Modeling Key Differences in Underrepresented Students' Interactions with an Online STEM Course

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ABSTRACT

Little is known about the ways that underrepresented students in online STEM courses interact and behave differently from their peers, or whether online courses offer learning opportunities that can better suit these under-served populations. The current study examines the logged behavioral patterns of 470 university students, spanning 3 years, who were enrolled in an online introductory STEM course. Cross-validated data mining methods were applied to their interaction logs to determine if first generation, non-white, female, or non-traditional (≥ 23 years old) students could be classified by their behaviors. Model classification accuracies were evaluated with the Matthews Correlation Coefficient (MCC). First generation (MCC = .123), non-white (MCC = .153), female (MCC = .183) and non-traditional students (MCC = .109) were classified at levels significantly above chance (MCC = 0). Follow-up analyses of predictive features showed that first-generation students made more quiz attempts, non-white students interacted more during night hours (8pm-8am), female students submitted quizzes earlier, and non-traditional students accessed discussion forums less than their peers. We show that understanding behaviors is crucial in this context because behaviors in the first two weeks alone (e.g., discussion forum participation, number of logins) predicted eventual grade in the course (MCC = .200). Implications are discussed, including suggestions for future research as well as interventions and course features that can support underrepresented STEM students in online learning spaces.

CCS CONCEPTS

• **Applied computing~E-learning**

KEYWORDS

STEM education, educational data mining, underrepresented students, online courses.

ACM Reference format:

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1 INTRODUCTION

Careers in science, technology, engineering, and mathematics (STEM) are valuable, being associated with higher and more equitable wages, better job security, and more employment opportunities [4, 13]. However, certain groups of people, including women and ethnic minorities, are underrepresented in STEM fields [4, 9, 16]. Encouraging and enabling members of underrepresented groups to pursue STEM careers thus has the potential to ameliorate economic inequality and promote scientific progress. In addition, it is widely believed that diversifying STEM fields will yield benefits to STEM and to society [6]. The majority of STEM jobs require post-secondary education [13], which may be tailored to support the needs of students who have traditionally made up the majority of STEM degree recipients and job holders [11]. In this paper, we explore how underrepresented students interact differently from their

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peers in online STEM courses to inform course design and interventions that are tailored to support these students in their pursuit of STEM degrees and eventual STEM careers.

Online courses have become increasingly popular for university students, and universities continue to offer more online options [1]. However, online versions of STEM courses are not always well suited for underrepresented students [16], although some of these students are also more likely to enroll in such courses [17]. Furthermore, underrepresented students are less likely to remain in STEM majors at the undergraduate level [17]. It is thus important to understand how underrepresented students interact with online STEM courses differently from their peers, and how these courses can better support underrepresented students.

Toward these goals, this study explores behaviors recorded in logs of university students' interactions with a learning management system (LMS) for an introductory online STEM course. Specifically, we model behavioral differences for traditionally underrepresented students, including first-generation (students of parents with no post-secondary education), minority ethnicity, female, and non-traditional (≥ 23 years) students. We also examine students who declared a STEM major versus those who did not, and show the importance of course behaviors by predicting final class grades from the first two weeks of logs (the deadline to withdraw for a full refund). Finally, we identify the specific behaviors that were most predictive in these models, to provide insights into student behaviors and implications for the design and implementation of future online courses.

This study employs a novel application of student-independent cross-validated data mining methods to model differences between underrepresented students and their peers, thereby improving generalization of findings to new students. We also make scientific contributions to the understanding of the characteristics and needs of underrepresented students, and provide insights from these findings that are unique, practical, and applicable.

2 RELATED WORK

We focus on two areas of related work. First, we discuss previous research on underrepresented students in online courses, with an emphasis on STEM courses. Second, we discuss educational data mining research that closely matches the methods we employed.

2.1 Underrepresented Students in Online Courses

In a national survey of undergraduates, including over 27,000 STEM majors, Wladis et al. [17] found that non-traditional student characteristics were especially important in predicting online STEM enrollment. Importantly, the more non-traditional features students had, the more likely they were to enroll in an online course (also see [16]).

