledge only mattered in the initial stages, and that, once the students picked up the content in the course, those without prior knowledge became equally engaged as those with prior knowledge. This finding, combined with the analogous interaction effect between milestone and precomputational thinking, led us to revisit our understanding of perseverance (or resilience).

Traditionally, students' perseverance was considered part of a personality trait (Duckworth, Peterson, Matthews, & Kelly, 2007; Rimfeld, Kovas, Dale & Plomin, 2016; Robertson-Kraft & Duckworth, 2014) or a conscious choice that students made at the beginning of an activity, based on their own motivation, expectation (Oxford & Bolaños-Sánchez; 2016; Prebhu, Sutton & Sauser, 2008), or self-efficacy (Bandura, 1977; Chemers, Hu, & Garcia, 2001; Multon, Brown & Lent, 1991). From this perspective, perseverance was conceptualized as a static parameter. This perspective is partially supported by our finding that students' self-reported motivation indeed had an effect on their perseverance and that its effect was constant over time. Had we only measured students' motivation, we would conclude that perseverance was substantially determined by the students' self-motivation at the beginning of the course. Nevertheless, we discovered that perseverance was partially explained by students' subject preparedness, and such an effect attenuated over the course milestones. This finding calls for a growth, rather than a static, perspective on students' course perseverance, at least in the MOOC setting. As student overcome the initial hurdles, their perseverance grows stronger, possibly via stronger self-efficacy.

Our study did not replicate the result from Greene, Oswald, and Pomerantz (2015) that showed students with higher degrees of education or students with more prior MOOC experience to be more likely to persist. Our study also found the opposite result from Allione and Stein's (2014) study that showed U.S. students were more likely to dropout. In our case, by contrast, the U.S. students were more likely to persist.

Caution should be taken when generalizing the result of this study to other MOOCs because this study only examined one MOOC, and the subject of CS programming was more technically difficult and time demanding than other subjects, as was shown in its below average completion rate. Another limitation of this study was that we omitted irregular participants, who made up 6% of the sample, because survival analysis was not applicable to modelling people who did not follow the same sequence. The irregular participants are an interesting subsample as they may be auditors and samplers who choose to learn the specific topics they are interested in, which in fact reflects a special strength of MOOCs (DeBoer, Ho, Stump, & Breslow, 2014).

The troubling news for proponents of the idea that MOOCs might become a transformative force in higher education is that, in the case of this MOOC, we found very high dropout rates. Nevertheless, one may detect also some good news and silver linings in this study. In light of the continuing gender imbalance in pursuing CS and CS-related careers (Bunderson & Christensen, 1995; Cheryan, Plaut, Davies, & Steele, 2009; Jadidi, Karimi, Lietz, & Wagner, 2018), it is encouraging that, by the second half of the MOOC, females had overcome their initially higher dropout hazard and participated in the course at no higher dropout rates than those experienced by males.

6 | CONCLUSION

As reviewed in the introduction, numerous studies have shown that precourse skills (such as precomputational thinking skills) and course engagement measures (such as making use of auto-feedback features) strongly predict students' grade performance. This study is, to the best of our knowledge, the first to show that these factors strongly predict students' persistence, at least in an MOOC setting. More interestingly, we discovered that several precourse variables, such as precomputational thinking skills, programming experience, and gender, which were previously considered to be constant predictors of students' retention, are actually not always equally effective. Their impacts diminish over the course milestones. MOOC educators should not only take a growth perspective towards students' knowledge and skill development, but also a growth perspective towards students' persistence: As students overcome the initial hurdles, their resilience grows stronger.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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REFERENCES

Anderson, T. (2013). Promise and/or peril: MOOCs and open and distance education. *Commonwealth of. Learning*, *3*, 1–9.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191–215.

Barr, V., & Stephenson, C. (2011). Bringing computational thinking to K-12: What is involved and what is the role of the computer science education community? *ACM Inroads*, *2*(1), 48–54.

Bau, D., Gray, J., Kelleher, C., Sheldon, J., & Turbak, F. (2017). Learnable programming: Blocks and beyond. *Communications of the ACM*, *60*(6), 72–80.

