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The Snowball Effect: Exploring the Influence of Changes in Academic Performance on Student Success in Co-enrolled Courses

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Researchers have paid considerable attention towards understanding why students experience academic difficulties in college, particularly with regards to student persistence (Pascarella & Terenzini, 2005). While much of the research on retention in higher education focuses on institutional factors, including social support structures, financial aid, and campus climate (Mayhew et al., 2016; Pascarella & Terenzini, 2005; Tinto, 1997), there remain several questions regarding how the design and organization of a college curriculum can impact college student success.

Among these questions is the impact of co-enrollment patterns and course-taking behaviors in a student's degree program. For example, several researchers have found that community college students with lower levels of progression in their degree programs and fewer co-enrolled courses – including taking less course credits per semester – were less likely to complete an associate's degree or successfully transfer to a bachelor's degree program, with similar findings for students in bachelor's degree programs (Calcagno, Crosta, Bailey, & Jenkins, 2007; Hodara & Rodriguez, 2013). However, it is unclear if similar effects can occur from co-enrolling in too many courses, or enrolling in several difficult "gateway" courses in the same semester. From a course-taking perspective, researchers have found that students often pick similar trajectories to complete degree requirements (Dawson & Hubball, 2014), but student success can be positively or negatively affected by a university's "curricular efficiency," or the efficiency of a program's course offerings and pathways to completing degree requirements (Slim et al., 2014).

While insightful, much of this existing research does not examine the effects of each individual course and the temporal aspects of students' academic struggles. Specifically, this research paper concentrates primarily on student failure or success in multiple courses measured at the end of the semester, rather than looking at each individual course on a week-to-week basis during the term (Zimmerman, 2008). When students experience academic difficulties in one course, they are almost certainly experiencing similar difficulties in their other courses simultaneously.

To address this gap in the literature on student success, this research paper presents findings from a study investigating the relationship between students' weekly academic performance and their co-enrollment in multiple courses during an academic semester. We focus on the potential hazards created by different patterns of concurrent course enrollment. Specifically, we model the risk of students' experiencing academic difficulty and their probability of recovering from academic difficulty in an introductory programming course given their week to week academic performance in their other coursework.

Academic Classifications and the Early Warning System

Our analysis uses weekly academic performance classifications generated by an early warning system (EWS) developed for academic advisors at a research-intensive university in the Midwest. The EWS, called Student Explorer (Krumm, Waddington, Teasley & Lonn, 2014), gives a weekly categorization of each student's performance on a course-by-course basis, designating one of three classifications: ''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). The classifications are calculated using various metrics including: gradebook data, students' interaction with online course tools and materials, and students' performances when compared to their peers in the course.

We acquired the weekly academic classifications for all students enrolled in one computer engineering course during the Fall 2016 academic semester. Additionally, we collected the same data from all of the other courses in which these students were enrolled to examine the impact of experiencing academic difficulty on students' academic success across courses during the semester. We used event history methods on students' performance data from the EWS to answer the following research questions:

- RQ1) Does experiencing academic difficulty in one course significantly increase students' odds of experiencing academic difficulty in any of their other courses during the semester?
- RQ2) What is the likelihood of students' recovery from academic difficulty (i.e., moving from an "Explore" or "Engage" status to an "Encourage" status) in one course during the semester? Two courses? Three or more courses?

Methodology

Sample

Students in our sample were enrolled in an introductory programming course in the Electrical Engineering and Computer Science program. 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 948 students who took this course from four instructors in the Fall 2016 academic semester. The course is structured as two lectures per week and one weekly lab section. All instructors used the same instructional resources, including all assignments and exams. Demographics for students in the course are shown in Table 1. Students in the sample were 61% male and predominantly White (49.6%) or Asian (31.3%). We included also included EWS data on all other courses in which these students were enrolled during the same semester in order to examine co-enrollment patterns and academic difficulties during the semester.