Kaupp [11] reviewed the successes of Latina/o and White students in online and traditional lecture classes across community colleges in California, finding that Latina/o students were less likely to succeed than White students and that this trend was more severe in online classes. This finding is indicative of both systemic disadvantages that Latina/o students face and the fact that online courses may not be developed or adapted for their needs. In general, studies investigating underrepresented students' behavior in online courses have found few areas of success [18, 19].

2.2 Related Educational Data Mining Research

The vast volume of research into predicting eventual course completion is beyond the scope of this paper (see [7] for a recent example and discussion of common methods). Instead, we focus on examples where predictive behaviors were related to those we examined in the current study.

Baker et al. [3] analyzed students' interaction logs from a university's online history course to predict success and failure. They examined three key behaviors: whether students accessed the course materials at all, whether they accessed materials recently, and how well they did on exercises. They found that a student model based on behaviors in the first four weeks of class predicted whether the student would eventually pass or fail the class with better than chance accuracy (Cohen's kappa = .344, where chance level = 0 and perfect = 1).

Crossley et al. [8], in an analysis of student behaviors in an educational data mining MOOC, measured interaction behaviors such as how often a student accessed course materials, interacted with other students in the discussion forum, submitted assignments, and overall interacted with the course. They also analyzed features of writing quality, cohesion, complexity, and sentiment (among others) from the students' forum discussion posts. A student model trained on a combination of these features predicted whether students would eventually earn a certificate in the course, with Cohen's kappa = .543.

In another study focused on students' interactions and discussion forum posts, Macfadyen et al. [14] found that the number of discussion forum posts made, number of assignments submitted, and number of messages sent explained 33% of the variance in undergraduate students' final grades. These findings highlighted the importance of peer interactions, as the number of discussion posts made was even more related to final grade than the number of assignments submitted (Pearson's r = .52 versus r = .31).

2.3 Current Study

Our goal is to combine these related lines of research by using data mining techniques to classify students' demographic variables, and analyze predictive interaction features to gain deeper insight into distinctive differences between underrepresented students and their peers.

3 METHOD

We analyzed data from 470 students (of 586 students initially enrolled) in an online introductory STEM course offered by a public university in the Midwestern United States. Data were from seven semesters, including summer sessions, spanning three years of the course. We removed 116 students who withdrew from the course, to focus on how students behaved throughout the course. Furthermore, it was not uncommon for students to "course shop" by enrolling and then withdrawing from more classes than they intended to complete. The remaining 470 students included several traditionally underrepresented groups in STEM: 21.5% first-generation college students, 53.6% non-white, 53.4% female, and 24.3% non-traditional.

3.1 Web-Based Learning Environment

The course was administered via an LMS called LON-CAPA [12]. In LON-CAPA, students can view their grades, interact with discussion forums, view lecture videos, view and submit assignments, take exams, and complete other course functions. Figure 1 shows the main screen of LON-CAPA, from which students can access all primary course features through a tree navigation view.

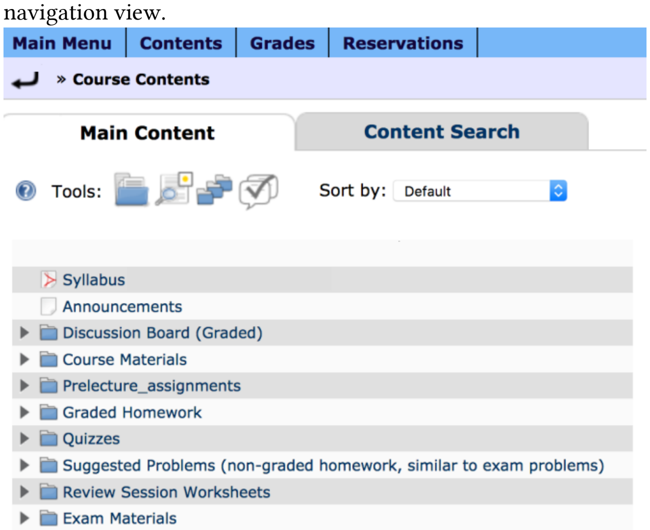

Figure 1: Course overview screen in LON-CAPA.