Belanger, Y., & Thornton, J. (2013). *Bioelectricity: A quantitative approach*. Duke University. Retrieved from. http://dukespace.lib.duke.edu/dspace/handle/10161/6216

Bernacki, M., Aguilar, A., & Byrnes, J. (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: IGI Global Publishers.

Brahimi, T., & Sarirete, A. (2015). Learning outside the classroom through MOOCs. *Computers in Human Behavior*, *51*, 604–609.

Breakwell, N., & Cassidy, D. (2013). *Surviving the avalanche: Improving retention in MOOCs*. In Sixth International Conference of MIT's Learning International Networks Consortium (LINC), Cambridge, MA. Retrieved from http://linc.mit.edu/linc2013/proceedings/Session3/Session3Breakwell.pdf

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.

Bunderson, E. D., & Christensen, M. E. (1995). An analysis of retention problems for female students in university computer science programs. *Journal of Research on Computing in Education*, *28*(1), 1–18.

Chemers, M. M., Hu, L. T., & Garcia, B. F. (2001). Academic self-efficacy and first year college student performance and adjustment. *Journal of Educational Psychology*, *93*(1), 55–64.

Cheng, G., & Chau, J. (2013). Exploring the relationship between students' self-regulated learning ability and their ePortfolio achievement. *The Internet and Higher Education*, *17*, 9–15.

Chen, C., Haduong, P., Brennan, K., Sonnert, G., & Sadler, P. (2019). The effects of first programming language on college students' computing attitude and achievement: a comparison of graphical and textual languages. *Computer Science Education*, *29*(1), 23–48.

Chen, C., Sonnert, G., Sadler, P. M., Sasselov, D., & Fredericks, C. (2019). The impact of student misconceptions on student persistence in a MOOC. *Journal of Research in Science Teaching*, 1–32. https://doi.org/10.1002/tea.21616

Cheryan, S., Plaut, V. C., Davies, P. G., & Steele, C. M. (2009). Ambient belonging: How stereotypical cues impact gender participation in computer science. *Journal of Personality and Social Psychology*, *97*(6), 1045–1060.

Cohen, A. (2017). Analysis of student activity in web-supported courses as a tool for predicting dropout. *Educational Technology Research and Development*, *65*(5), 1285–1304. https://doi.org/10.1007/s11423-017-9524-3

Cohen, A., & Soffer, T. (2015). Academic instruction in a digital world: The Virtual TAU case. *Procedia—Social and Behavioral Sciences*, *177*, 9–16. https://doi.org/10.1016/j.sbspro.2015.02.322

Cusumano, M. A. (2014). MOOCs revisited, with some policy suggestions. *Communications of the ACM*, *57*(4), 24–26.

DeBoer, J., & Breslow, L. (2014). Tracking progress: Predictors of students' weekly achievement during a circuits and electronics MOOC. In *Proceedings of the First ACM Conference on Learning @ Scale Conference, L@S '14* (pp. 169–170). New York, NY: ACM.

DeBoer, J., Ho, A. D., Stump, G. S., & Breslow, L. (2014). Changing "course": Reconceptualizing educational variables for massive open online courses. *Educational Researcher*, *43*(2), 74–84.

Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology*, *92*(6), 1087–1101.

Evans, B. J., Baker, R. B., & Dee, T. S. (2016). Persistence patterns in massive open online courses (MOOCs). *The Journal of Higher Education*, *87*(2), 206–242.

Fini, A. (2009). The technological dimension of a massive open online course: The case of the CCK08 course tools. *The International Review of Research in Open and Distance Learning 10*(5), 1–26. Accessed March 16, 2013. http://www.irrodl.org/index.php/irrodl/article/view/643/1410

Gerdes, A., Heeren, B., Jeuring, J., & van Binsbergen, L. T. (2017). Ask-Elle: An adaptable programming tutor for Haskell giving automated feedback. *International Journal of Artificial Intelligence in Education*, *27*(1), 65–100.

Gillani, N., & Eynon, R. (2014). Communication patterns in massively open online courses. *The Internet and Higher Education*, *23*, 18–26.

