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Keywords
Educational Technology, Curriculum Analytics, Survival Analysis, Early Warning Systems, Undergraduate Education

Disciplines
Curriculum and Instruction | Educational Technology | Higher Education

Comments
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Conceptualizing Co-enrollment: Accounting for student experiences across the curriculum

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ABSTRACT

In this study, we develop and test three measures for conceptualizing the potential impact of co-enrollment in different courses on students' changing risk for academic difficulty in a focal course. Two of these measures, concurrent enrollment in at least one difficult course and academic difficulty in the prior week in courses other than the focal course, significantly increase students' odds of academic difficulty in the focal course in our models. Our results have implications for the designs of Early Warning Systems and suggest that academic planners consider the relationship between course co-enrollment and students' academic success.

CCS CONCEPTS

• Information Systems~Data Analytics • Applied computing~Learning Management Systems

KEYWORDS

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1. INTRODUCTION

Considerable attention has been paid to students as they experience academic difficulty in higher education [1]. Institutions in North America invest in tutoring resources, supplemental instruction, summer transition programs, and instructional technology in an effort to promote student success in the classroom [2]. Many of the investigations into academic difficulty focus on students in a specific course. Yet, the students who are the most at risk may in all likelihood be experiencing difficulty across the curriculum.

The advent of Early Warning Systems provides researchers an opportunity to look at how students perform across the curriculum over time. Specifically, we might be better able to identify patterns of difficulty—in certain courses, certain disciplines, or certain course combinations—that merit specific intervention to help students recover academically. Temporal learning analytics data affords analysis of this type for perhaps the first time.

The increased collection of temporal learning analytics data about post-secondary students has resulted in a number of investigations that explore how students perform and self-regulate in their coursework over time [e.g. 3, 4]. The organization of the curriculum and the timing of events in the curriculum can impact student success [3]. Every student typically registers for multiple courses in a single term selected from a university's offering of hundreds of classes and they typically enroll in a number of courses such that their performance in an individual course does not happen in isolation [5]. Students are engaged in multiple concurrent academic tasks, over time, with competing goals, aspirations, and requirements. Therefore, what happens in course

A might be influenced by difficulty (or ease) experienced in course B (and course C, D, etc.).

In order to leverage temporal data about behavior and performance we need to conceptualize concurrent enrollment for the purpose of modeling and explaining students' experience of academic difficulty and their recovery efforts. In a large lecture course of hundreds of students who are each taking three to five classes concurrently, there may be hundreds of additional courses that need to be accounted for, especially if we are interested in the way that difficulty might spread through a students' coursework.

In this study, we explore three methods for conceptualizing concurrent coursework in order to develop analytical methods for exploring students' experiences across the curriculum. We describe the strengths and limitations of each approach, and offer future directions for the development of conceptual mechanisms for curriculum analytic and temporal learning analytic investigations.

2. LITERATURE REVIEW

Much of the literature on undergraduate persistence in North American higher education focuses on within college effects [6]. This includes a host of institutional factors like quality of instruction, programmatic interventions, financial aid, and the campus environment [1]. What is left largely unaddressed in the literature on institutional factors is the question of the design and organization of the curriculum [7].

The common approach in research on post-secondary education is to treat curriculum as content, when in reality curricula constitute a complex network of interdependencies [7]. In this way, the undergraduate curriculum is more like a trajectory that students need to navigate within and across academic terms. Instructional and assessment events are temporally ordered throughout the term for each individual course, but the student experience brings multiple academic demands into connection. Examining students' performance as if each course was taken in isolation obscures the potential impact of course combinations. In fact, particular combinations of courses taken within the same term can be academically hazardous to individual students [8].

The growing body of learning analytics research has provided empirical evidence about the relationship between online activity and performance [e.g., 9]. In particular, temporal analytics has been utilized for modelling student behavior and creating prediction models. For example, researchers developed an analytical model to explore students' progression through a core curriculum in a community college system [10]. They observed that students with lower levels of progression through the core curriculum were unlikely to either successfully complete an associate's degree program or successfully transfer to a bachelor's degree program [10]. Dawson and Hubbal [11] outlined an approach to curriculum analytics where courses are connected through directed network graphs, identifying the most common pathways students take to a degree. Researchers at the University of New Mexico developed a similar approach to identify curricular efficiency, identifying how a student might move through a curriculum given the frequency of course offerings [12].