3.2 Feature Extraction

We extracted a variety of features from the students' clickstream to categorize students' interaction with the LMS. Access-related features included: the number of weeks students logged in, total logins, events per login, total interaction events, times accessing written materials, grade views, quiz attempts, correct quiz answers, attempted exam questions, correct exam attempts, discussion forum post views, and forum posts made. Per-week normalized versions of these features were also extracted where possible. A feature was also extracted to capture the mean length of forum posts made.

Timing features consisted of seconds until quiz due at time of attempt, seconds until exam due at time of attempt, rank among peers of first course access time (i.e., first student to access course website vs. last student), proportion of interaction events occurring on Sunday (and Monday, Tuesday, etc.), proportion of events occurring between 8:00am and 8:00pm, and the hour of the day with the most interaction events.

Finally, we *z*-standardized features and performed tolerance analysis to eliminate highly multicollinear features (variance inflation factor > 5) [2]. There were 24 features after tolerance analysis.

3.3 Supervised Classification (Data Mining Approach)

We trained logistic regression models to classify whether students were members of underrepresented groups. A separate model was trained for each demographic variable (first generation, non-white, female, non-traditional) as well as models to classify STEM major students and students who achieved a high grade (B- or better). Grade prediction was performed with features derived from only the first two weeks of class interactions, and only for students who interacted with the LMS for at least two weeks (N = 444 because some students stopped interacting in the first two weeks but did not withdraw).

Models were evaluated in a student-independent fashion with ten-fold cross-validation, i.e., models were trained on data from 90% of students and evaluated on the remaining 10% and the process was repeated 10 times so that each student was in the testing set once.

Model complexity was controlled with L_2 regularization, which penalizes models with vastly different weights for input features [15]. The amount of regularization was tuned by dividing the penalty by a constant factor *C*, which was varied from 10^{-4} to 10^4. The optimal value of *C* was selected with three-fold nested cross-validation within training data, to avoid over-fitting *C* to the testing data.

Predictive features were found with forward feature selection. For each feature, a model was trained with only that feature, to determine which feature was most predictive. Then, each remaining feature was added to the best one-feature model to find the best two-feature model and so on, until the model ceased to improve. Forward feature selection was also performed with three-fold nested cross-validation, within training data only, to ensure that selected features were not based on performance in the testing data. The average number of features selected per model was 8.2 (out of 24 possible).

We evaluated model classification results with Cohen's kappa and the Matthews Correlation Coefficient (MCC). Kappa measures the agreement between model predictions and true labels, and is often reported in student modeling literature (e.g., [3]). MCC measures the correlation between predicted and actual labels, and can be checked for significance with a χ^2 test. We performed Benjamini-Hochberg procedures for all significance tests reported in this paper, to reduce the chance of Type I errors with multiple tests [5].

3.4 Feature Ranking Analysis

Forward feature selection produces a ranking of features according to the order in which they were added to the model. This ranking indicates how predictive each feature was, given the model performance already obtained with the better-ranked features. For example, the number of times a student viewed their grades, both throughout the course and per week, may characterize some demographic variable. However, if one feature is slightly more predictive it will be selected first, and the other will not be selected next if it does not add additional predictive value.

We examined the rankings produced by forward feature selection to discover key interaction behaviors that provide unique information and generalize across students. We considered only features that were selected in over half of the ten rounds of cross-validation and averaged the rank of each feature across folds to find the most consistently predictive features overall. The direction of effect for each feature was evaluated with *t*-tests to determine whether higher or lower values of the feature were associated with each demographic variable.

4 RESULTS

We present results in two main parts. First, we show the overall performance of machine-learned models to determine if demographics can be inferred from students' behaviors. Second, we present feature analysis results that examine these behaviors.

4.1 Machine Learning Results

Overall model results can be seen in Table 1. Most importantly, despite modest model performance, we note that all four demographic variables of interest could be detected at levels above chance (mean MCC = .142). This indicates that there are indeed behavioral differences between underrepresented groups of students and their peers.

Female students were most accurately distinguished from their peers (MCC = .183). Also notable is the fact that female students were well-represented in this introductory course (53.4%), although previous research has found that female students are less likely to continue on in STEM majors and occupations than male students [9, 10].