Greene, J. A., Oswald, C. A., & Pomerantz, J. (2015). Predictors of retention and achievement in a massive open online course. *American Educational Research Journal*, *52*(5), 925–955.

Guo, P., & Reinecke, K. (2014). Demographic differences in how students navigate through MOOCs. In *Proceedings of the First ACM Conference on Learning @ Scale Conference, L@S '14* (pp. 21–30). New York, NY: ACM.

Gregori, E. B., Zhang, J., Galván-Fernández, C., & de Asís Fernández-Navarro, F. (2018). Learner support in MOOCs: Identifying variables linked to completion. *Computers & Education*, *122*, 153–168.

Haggard, S., Brown, S., Mills, R., Tait, A., Warburton, S., Lawton, W., & Angulo, T. (2013). The maturing of the MOOC: Literature review of massive open online courses and other forms of online distance learning. Department for Business, Innovation and Skills, UK Government. Retrieved from https://www.gov.uk/government/publications/massive-open-online-courses-and-online-distance-learning-review

He, J., Bailey J, Rubinstein, B. I. P., & Zhang, R. (2015). *Identifying at-risk students in massive open online courses*. In Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (pp. 1749–1755). Austin, TX.

Hew, K. F. (2016). Promoting engagement in online courses: What strategies can we learn from three highly rated MOOCS. *British Journal of Educational Technology*, *47*(2), 320–341. https://doi.org/10.1111/bjet.12235

Jacobs, A. J. (2013). Two cheers for Web U. *New York Times*, *162*(56113), 1–7.

Jadidi, M., Karimi, F., Lietz, H., & Wagner, C. (2018). Gender disparities in science? Dropout, productivity, collaborations and success of male and female computer scientists. *Advances in Complex Systems*, *21*(3 & 4), 1750011–1750033.

Jiang, S., Williams, A. E., Schenke, K., Warschauer, M., & O'Dowd, D. (2014). *Predicting MOOC performance with week 1 behavior*. *Proceedings of the 7th International Conference on Educational Data Mining*, 273-275. London: UK.

Joo, Y. J., So, H. J., & Kim, N. H. (2018). Examination of relationships among students' self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs. *Computers & Education*, *122*, 260–272.

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), 133–159.

Jung, Y., & Lee, J. (2018). Learning engagement and persistence in massive open online courses (MOOCs). *Computers & Education*, *122*, 9–22.

Kahan, T., Soffer, T., & Nachmias, R. (2017). Types of participant behavior in a massive open online course. *The International Review of Research in Open and Distributed Learning*, *18*(6). https://doi.org/10.19173/irrodl.v18i6.3087

Kazimoglu, C., Kiernan, M., Bacon, L., & Mackinnon, L. (2012). A serious game for developing computational thinking and learning introductory computer programming. *Procedia-Social and Behavioral Sciences*, *47*, 1991–1999.

Kelleher, C., & Pausch, R. (2005). Lowering the barriers to programming: A taxonomy of programming environments and languages for novice programmers. *ACM Computing Surveys (CSUR)*, *37*(2), 83–137.

Khalil, H., & Ebner, M. (2014). *MOOCs completion rates and possible methods to improve retention—A literature review*. In *EdMedia* (pp. 1305–1313). Finland: Tampere.

Kloft, M., Stiehler, F., Zheng, Z., & Pinkwart, N. (2014). Predicting MOOC dropout over weeks using machine learning methods. In *Proceedings of the EMNLP 2014 Workshop on Analysis of Large Scale Social Interaction in MOOCs* (pp. 60–65). Qatar: Doha.

Knox, J. (2014). Digital culture clash: "Massive" education in the e-learning and digital cultures MOOC. *Distance Education*, *35*(2), 164–177.

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.

Kovanović, V., Joksimović, S., Gasević, D., Siemens, G., & Hatala, M. (2015). What public media reveals about MOOCs: a systematic analysis of news reports. *British Journal of Educational Technology*, *46*(3), 510–527. http://doi.org/10.1111/bjet.12277

Lee, I., Martin, F., Denner, J., Coulter, B., Allan, W., Erickson, J., … Werner, L. (2011). Computational thinking for youth in practice. *ACM Inroads*, *2*(1), 32–37.

