Attrition in Online Learning: Understanding Persistence and Dropout in Massive Open Online Courses

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ABSTRACT

Persistence and attrition in MOOCs are systematically analyzed using self-report and behavioral data collected from [N] online learners in [M] courses. Study 1 offers insights into reasons for disengaging from MOOCs and explores relationships with prior behavior and reported intentions. Study 2 is a case study to develop a deeper understanding of attrition in MOOCs by conducting a case study. Targeting online learners who were predicted likely dropouts in a particular course were invited to provide feedback via a survey. (abstract needs work...)

Author Keywords

Online learning, persistence, attrition, dropout, disengagement, massive open online courses, MOOC, psychological factors

ACM Classification Keywords

H.5.m. Information Interfaces and Presentation (e.g. HCI): Miscellaneous; K.3.1. Computers and Education: Computer Uses in Education

INTRODUCTION

Educational environments has become increasingly diverse. Traditional schools and universities have a characteristically rigid structure, including instructor-defined—even nationally agreed—syllabi, fixed time schedules, entry requirements, and material costs to enter and exit. Novel institutional structures have been developed to overcome particular constraints. Community colleges, for instance, were created in an attempt to democratize education by offering instruction at a lower cost and by accommodating people with less flexible schedules [8]. Distance learning programs intended to deliver education in remote parts of the world and for people who simply could not attend in-person classes. Course materials, including assessments, were delivered through mail ("correspondence education"), radio, television, and eventually the Internet, thereby addressing geographical and time related constraints of traditional instruction [18].

L@S'15, March 14–15, 2015, Vancouver, Canada.

DOI string from ACM form confirmation

The latest generation of online learning environments, characterized by massive open online courses (MOOCs), has pushed the boundary on the scale of education [28]. By design, MOOCs provide course materials to millions of people worldwide. This scale could be achieved by pre-recording lectures, designing assessments that can be graded automatically, and by leveraging the momentum of the number of people involved (e.g., to facilitate peer learning or peer grading [16, 4]). Maybe by virtue of their large scale, their prominent instructors, or their adherence to contemporary interface designs, MOOCs rapidly became an online media phenomenon. People would sign up weeks in advance of the course launch date, many of whom would never even enter the course site. And among those who enroll and enter the site, a large proportion tends to only "sample" some content and leave again [14]. Many of the prototypical behaviors observed in MOOCs [14, 3] (other?) resemble those on online media platforms, such as YouTube or tumblr. This trend has also been reflected in the diversity of MOOC learners' motivations for enrolling [15].

Shortly after the first wave of courses had finished, extensive media coverage led to MOOCs becoming associated with high attrition rates [17, 21, 9]. Early MOOC research cautioned against dichotomizing learners into successes and failures based on course completion [14, 23]. Instead, more nuanced categorizations based on learner behavior [14, 5] (other?), motivations [15], or intentions [30] have been suggested. Ultimately, perspectives on persistence and attrition in MOOCs depend on how MOOCs have been conceptualized. Kizilcec and Schneider [15] proposed that MOOCs have bridged two different world: one world is governed by the user-centric norms of online media, where everyone is encouraged to be as active as they wish; the other world adheres to the "grammar of schooling", which presupposes instructor-defined goals that students strive to achieve [27]. Viewing MOOC participation as bridging these two worlds undoubtedly adds a layer of complexity to interpretations of attrition.

This paper presents a systematic investigation into attrition in MOOCs, based on self-report and behavioral data collected from [N] online learners in [M] courses. We begin by briefly reviewing the large literature on attrition in educational environments with a focus on important developments in understanding its causes. Building on this foundation of prior work, Study 1 offers insights into reasons for disengaging from MOOCs and explores relationships with prior behavior and reported intentions. In Study 2, we sought to develop a

deeper understanding of attrition in MOOCs by conducting a case study. Targeting around 7,000 online learners who were predicted likely dropouts in a particular course were invited to provide feedback via a survey. TODO: complete paragraph based on what we actually do in Study 2.

RELATED WORK

Research and theorizing on attrition in education has a rich history. This review is intended to serve as a foundation to build on with the current research. We therefore simultaneously develop research questions and hypotheses to investigate and test in the current work. The focus of this brief review is on how ways of thinking about attrition have developed over the last decades.