Variables

The EWS gives a weekly categorization of each student's performance for each course and designation of performance as a status of ''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). To eliminate confusion between the 3 “Es” of the classification system, these categories are hereafter referred to as “green,” “yellow,” and “red.”

Table 1
Demographic Characteristics of Participants (n=948)

Characteristics	N	%
Female	362	38.08
White	414	43.67
Black	35	3.69
Hispanic	30	3.16
Asian	364	38.40
Multi	105	11.08
International	206	21.73
First-Year	312	32.91

The dependent variable for our analysis is a dichotomous variable measuring the change in level for each student’s weekly classification (1=change in classification; 0=no change in classification). All students begin the semester in the green classification. If a student changed from green to yellow in the third week of the semester, she is flagged as entering the yellow classification for that week—showing declining performance for that week (i.e., the dependent variable would be flagged as “1” instead of “0”). Similarly, students changing from green or yellow to red would be flagged as entering the red classification.

We also created dependent variables for exiting out of either the yellow or red classifications—showing improved performance. Exiting the yellow classification represents a status change from yellow to green, and exiting the red classification represents a status change from red to either yellow or green. Students must have entered the classification in order to exit it, and once students enter the classification, the exit models indicate how long it takes before the student exits the classification. For example, if a student entered into the yellow classification in the third week of the semester and exited the yellow classification in the fifth week of the semester, the dependent variable in week 2 (the second week in the classification) would be flagged as “1” indicating that they also exited the classification in that week.

The independent variable of interest is academic difficulty in co-enrolled courses. Specifically, we wanted to examine whether experiencing academic difficulty in one course significantly increases students’ odds of experiencing academic difficulty in any of their other courses during the semester. We modeled a similar independent variable in the exit model, which predict whether being in red/yellow classifications in several courses impacts students’ ability to exit these classifications in any of their courses. We also included several demographic characteristics (e.g., gender, race, international status, and first-year students) as control in our model, as well as controls for the students’ academic major. Because of the wide variety of academic majors in our sample, we grouped these majors using Biglan's (1973) four academic classification schemes, along with a fifth control for undeclared majors.

Analysis

Our analysis utilizes event history (or hazard) modeling to determine the probability that students will either enter or exit the "yellow" or "red" classification in a given week. Considering classifications in the Student Explorer system are reported on a weekly basis, we utilized a discrete-time hazard model for this analysis, as our data is reported in discrete-time periods. In other words, while we do not know the exact date and time that the student entered the classification (this is dependent upon when the instructional team grades their assignments), we do know the week in which the student experienced academic difficulty.

Discrete-time hazard models employ 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). We created a weekly observation for whether an individual student entered or exited a classification ("explore" or "engage"). The probability (p_{ti}) is then 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 known the discrete-time hazard function because it represents the probability of the individual entering or exiting a classification during a specific weekly interval. After determining 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 occurring for the individual (i) during the time interval (t), D_{ti} is a vector of functions representing the total cumulative hazard during the duration by interval (t) with a baseline coefficient (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 presented below are provided in terms of odds ratios for ease of discussion. In total, four models were estimated for our analysis. Two models predict student decline in academic performance: entering the yellow classification from green and entering the red classification from yellow or green. The other two models predict student improvement in academic performance: exiting the yellow classification to green and exiting the red classification to yellow or green. We also included multiple events in our model. In other words, if a student entered a classification, exited it promptly, and then reentered it later in the semester, we recorded this reentry in our analysis; however, this occurred in less than 8% of students in our sample.

Results

Before analyzing our model for co-enrollment and academic difficulty, we fitted a cumulative hazard model using only weekly predictors (i.e., the risk of entering a yellow or red classification each week) and the number of courses in which each student was experiencing academic difficulty to determine whether or not the effects of experiencing academic difficulty in one course increased the likelihood of experiencing similar difficulties in additional courses. The model for entry into the yellow classification is illustrated in Figure 1.