Lee, K. (2017). Rethinking the accessibility of online higher education: A historical review. *The Internet and Higher Education*, *33*, 15–23.

Levy, F., & Murnane, R. J. (2004). *The new division of labor: How computers are creating the next job market*. Princeton, NJ: Princeton University Press.

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.

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

Milligan, C., Littlejohn, A., & Margaryan, A. (2013). Patterns of engagement in connectivist MOOCs. *Journal of Online Learning & Teaching*, *9*(2), 149–159.

Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analytic investigation. *Journal of Counseling Psychology*, *38*(1), 30–38.

Oleksandra, P., & Shane, D. (2016). Untangling MOOC learner networks. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge* (pp. 208–212). New York, NY: ACM.

Resnick, M., Maloney, J., Monroy-Hernandéz, A., Rusk, N., Eastmond, E., Brennan, K., & Kafai, Y. (2009). Scratch: Programming for all. *Communications of the ACM*, *52*(11), 60–67.

Rice, J. (2014). MOOCversations: Commonplaces as argument. In S. D. Krause & C. Lowe (Eds.), *Invasion of the MOOCs: Promises and peril of massive open online courses* (pp. 86–97). San Francisco: Parlor Press.

Rivers, K., & Koedinger, K. R. (2013). Automatic generation of programming feedback: A data-driven approach. In Proceedings of AIEDCS 2013: The First Workshop on AI-supported Education for Computer Science.

Rivers, K., & Koedinger, K. R. (2014). Automating hint generation with solution space path construction. In S. Trausan-Matu, K. E. Boyer, M. Crosby, & K. Panourgia (Eds.), *Proceedings of ITS 2014: The 12th International Conference on Intelligent Tutoring Systems, 8474* (pp. 329–339). Cham, Switzerland: Springer.

Robertson-Kraft, C., & Duckworth, A. L. (2014). True grit: Trait-level perseverance and passion for long-term goals predicts effectiveness and retention among novice teachers. *Teachers College Record*, *116* (3), 1–27.

Rovai, A. P. (2003). In search of higher persistence rates in distance education online programs. *The Internet and Higher Education*, *6*, 1–16. https://doi.org/10.1016/S1096-7516(02)00158-6

Sadler, P. M., Sonnert, G., Coyle, H. P., & Miller, K. A. (2016). Identifying promising items: The use of crowdsourcing in the development of assessment instruments. *Educational Assessment*, *21*(3), 196–214.

Schophuizen, M., Kreijns, K., Stoyanov, S., & Kalz, M. (2018). Eliciting the challenges and opportunities organizations face when delivering open online education: A group-concept mapping study. *The Internet and Higher Education*, *36*, 1–12.

Seehorn, D., Carey, S., Fuschetto, B., Lee, I., Moix, D., O'Grady-Cuniff, D., … Verno, A. (2011). *CSTA K-12 Computer Science Standards: Revised 2011*. CSTA, New York: CSTA Standards Task Force.

Shah, D. (2018). A product at every price: A review of MOOC stats and trends in 2017. Class Central. Retrieved from https://www.class-central.com/report/moocs-stats-and-trends-2017/

Shah, D., (2015). MOOC trends in 2015: Big MOOC providers find their business models. Retrieved from https://www.class-central.com/report/mooc-business-model/

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.

Sharples, M., McAndrew, P., Weller, M., Ferguson, R., FitzGerald, E., Hirst, T., … Whitelock, D. (2012). *Innovating Pedagogy 2012: Open University Innovation Report 1*. Milton Keynes: The Open University.

Shen, C. W., & Kuo, C. J. (2015). Learning in massive open online courses: Evidence from social media mining. *Computers in Human Behavior*, *51*, 568–577.

Siemens, G. (2010). What are learning analytics? Retrieved February 10, 2012, from http://www.elearnspace.org/blog/2010/08/25/what-are-learning-analytics/

Singer, J. D., & Willett, J. B. (2003). *Applied longitudinal data analysis*. New York: Oxford University Press.