In-person Education

The majority of early work on attrition centered around theoretical models of students' decision to persist or dropout of a traditional higher education setting. An early model suggested that students' presistence is largely driven by their prior behavior, attitudes, and norms [7]. The psychological processes involved in turning an intent to learn into the decision to persist were thought to be mediated by volition, i.e., the extent to which the student engages in goal-direct behaviors in the face of distraction [6]. Hence, motivation alone is necessary but not sufficient for persistence. Students may fail to sustain efforts in the absence of strong self-regulatory skills.

RQ1 How do prior learner characteristics (demographics, geographic location, intentions and motivations, and previous online courses) influence learners' likelihood of dropping out of a MOOC?

H1 Successful MOOC learners exhibit higher levels of goal striving than unsuccessful ones.

The next generation of psychological models, which were highly influential in the literature, emphasized the critical role of students' "fit" in the institution. Tinto's [26] student integration model posited that college students' decision to persist is a function of prior experiences and individual students' characteristics, and experiences during college. While prior experiences and characteristics are fixed, schools can influence the college experience, including the degree of social and academic integration. Tinto operationalized academic and social integration by GPA scores and the frequency of positive interactions with peers and instructors, respectively. This resonates with recent work highlighting the critical role of students' feelings of social belonging in achievement-oriented environments [29].

H2 Successful MOOC learners exhibit a greater sense of social belonging than unsuccessful ones.

Tinto's work, which specifically targets traditional college students, prompted universities to be proactive in establishing environments that support student integration. Research on attrition in community college settings reiterates the importance of academic and social integration, but points out that non-persistence could indicate success depending on students' intent—students may leave after accomplishing their goal [2]. Nevertheless, a brief psychological intervention that taught community college students an incremental theory of intelligence (i.e., instilling a growth mindset) was found to halve attrition rates and increase academic achievement [22]. The results highlight the powerful influence of mindset and caution against overinterpreting non-persistence as an indicator of goal achievement.

RQ2 What proportion of learners who dropped out were satisfied with their achievements in the course?

H3 Successful MOOC learners have a more fluid conception of intelligence (i.e., more of a growth than fixed mindset) than unsuccessful ones.

Distance Education and e-Learning

Distance education, in contrast to traditional in-person education, attracts a different student demographic and typically provides fewer opportunities for social integration. However, students in distance learning programs tend to lead social lives outside of school, maybe working part-time and living with their partner. Building on Tinto's model, Bean and Metzner [1] proposed a conceptual model of persistence that would be more applicable to nontraditional students. Persistence is thought to be a function of background characteristics (e.g., demographics), academic and environmental variables (e.g., study habits, financial resources, work and family obligations), and academic and psychological outcomes (e.g., GPA, satisfaction). The significant change from Tinto's orginal model was the inclusion of environmental variables to account for the added complexity of nontraditional students' lives (see [12], for another adaptation of Tinto's model for distance education).

Rovai [24], combining Tinto's and Bean and Metzner's models with factors specific to online learning and pedagogical styles, proposed a composite persistence model specifically for students in online distance education programs. Among other novel factors, Rovai's model acknowledges the critical role of computer literacy in online learning. And yet, while the theoretical models become more developed, they became harder to apply to real-world settings, and hence, the empirical evidence to support them remained sparse. An exploratory study of reasons for attrition suggested the following eight constructs, based on over 1,000 online education students: academic and technical skills, learner motivation, time and support for studies, cost and access to the Internet, and technical problems [20]. An analysis of student behavior on an online education platform showed that 31% of variation in achievement could be accounted for by a small set of participation measures [19].

MOOCs

A survey of over one hundred learners who dropped out of a MOOC showed that the majority indicated having too little time due to work responsibilities, not enough social support inside and outside of the course, and insufficient academic and technical support from the course [10]. A qualitative analysis of public records, especially forum posts, from 42 MOOCs suggested the following reasons for attrition: lack

of time, learner motivation, feelings of isolation, lack of interactivity, insufficient prior knowledge or skills, and hidden costs [13]. A survival analysis of close to 800 learners who had posted on a MOOC discussion forum suggested that the likelihood of dropout was lower for those who i. actively participated in the first week of the course; ii. served as an authority figure in the community on the forum, and iii. did not engage in a particular subcommunity on the forum [31]. In addition, a number of machine learning approaches yielded promising results for early dropout prediction (e.g. [25, 11]), but fell short of offering insights into why a given learner would leave the course.

RQ3a What reasons do learners report for dropping out of a MOOC?