The work outlined above tends to focus on end of semester outcomes like final grade or receiving course credit. While a semester-to-semester view on student success can offer important implications, an advantage of learning analytics data is that researchers can take a more granular view of changes in students' performance *within* an academic term. For example, in two prior studies the authors found that (1) the timing of assessments may influence students' ability to be successful in a course, where students who are struggling in the last third of a semester may have passed a point of no return in science, math, and engineering courses [3], and (2) students appear to adopt study strategies early in a course that have implications for their ability to recover from academic difficulty; such that students who fail to adopt some study strategies appear at greater risk for long term academic difficulty [4].

By tracing students' trajectory through the curriculum, we can start to make inferences about the structure of the curriculum [7]. A more accurate accounting of co-enrollment as pathways with greater difficulty or ease has implications for our understanding of undergraduate completion, as well as the design and development of early warning and course recommender systems.

3. RESEARCH QUESTIONS

Building on our prior work, in this paper we ask what curricular factors might be significantly related to an increase in a student's odds of experiencing academic difficulty, as a way to conceptualize co-enrollment. For the analysis presented here we selected a high-stakes STEM-related course as a focal course and then examined the array of classes in which students in the focal course were concurrently enrolled. We investigated the following research questions:

RQ 1: Is co-enrollment in science, math, and engineering courses significantly related to a students' increased odds of experiencing academic difficulty?

RQ 2: Is co-enrollment in other difficult courses, as defined by the proportion of students in the course who experienced academic difficulty, significantly related to a students' increased odds of experiencing academic difficulty?

RQ 3: Is prior academic difficulty in another course significantly related to increased odds of experiencing academic difficulty in the focal course?

4. METHODOLOGY

Students in our sample were enrolled in an introductory programming course in the Electrical Engineering and Computer Science program at a 4-year residential research university in the USA. This course is a prerequisite for many computer science and computer engineering students, while also serving a substantial non-major population at the institution. Our sample includes 987 students who took this course in the Fall 2016 academic term. The course involved lectures twice a week and a weekly lab section. Although taught by three instructors, all instructors used the same instructional resources, including assignments and exams. Students in the sample were 38% Women, and predominantly White (44%) or Asian (38%). Most students were in their first (33%) or second (36%) year.

4.1 Early Warning System (EWS)

The university's EWS [8] gives a weekly categorization of each student's standing within each course with a designation of performance as ''ENCOURAGE'' (green – student performing *at or above* the course mean), ''EXPLORE'' (yellow - students performing *below* the course mean), or ''ENGAGE'' (red - students in the *lowest quartile* of performance), based on various metrics, including: currently available grade data, students' interaction with course tools and materials, and students' performances when compared to their peers in the course.

4.2 Co-enrollment measures

In this study, we explore three ways of conceptualizing co-enrollment as predictors of academic difficulty across the term. First, we examined the array of classes in which students in the focal course were also enrolled. In the vast majority of these classes, fewer than 25% of students experienced an 'EXPLORE' classification during the term and fewer than 10% experienced an 'ENGAGE' classification. Therefore, any course that exceeded those thresholds was classified as difficult.

Next, we identified broad course types because prior research suggests that the disciplinary norms in a course related to assessments may be significantly related to students' odds of experiencing academic difficulty [4]. We collapse courses into groups by course type because there were too many courses with too few students in them to include each individual course as a covariate. The six course types were Art and Design, Business, Engineering, Humanities, Math, Science, and Social Science.

Finally, we examined student's academic performance across all the other courses they were enrolled in. In any individual week, if students were classified as ENGAGE or EXPLORE, we created a dummy variable for prior academic difficulty. This variable varied from week to week, so that a student who was classified EXPLORE one week and then improved would not be said to have prior academic difficulty in the next week. In contrast, students who received a consistent classification in at least one of their other courses would be said to have ongoing academic difficulty. This time varying predictor is only included in the survival analysis.

4.3 Data Analysis

Initially, we estimated three binary logistic regression models to identify a significant relationship between predictors and the outcome of interest (whether a student ever experienced academic difficulty in the course, as indicated by a EXPLORE or ENGAGE classification). The first base model contained only a student's standardized score on the university placement exam (MATH ONLY). During our model building we also considered including demographic characteristics in the model (e.g., gender, undergraduate year, academic major program), but none were significant predictors. In the next model, we included a binary variable for whether a student was co-enrolled in at least one difficult course (DIFFICULT COURSE). In the final model, we included a set of binary variables for different courses that students are simultaneously co-enrolled in (COURSE TYPE).