Figure 1 depicts the Nelson-Aalen cumulative hazard estimates (y-axis) by week (x-axis) for the number of courses in which a student was already experiencing academic difficulties. For example, the cumulative hazard for entering the yellow classification in another course appears to be similar until Week 8. Thereafter, the hazard for entering an additional classification if they already have a classification in two, three, or four courses increases exponentially if students still have not recovered from these academic difficulties.

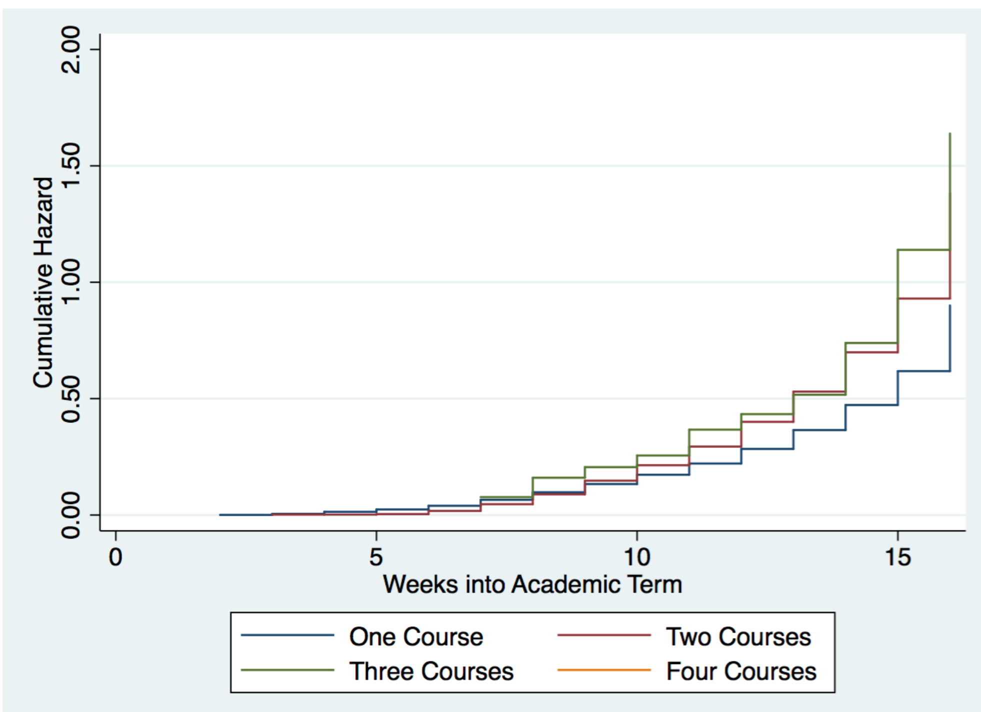

Figure 1. Risk for Entry into Yellow Classification by the Number of Yellow Classifications Already Experienced.

The model for entry into the red classification is illustrated in Figure 2. This model is similar to the yellow classification model in Figure 1 in that the cumulative hazard for entering another red classification appears similar across the number of courses where academic difficulties are being experienced until Week 10. Afterwards, students in two, three, or four courses with red classifications are at exponentially greater risk of entering another red classification than students with only one red classification. The results in

Figure 1 and 2 suggest a "snowball effect," whereby students experiencing academic difficulties in two or more courses are much more likely to experience academic difficulties in their other courses.