RQ3b How do reasons for dropping out vary across prior learner characteristics (cf. RQ1)?

RQ4 How does behavior in MOOCs vary by reasons for dropping out?

STUDY 1: REASONS FOR DISENGAGING

Methods

TODO: Outline different courses and go through variabels in the course info table.

Table: course name; enrollment; pre-survey response rate; prop. demographics (age, gender, educ); who intended to do all; post-survey response rate; self-identified dropout rate

Results

Table: proportions for each dropout reason for each course

Table: correlations between reasons and one with cors between reasons and intentions

Plot: ecdf curves for proportion videos watched for each disengagement reason

Discussion

STUDY 2: UNDERSTANDING DISENGAGEMENT

To gain a better understanding of the attrition patterns identified in Study 1, we designed a smaller, more focused follow-up study. In Study 2, we reached out to learners who were likely to drop out of a course and asked them to provide feedback. We developed a predictive model to identify learners who were likely to drop out and ask them to complete a survey.

H4a Learners who report having 'not enough time' can be divided into those with too many higher priority obligations (work, school, family) and those with low volition.

H4b Learners who do not report specific obligations (e.g., work, school, family) tend to fall in the low volition than in the high-priority obligations group, and vice versa.

Methods

The particular MOOC under observation was an undergraduate level course on an advanced topic in computer science. It was offered in 2014 through Coursera. There were [N1] enrolled learners; [N2] watched more than one video, and [N3] attempted more than one assignment.

Predicting Disengagement

SHERIF TODO: Details of the prediction algorithm.

Feedback Survey

Every learner who was predicted to disengage from the course was sent an email kindly requesting their help: "You are enrolled in [course name], but you've been less active recently. Could you help us understand why?" A low response rate was expected for a subpopulation that was defined by low engagement. And yet, 756 out of 6,050 learners started the survey (12.5% response rate), and 459 completed it (61% completion rate). Missing values were multiply imputated by predictive mean matching using responses to all survey questions[1]. All estimates were pooled across ten imputations, with standard errors adjusted for added variance. The majority of respondents were male (85%), 35.6 years old on average ($SD = 12.5$), and 80% had achieved a bachelors' or more advanced degree.

Learners were asked to report how satisfied they were with their progress in the course, and whether they were using the course materials more, less, or exactly as much as they would have liked. In addition, they reported intentions for engaging with each week's course content. Then, they were asked to openly report "what challenges, inside or outside of the course, [they] experienced while [they were] taking this course, if any?" The instructions encouraged them to list all challenges they could think of. This question was deliberately asked prior to any survey questions that could suggest particular reasons for disengagement.

Two research assistants independently developed codebooks for the resulting 448 non-empty open responses. Their codebooks were consolidated and applied on Mechanical Turk in three iterations. The codebook was updated in each iteration to reliably fit the open response data. Specific updates to the initial codebook were informed by code frequency, code correlations, and inter-coder agreement. In the first iteration, 250 randomly selected responses were each coded by four 'classification experts'. In the second iteration, the remaining responses were coded in the same way. In the final iteration, all responses were coded by two classification experts (ties were resolved by two researchers).[2] The iterative coding yielded 399 relevant coded responses, which were analyzed in combination with the remaining survey data.

Besides these open responses, learners rated their relative progress and satisfaction with their progress in the course, which served as measures of personal success. They also rated the extent to which their progress was hindered by a number of obstacles. The survey also included a measure of learners' sense of social and academic fit [29] (17 items, $M = 4.66, SD = 0.71, \alpha = 0.86$); mindset (4 items on the nature

[1]The R mice package was used to perform multiple imputation and subsequent analyses.

[2]For additional details on the coding procedure and codebooks, see [URL].

of intelligence and talent[3]; $M = 4.44, SD = 0.92, \alpha = 0.77$), goal striving (4 items on motivation, perceived importance, committment, and confidence; $M = 3.12, SD = 0.95, \alpha = 0.82$), and one item on volition (about lower-priority distractions hindering the learner's course progress; $M = 2.73, SD = 1.29$).

Results

Predicting Likely Dropouts

SHERIF TODO: Add results of prediction. How well did the prediction work? And who took the survey; how sure was the model that those who took the survey would actually drop out, relative to those who didn't take the survey?