After identifying any significant relationship between experiencing course difficultly and our indicator variables, we then estimated a survival model to estimate how students' risk of academic difficulty changed over time. The purpose of this analysis was to identify if 1) being co-enrolled in a DIFFICULT COURSE, 2) in a course within a broad category describing the field of study (e.g. Humanities, Engineering, or Science; COURSE TYPE), or 3) experiencing academic difficulty in a course other than the focal course in the prior week (PRIOR DIFFICULTY) was significantly related to changes in the odds of experiencing academic difficulty during the semester.

We used a survival analysis to measure the probability that a student might enter into an ENGAGE or EXPLORE alert status given the independent variables listed above. Given the non-continuous nature graded assessments, we opted to use a discrete-time hazard model in this analysis.

In order to create this type of model, the data must be restructured to capture a sequence of binary responses (y_{ti}, where the outcome represents whether the event occurred (1=yes; 0=no) during sequential time periods (t) for each individual (i). In doing so, we created an observation for each time interval that an individual student received a classification (ENGAGE or EXPLORE) and was therefore included in the model (i.e., until they either experienced the event or the data collection stopped). The probability (p_{ti}) is estimated for each individual (i) to experience the event during each time interval (t), given that no event has occurred prior to the start of t:

$$p_{ti} = \Pr(y_{ti} = 1 | y_{t-1,i} = 0)$$

p_{ti} is called the discrete-time hazard function because it represents the probability of the individual receiving a classification (or exiting that classification) during a specific time period.

After computing the probabilities for each individual's time hazard, the data is fit to a binary response model (i.e., logistic regression model):

$$\log\ (p_{ti} / 1 - p_{ti}) = \alpha D_{ti} + \beta x_{ti}$$

In this model, p_{ti} represents the probability of the event during the time interval t, D_{ti} is a vector of functions representing the total cumulative hazard during the duration by interval t with coefficients (α), and x_{ti} is a vector of covariates with coefficients (β). Each individual receives a baseline hazard function (represented by D_{ti}), while the covariates can either increase or decrease the hazard function for each individual. The results of the logistic regression model are given in terms of log odds.

5. FINDINGS

To evaluate initial significant relationships, we estimated a binary logistic regression for the odds that a student ever experienced academic difficulty (see Table 1). In general, students who scored higher on the standardized math placement exam had a significantly lower risk of entering an academic difficulty category. Students who were enrolled in at least one DIFFICULT COURSE during the semester had 71% greater odds of entering an academic difficulty classification in the focal course (β =1.71, $p<0.01$). In contrast, co-enrollment in courses by course type was not significantly related to a change in risk for academic difficulty.

Table 1. Logistic Regression for Academic Difficulty

	MATH ONLY	DIFFICULT COURSE	COURSE TYPE
Intercept	1.91**	1.79**	1.22**
Math Score	0.90***	0.89***	0.88***
Co-enrolled in difficult course		1.71**	
Disciplines			
Business[1]			0.04
Engineering			0.19
Humanities			0.25
Math			0.35
Science			0.39
Social Science			0.22

$^{***}p<0.001$ $^{**}p<0.01$ $^{*}p<0.05$

[1] *All disciplines are in reference to Art, Design, & Music classes*

A similar pattern emerges when we estimate the survival analysis models (see Table 2 below). Being co-enrolled in a DIFFICULT COURSE was significantly related to a 60% increase in students' odds of experiencing academic difficulty. None of the courses in which students were co-enrolled were significantly related to a change in odds, when collapsed into course type groups.

Table 2. Survival Analysis for Academic Difficulty

	DIFFICULT COURSE	COURSE TYPE	PRIOR WEEK
Math Exam Score	0.91***	0.92***	0.98***
Co-enrolled in difficult course	1.60**		
Disciplines			
Business[1]		0.33	
Engineering		0.31	
Humanities		0.44	
Math		0.57	
Science		0.62	
Social Science		0.39	
Week prior academic difficulty in a different course			1.24***

$^{***}p<0.001$ $^{**}p<0.01$ $^{*}p<0.05$

We observe that across the semester, receiving a classification in a different course in the prior week is significantly related to a 24% increase in odds of academic difficulty in the focal course. As Figure 1 below demonstrates, accounting for academic difficulty in co-enrolled courses allowed us to identify different survival rates among students who did and did not experience academic difficulty outside of the focal course. Especially early in the term (before week 5), students who are experiencing academic difficulty outside of our focal course are estimated to experience academic difficulty earlier in the term in the focal course at higher rates. Decline in their survival rates is more rapid when compared to students who are not experiencing academic difficulty in their other courses.