Similarly, we note that students of non-white ethnicity were distinguishable from their peers based on behavioral patterns (MCC = .153). These students were an apparent majority, representing 53.6% of the students in this course, but this figure includes Asian, Black/African American, Hispanic, and others, many of whom are traditionally underrepresented in STEM fields [17]. First-generation and non-traditional students were also detectable at levels above chance (MCC = .123 and .109 respectively), and were minorities in the class (21.5% and 24.3%), which was not unexpected, given the university's demographics.

Finally, we note that students who earned high grades could be distinguished from other students based on interaction patterns in the first two weeks of class alone (MCC = .200). This is particularly interesting because it implies early behavioral patterns are related to eventual course outcome, and thus the differences in behaviors between underrepresented groups and their peers are also worthwhile to explore.

Table 1: Performance of machine learning models for classifying demographics and outcomes. * indicates significantly above chance performance.

Prediction Task	Base Rate	N	Kappa	MCC
First generation	21.5%	470	.106	.123*
Non-white	53.6%	470	.153	.153*
Female	53.4%	470	.182	.183*
Non-traditional (≥ 23 years old)	24.3%	470	.095	.109*
STEM major	68.3%	470	.083	.085
High grade (B- or better)	42.6%	444	.198	.200*

4.2 Feature Analysis Results

Feature rankings are shown in Table 2. Positive *t*-test results indicate the value of the feature was higher for the group of interest, e.g., non-traditional students accessed the discussion forums fewer times per week and attempted quiz problems more often. Several key results can be drawn from this analysis.

The most predictive feature for each demographic model (lowest mean rank) varied between the different models. First-generation students were distinguished primarily by higher per-week quiz attempts, non-white students by longer discussion forum posts, female students by earlier submission of quizzes, and non-traditional students by less access of the discussion forums. This indicates that underrepresented groups behaved differently from their peers in unique ways, not in ways that consistently identified underrepresented students versus their peers overall.

Table 2: Feature selection rankings (lower is more important) and effect directions. * indicates significant t-test.

	Mean Rank	*t*
First generation		
Quiz attempts per week	1.500	*2.484
Quiz attempts	1.800	*2.750
Proportion of events on Saturday	2.667	-1.454
Mean exam problem correctness	4.333	-1.239
Non-white		
Mean discussion post length	2.000	1.930
Proportion of events on Saturday	2.625	1.707
Proportion of events 8am-8pm	3.100	*-3.381
Logins per week	5.571	1.685
Proportion of events on Tuesday	5.625	-2.157
Female		

Seconds until quiz due at submission	2.000	*2.422
Mean exam problem correctness	2.800	*-2.566
Logins per week	3.400	*2.650
First course access time ranking	5.500	-1.787
Events per login session	5.667	0.584
Exam attempts	6.333	0.427
Seconds until exam due at submission	6.556	-1.375
Proportion of events on Saturday	7.000	*2.278
Non-traditional		
Discussion forum accesses per week	1.000	*-3.329
Quiz attempts per week	2.167	1.830
Total discussion forum posts	3.167	-2.057
Discussion forum posts per week	4.429	-1.391
STEM major		
Events per login session	2.250	*-3.696
Quiz attempts	4.333	0.221
Logins per week	5.000	*-2.246
High grade (features from first two weeks only)		
Logins per week	1.000	*4.437
Total discussion forum accesses	2.000	*3.033
Mean exam problem correctness	3.286	-1.495
Mean discussion post length	5.333	*4.267
Events per login session	5.429	-0.783
Seconds until exam due at submission	5.750	1.185
Mean quiz problem correctness	6.111	*3.242

The model distinguishing STEM major students from their peers was not accurate at significantly above chance level (Table 1), but it is interesting to note that STEM major students logged in significantly fewer times (t = -2.246) and performed fewer events in each login (t = -3.696), indicating less total interaction with the LMS. Conversely, students who eventually got a high grade (B- or better) in the class logged in more frequently, at least in the first two weeks (t = 4.437). They also viewed the discussion forum more frequently (t = 3.033), the opposite of the behavior observed for non-traditional students (t = -3.329). Perhaps unsurprisingly, higher overall engagement (e.g., logins, discussion forum participation) and better quiz scores in the first two weeks were indicative of students who would eventually receive a high grade in the class.