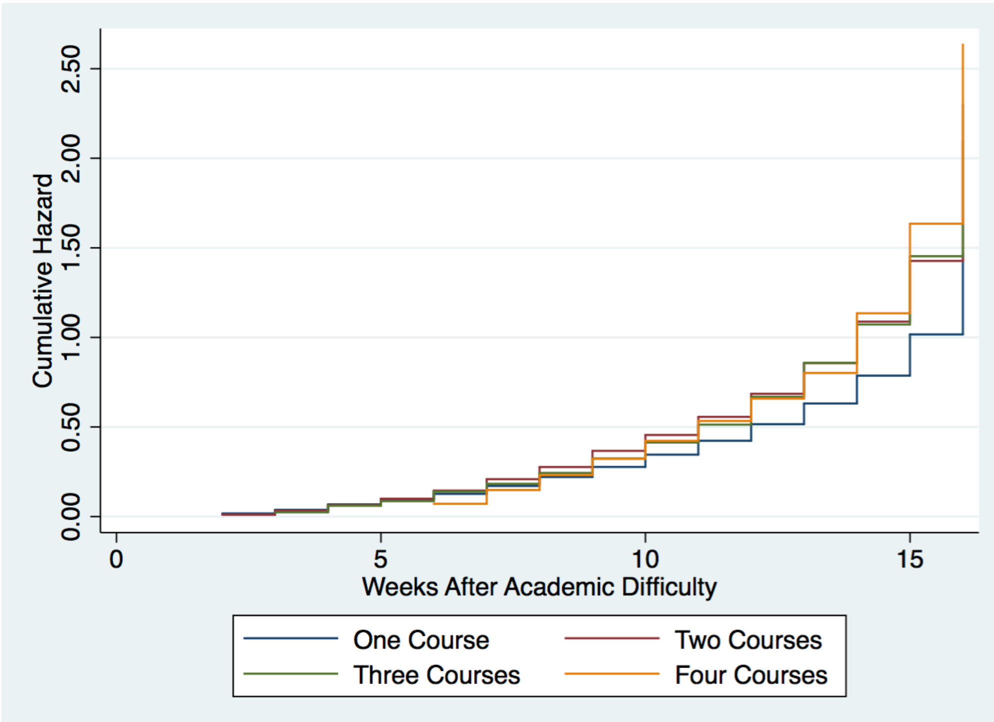

Figure 2. Risk for Entry into Red Classification by the Number of Red Classifications Already Entered.

Predictors for Entry Models

After predicting the baseline models for co-enrollment and academic difficulties, we controlled for additional demographic, academic, and organizational characteristics for each hazard model to examine the overall impact of these controls on entry into and exit out of each performance classification. The results of this analysis are presented in Table 2. All coefficients are presented as odds ratios (i.e., the odds of entering/exiting the classification) for ease in interpretation.

As shown in Table 2, female students were 21% ($p<0.001$) and 12% ($p<0.05$) *less likely* to enter the yellow and red classifications, respectively, when compared to their male peers. When examining racial characteristics, Hispanic students were over 70% *more likely* to enter the yellow classification ($p<0.001$), while multi-racial students were over 30% *more likely* to enter the red classification ($p<0.001$). Given that first-year students often experience academic difficulty when transitioning to college, we found similar results in our models as first-year students were nearly 20% *more likely* to enter a yellow classification ($p<0.01$). They did not significantly differ from their more senior peers in risk of entering the red classifications, however.

Table 2
Odds Ratios of Predictors for Entering and Exiting EWS Classifications

	Entry		Exit	
	Yellow	Red	Yellow	Red
Gender (vs. Male)				
Female	0.79***	0.88*	0.88**	0.70***
Race (vs. White)				
Black	0.88	1.16	0.93	1.37**
Hispanic	1.71***	1.13	1.27*	0.77*
Asian	0.99	0.88	1.13*	0.81***
Multi	1.08	1.33***	1.35***	1.14*
Intl. *(vs. U.S. Citizen)*	0.99	1.07	0.85**	1.52***
First-Year Student	1.19**	0.91	1.19***	1.19***
Discipline of Major (vs. Hard Applied)				
Soft Pure	1.72*	0.97	0.37***	0.29***
Soft Applied	1.12	0.64**	0.78*	0.99
Hard Pure	0.88	1.32	1.14	1.17
Undeclared	1.22	0.97	0.99	0.78**
Time Indicators for First Entry/Exit				
Time	2.51***	1.12	4.02***	4.47***
$Time^2$	0.93***	0.99	0.89***	0.87***
$Time^3$	1.01***	1.00	1.01***	1.01***
Risk of Entry/Exit				
2 Courses	1.93***	2.80***	0.72*	0.87*
3 Courses	3.08**	7.33***	0.47*	0.20*
4 Courses	2.64***	10.34***	0.47*	0.05***