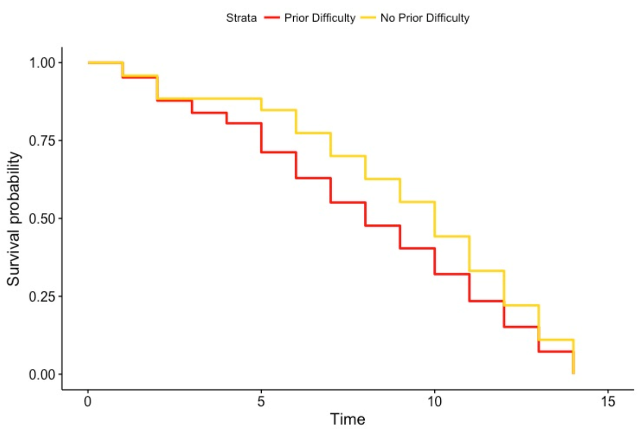

Figure 1. Weekly survival rate in focal course by prior difficulty in a different course

6. DISCUSSION

Our objective in this analysis was to conceptualize methods for exploring the influence of co-enrolled courses on student performance. Two methods stood out. First, the difficulty level of co-enrolled courses was a significant predictor of increased odds of experiencing academic difficulty in the focal course. Second, incorporating changing academic performance in co-enrolled courses helped explain changing risk of academic difficulty in a focal course. Our goal was to develop parsimonious ways of accounting for what students are doing across the undergraduate curriculum during the semester.

Given the increased emphasis on timely college completion in undergraduate higher education, academic planners might use these methods to identify course pathways that ease instead of complicate students' trajectory through undergraduate education. Additionally, accounting for co-enrollment in difficult courses could help academic planners identify combinations of courses that prove particularly challenging for some students. Our work builds on similar efforts at building course recommender systems [13], such as Degree Compass [14], but extends that work by focusing on student performance throughout a semester rather than prediction models based on prior students' final grades or peer recommendations about courses.

Academic advisors, faculty, and instructional support staff might use these methods to explore unintended challenges for students created by the organization of the curriculum. Many of the students in this study were co-enrolled in the same set of courses. Although not the focus of this analysis, practitioners may be able to use the indicators we describe here to identify courses that when taken simultaneously are related to increased risk of academic difficulty. The methods we outline here could also be beneficial for building recommender systems like Degree Compass to help students make informed decisions about the challenges they may encounter when selecting courses.

Incorporating indicators that examine students' academic experiences during a semester across the curriculum could also improve EWS classification of student performance. For example, classification could (and perhaps should) reflect the difficulty of all of a students' coursework, as students who are taking a number of difficult courses simultaneously may need intervention and direction to academic support resources earlier in the semester (as suggested by Figure 1). Specifically, co-enrollment information could be added to the underlying algorithms in the EWA to produce more student-tailored assessment of risk as the semester progresses.

7. FUTURE DIRECTIONS

Our results point to several promising future directions for learning analytics work aimed at improving student success across a curriculum, rather than only in individual courses. We invite our colleagues in other post-secondary institutions to replicate this work with courses on their own campuses to identify how common these significant relationships might be. We have created parsimonious metrics in order to facilitate reproduction of this analysis, even in the absence of EWS data.

Our hope is that other researchers and practitioners will take up these methodological approaches in combination with the curriculum analytic approaches described above [e.g. 9-12] and innovative course recommender systems [e.g. 13-14] to rethink how we can best support students' academic planning.

Translating this work to scale, conceptualizing co-enrollment could support the re-organization of general education by helping institutions of higher education reflect on the organization of the system-wide curriculum. Examining co-enrollment risk factors across institutions and among national systems could help researchers identify issues that are local and perhaps ingrained in the system. Local risk factors could be addressed through the better allocation of help-seeking and academic support resources (for high risk courses) and organization of academic major programs (to avoid course combinations that increase student risk of experiencing academic difficulty). When these problems are endemic to the system, examining co-enrollment could supplement pedagogical knowledge as faculty plan their courses, develop major programs, and participate in academic planning.

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