Non-white students interacted with the LMS significantly less often during the daytime (8am-8pm) than their peers (t = -3.381). This is a particularly interesting finding as it indicates that these students are taking advantage of an affordance that in-person university lectures do not typically provide, i.e., the opportunity to consume lecture materials at night.

Also notable is the fact that female students submitted quizzes significantly earlier than their peers (t = 2.422), suggesting they procrastinated less on quizzes. Interacting on Saturday was also characteristic of female students (t = 2.278), which may be related to submission times for quizzes due the next week. However, their exam scores were lower on average (t = -2.566, perhaps indicating that they were "jumping the gun" and submitting quizzes before they optimally should have).

5 DISCUSSION

5.1 Main Findings and Implications

We expected that students' logged interaction behaviors in a web-based course would be indicative of their demographics, and specifically that underrepresented STEM students would interact with an LMS differently from their peers. Indeed, we found that machine-learned classification models distinguished first generation, non-white, female, and non-traditional students from their peers at significantly above chance levels (Table 1), based on features capturing interaction behaviors. Additionally, students who received high grades in the class could be detected from just the first two weeks of their interaction patterns. These results imply that underrepresented students interact with an LMS differently from their peers, and that such differences are important to understand because they can be related to eventual success in the course. For example, female students logged in more frequently, which was the most consistent predictor of eventual grade in the first two weeks of logged behaviors.

We explored the specific ways in which underrepresented students' behaviors differed from their peers to understand these differences more deeply. Several behaviors were consistently indicative of underrepresented students. The most predictive features (lowest mean rank in feature selection) with significant differences were that first-generation students made more quiz attempts, non-white students worked less during the daytime, female students submitted quizzes earlier, and non-traditional students accessed the discussion forums less often.

These findings have implications for online course design. For example, some online courses place limitations on the number of quiz attempts that students make. First-generation students made more quiz attempts, which might imply that unlimited attempts are helpful for this demographic. It is also possible that unlimited attempts encouraged unproductive behaviors like systematically guessing to find correct answers. Further research is needed to discover if unlimited attempts help or hinder first-generation students.

Interacting with the LMS during nighttime hours (8pm to 8am) was characteristic of non-white students. This finding is an example of an affordance that online classes can provide to better suit the preferences or needs of underrepresented students, versus what is offered by traditional university classes, which typically take place during the day.

We found that female students tended to submit quiz answers earlier than their peers, but they also had lower mean quiz scores than their peers. Encouraging students to wait until they have studied the material, rather than rushing to get the quiz done, may support these students in succeeding in the course.

Non-traditional students were less likely to participate in the discussion forums, especially in terms of total accesses but also in number of posts made. There are several possible explanations for this behavior, such as lack of a sense of community with younger students or lack of familiarity with new technologies. We also found that forum participation in the first weeks of class was predictive of high grades. Thus, it might be productive to specifically encourage non-traditional students to participate in discussion forums.

5.2 Limitations and Future Work

We identified two key limitations of this study and opportunities for future improvement. First, the sample of students considered in this study was limited to a single university, LMS, and course, although it did span several years of the course. Future work should consider a broader sample to determine if the behaviors of underrepresented students differ in different environments. Second, the behavioral features we examined did not consider detailed temporal effects or in-depth analyses of discussion forum posts. It might be, for example, that underrepresented students' behavioral trends change throughout a course differently than their peers, or that their forum discussions are remarkably different. Additional features (e.g., those in [8]) will be added to further study the behaviors of underrepresented students in STEM and discover opportunities for improving their online learning experiences.

Finally, our future work will also consider students in blended lecture versions of classes who not only have access to the same LMS but also have in-person lectures and discussion opportunities. An initial analysis of enrollment numbers indicated that female students and non-traditional students were more likely to enroll in online versions of the course (Wilcoxon-Mann-Whitney $p < .01$), suggesting that online courses may suit their preferences better than traditional classes.

6 CONCLUSION

We were interested in discovering how underrepresented students in an online STEM course interact differently from their peers. Our results uncovered key differences that will inform experimental course designs and interventions in future online courses to provide better support for underrepresented students. Eventually, a better understanding of the needs of these students will allow STEM educators to offer equitable learning opportunities that benefit all students and equip them to be the next generation of scientists and engineers.

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