Soffer, T., & Nachmias, R. (2018). Effectiveness of learning in online academic courses compared with face-to-face courses in higher education. *Journal of Computer Assisted Learning*, *34*, 534–543. https://doi.org/10.1111/jcal.12258

Stich, A. E., & Reeves, T. D. (2017). Massive open online courses and underserved students in the United States. *The Internet and Higher Education*, *32*, 58–71.

Thompson, K. (2011). 7 things you should know about MOOCs. In *EDUCAUSE Learning Initiative*. Retrieved from. http://www.educause.edu/library/resources/7-things-you-should-know-about-moocs

Tukiainen, M., & Mönkkönen, E. (2002). Programming aptitude testing as a prediction of learning to program. In J. Kuljis, L. Baldwin & R. Scoble (Eds.), *Proceedings – Psychology of Programming Interest Group 14* (pp. 45–57). http://www.ppig.org/sites/ppig.org/files/2002-PPIG-14th-tukiainen.pdf

van de Oudeweetering, K., & Agirdag, O. (2018). Demographic data of MOOC learners: Can alternative survey deliveries improve current understandings? *Computers & Education*, *122*, 169–178.

Vihavainen, A., Luukkainen, M., & Kurhila, J. (2012). Multi-faceted support for MOOC in programming. In *Proceedings of the 13th annual conference on Information technology education* (pp. 171–176). New York, NY: ACM. https://doi-org.ezp-prod1.hul.harvard.edu/10.1145/2380552.2380603

Watted, A., & Barak, M. (2018). Motivating factors of MOOC completers: Comparing between university-affiliated students and general participants. *The Internet and Higher Education*, *37*, 11–20.

Wen, M., Yang, D., & Rosé, C. P. (2014). *Sentiment analysis in MOOC discussion forums: What does it tell us? Paper presented at the 7th International Conference on Educational Data Mining*. London: UK.

Xiong, Y., Li, H., Kornhaber, M. L., Suen, H. K., Pursel, B., & Goins, D. D. (2015). Examining the relations among student motivation, engagement, and retention in a MOOC: A structural equation modeling approach. *Global Education Review*, *2*(3), 23–33.

Zhu, M., Sari, A., & Lee, M. M. (2018). A systematic review of research methods and topics of the empirical MOOC literature (2014–2016). *The Internet and Higher Education*, *37*, 31–39.

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APPENDIX A.

Test items for precomputational thinking test (pretest):

#1. Grace thought of a number, added 7, multiplied by 3, took away 5 and divided by 4 to give an answer of 7. What was the starting number?

a) 2 b) 3 c) 4 d) 5 e) 6 f) 7

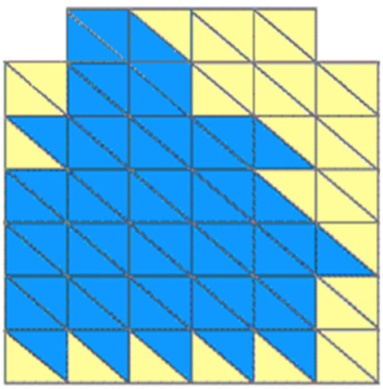
#2. Alan thinks of a number. He squares it, then takes away 5, next multiplies it by 4, takes away 7, divides it by 3 and finally adds 6. His answer is 9. What number did he start with?

a) 1 b) 2 c) 3 d) 4 e) 5 f) 6

#3. If the hour hand of a clock is turned anticlockwise from 2 p.m. to 9 a.m., through how many degrees will it have turned?

a) 120° b) 135° c) 150° d) 165° e) 180° f) 205°

#4. What percentage of this shape is blue (to nearest percent)?



a) 60% b) 63% c) 66% d) 69% e) 72% f) 75%

#5. In a counting system used by intelligent apes,

A banana = 1;

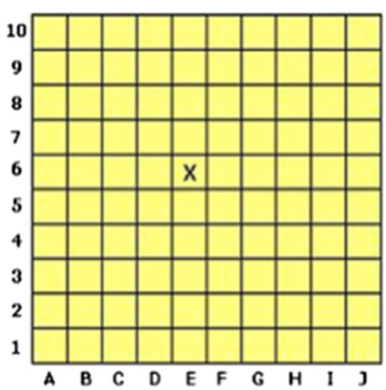
6 is represented by an orange and 2 bananas;

An orange is worth half a mango.