Reasons for Dropout

The majority of survey respondents (73%; 550 of 756) reported being only somewhat or less satisfied with their progress in the course. While many of them (66%) were substantially held back by other committments that took up time they had planned to spend on the course, only one in four (25%) indicated being hindered by distractions of lower priority than the course (i.e. volition). These two time-related measures, which only differ in the assigned level of priority, were not significantly correlated, $r = .05, t_{548} = 1.3p = .21$.

Reasons for learner attrition were measured using open response as well as multiple-choice questions. Based on learners' coded open responses ($n = 399$), 84% had 'not enough time for the course', 18% indicated that 'the course format or teaching style was not a good fit', 10% expressed that 'the level of the course was too advanced', 7% found that 'the course was not interesting or valuable enough', 4% expressed a need for 'additional course materials to learn the topic', 2% experienced 'technical difficulties', and 1% reported facing a 'language barrier'. A number of significant correlations between these challenges stood out: having not enough time was negatively associated with disliking the format or teaching style ($r = -.52$), needing additional course materials ($r = -.26$), finding the course uninteresting or not valuable ($r = -.45$), and facing technical difficulties ($r = -.29$).

To test hypotheses $H4a$ and $H4b$, we examined the 336 open responses that indicated having too little time, which revealed that about half of them (53%) did not specify a particular committment. This distinction was a salient feature in the initial codebooks, but could not be coded with sufficient reliability across coders. Coders would have required additional training to avoid reading specific reasons into unspecific resposnes. We thus operationalized the distinction by string matching to caputre professional, academic, and personal reasons for having not enough time.[4] Relative to those who specified a reason, learners who indicated too little time without specifying a reason also reported a significantly lower level of volition, i.e. their progress was more severely hindered by lower-prioirty distractions ($t_{331} = 2.9, p = .003, d = .32$). However, the two groups did not significantly differ in how much they were held back by committments that took up time they had planned to spend on the course ($t_{333} = -.75, p = .45$). These findings lend strong support to hypotheses 4a and 4b: while the large group of learners who report having not enough time generally faced higher-priority obligations, a substantial proportion suffered from low volition and reporting no specific reasons for having not enough time was indicative thereof.

Psychological Factors

Hypotheses $H1$, $H2$, and $H3$ about goal striving, perceived social belonging, and mindset, respectively, were tested by comparing self-described successful with unsuccessful learners. Success was measured by relative progress, and satisfaction with progress: 68% of respondents reported using the course materials less than they would have wanted, and 57% reported not being satisfied with their progress in the course (18% were very or extremely dissatisfied). The two measures were correlated, $r = .35, t_{754} = 10, p < .001$; satisfied respondents were, however, equally likely to be successful and unsuccessful in terms of their progress. Table 1 provides summary statistics for each psychological measure by these two success metrics. Successful learners exhibited higher levels of goal striving according to both progress and satisfaction measures. Social belonging was significantly higher for learners who were successful in terms of satisfaction but not progress. The pattern was reversed for growth mindset, with evidence for the hypothesized effect for progress but not satisfaction. The results fully support $H1$, and partially support $H2$ and $H3$.

Discussion

GENERAL DISCUSSION

CONCLUSION

ACKNOWLEDGMENTS

Omitted for blind review.

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[3]Items were adpated from the mindset questionnaire available at `http://mindsetonline.com/testyourmindset/`.

[4]Pattern: *work|job|school|university|college|family|kids|health*

Table 1. Descriptive and inferrential statistics for psychological measures by learner success

	N	Goal Striving ($H1$)	Social Belonging ($H2$)	Growth Mindset ($H3$)
Relative Progress				
Successful	241	3.46 ($SD = 0.91$)	4.70 ($SD = 0.74$)	4.58 ($SD = 0.99$)
Unsuccessful	515	2.96 ($SD = 0.93$)	4.63 ($SD = 0.70$)	4.38 ($SD = 0.87$)
		$t_{201} = 6.3, p < .001, d = 0.55$	$t_{60} = 1.0, p > .25, d = .09$	$t_{152} = 2.4, p = .017, d = 0.21$
Satisfaction				
Successful	325	3.43 ($SD = 0.83$)	4.76 ($SD = 0.70$)	4.47 ($SD = 0.93$)
Unsuccessful	431	2.88 ($SD = 0.97$)	4.58 ($SD = 0.71$)	4.42 ($SD = 0.91$)
		$t_{166} = 7.2, p < .001, d = 0.59$	$t_{158} = 3.1, p = .002, d = .26$	$t_{175} = 0.6, p > .25, d = .05$

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