What is the value of two mangos, an orange and a banana?

a)21 b)24 c)27 d)30 e)33 f)36

#6. You start in square E6 facing East. Move 3 squares forward. Turn 90° clockwise, move two squares forward. Turn 180° anticlockwise. Move 5 squares forward. Turn 90° anticlockwise. Move 4 squares forward. Turn 90° clockwise. Move two squares backward. What is the Y COORDINATE of the square you are now in?



a) 6 b) 7 c) 8 d) 9 e) 10 f) 11

#7. Using the table below, what is A4 multiplied by D3 divided by C2?

	A	B	C	D	E	F
1	9	7	8	4		
2	8	2	3	7		
3	11	1	5	6		
4	13	9	6	3		

a) 24 b) 26 c) 28 d) 30 e) 33 f) None of these

#8. Let i be an integer between 1 and 9, inclusive. The expression (i > =1) and (i<=5) is true when i has values:

a) 1 2 3 4 5 b) 2 3 4 c) 1 2 3 4 6 7 8 9 d) 6 7 8 9

#9. Select in the missing letter sequence: acbcd, acbcbcbcd, acbcbcbcbcbcd, ________________________.

a) acbcbcbcbcbcbcbcd b) acbcbcbcdacbcbcbcd c) acbcbcbcbcbcbcd d) acbcdacbcdacbcd.

#10. Select in the missing letter sequence: _________________, ebcccdd, ebbccccdd, ebbbcccccdd, …

a) eccd b) ebcd c) eccdd d) ebccd

#11. Your job is to decide which of a set of given numbers is the smallest. How many comparisons (of 2 numbers at a time) do you have to make if you have 8 numbers?

a) 5 b) 6 c) 7 d) 8

#12. At a certain school, students receive letter grades based on the following scale.

Numeric Score	Letter Grade
92 or above	A
From 84 to 91 inclusive	B
From 75 to 83 inclusive	C
Below 75	F

Which of the following code segments will assign the correct grade for a given integer score?

Segment I.

if (score > = 92) grade = "A";
if (score > = 84 AND score < = 91) grade = "B";
if (score > = 75 AND score > = 83) grade = "C";
if (score < 75) grade = "F";

Segment II.

if (score > 92) grade = "A";
if (score > 84 AND score < 91) grade = "B";
if (score > 75 AND score < 83) grade = "C";
if (score < 75) grade = "F";

Segment III.

if (score > = 92) grade = "A";
else if (score > = 84) grade = "B";

else if (score > = 75) grade = "C";
else grade = "F";

a) II only b) III only c) I and II only d) I and III only e) I, II, and III

Additional notes about item selection:

We drew on several types and sources of questions to create the pretest. From the University of Kent Computer Programming Aptitude Test (https://www.kent.ac.uk/ces/tests/computer-test.html), we took questions on logical thinking, pattern recognition, and ability to follow complex procedures, with the authors' kind permission. From Tukiainen and Mönkkönen (2002), we adapted questions targeting mathematical and logical reasoning and pattern recognition. From sample AP Computer Science Exam questions released by the College Board, we adapted questions on programming in the Java. Inspired by the American Computer Science League (ACLS) contests, we also adapted questions on calculating the values of recursive functions. In the case of questions adapted from Tukiainen and Mönkkönen (2002), the AP Computer Science Exam, and the ACLS, we modified the numerical values, item format (all our questions were multiple choice), or programming language. In this way, we generated a preliminary pretest of 31 questions and evaluated it by administering it to 911 Amazon Mechanical Turk (AMT) participants. Based on classical test theory and item response theory analyses, we identified the top 12 questions, which explained 83.8% of the variance in the total pretest scores. We used these 12 questions as the pretest given to CS50x students. The mathematical reasoning, pattern recognition, and following complex procedures questions from the University of Kent Computer Programming Aptitude Test and those based on Tukiainen and Mönkkönen (2002) were most predictive and hence heavily represented in the CS50x pretest (seven items from Kent; four items adapted from Tukiainen & Mönkkönen, 2002). One item was a modified AP Computer Science Exam question.