*p<0.05; **p<0.01; ***p<0.001

When examining disciplinary majors, we found that students in "soft pure" majors were over 70% *more likely* to enter a yellow classification ($p<0.05$), while students in soft applied majors were actually 56% *less likely* to enter the red classification. It should be noted, however, that these models do not account for which course student experienced their first yellow or red classifications, thus we do not know if "soft pure" majors first experienced academic difficulties in the course selected for this research study (EECS), or if this was in another of their co-enrolled courses. We included time indicators as a measure of first experiencing entering either the yellow or red classifications. We also included non-linear coefficients (squared and cubed terms) to examine whether or not these difficulties were non-linear in nature. We only found significant differences in the yellow classification model for all three time-dependent terms. Thus, it should be noted that students likely experience a higher risk of entering the yellow classification towards the middle of the term, which tapers off shortly between midterms and final exams, and then increases in risk toward the end of the term. This is consistent with our prior analyses examining the time-dependent effects of academic difficulties (BLINDED FOR REVIEW); however, it should be noted that none of these predictors were significant for entering the red classification model, thus this risk is neither linear nor exponential in nature.

For our independent variable of interest (co-enrollment), we found significant results for both the yellow and red entry models. Specifically, students who had experienced academic difficulties in one course were nearly twice (for the yellow classification; $p<0.001$) and three times (for the red classification; $p<0.001$) as likely to experience academic difficulties in a second course. These coefficients are multiplicative; the effects for entering the red classification are exponential, as students in the red classification for two courses are over 7 times as likely to enter a third red classification ($p<0.001$) and those in three courses are over 10 times as likely to enter a fourth classification ($p<0.001$).

Predictors for Exit Models

Table 2 also presents the additional demographic, academic, and organizational characteristics that predict students' likelihood of exiting each of the yellow and red classifications. Interestingly, despite a lower risk of entering the yellow and red models, female students who did experience academic difficulty were significantly *less likely* to exit either of these models when compared to their male peers – over 40% *less likely* for the red classification ($p<0.001$). The racial characteristics also presented interesting findings. Hispanic ($p<0.05$), Asian ($p<0.05$), and multi-racial ($p<0.001$) students were significantly *more likely* to exit the yellow classification to green when compared to their White peers; however, Hispanic ($p<0.05$) and Asian ($p<0.001$) students were *less likely* to exit the red classification. Black ($p<0.01$) and multi-racial ($p<0.05$) students were *more likely* to exit the red classification models. International students were *less likely* to exit the yellow classification ($p<0.01$), while being *more likely* to exit the red classification ($p<0.001$). Also interestingly, first-year students were actually 20% *more likely* to exit the yellow and red classification models ($p<0.001$) when compared to their more senior peers.

In addition to being more likely to enter the yellow classification, we found that students in "soft pure" majors were over 60% *less likely* to exit these models ($p<0.001$). Similarly, these students were over 70% *less likely* to exit the red classification ($p<0.001$). Students in soft applied fields were also *less likely* to exit the yellow classification ($p<0.05$), while undeclared students were *less likely* to exit the red classification. The linear and non-linear predictors were significant for the yellow and red exit models, and like the yellow entry model, the coefficients suggest that the risk of exiting either model increases until a mid-term point, tapers off, and then increases again towards the end of the semester. This finding is likely explained by the weight of assignments during these periods of the semester (midterm and final examinations), and thus, may simply reflect the points in time after high-stakes assessments.

For our independent variable of interest (co-enrollment), we again found significant results for both the yellow and red exit models. Specifically, the coefficients suggest that students who had exited a yellow or red classification were less likely to do so if they experienced academic difficulties in several courses. For these models, the coefficients are in reference to students who experienced academic difficulties in only one course. For example, students who entered the yellow classification in two courses were nearly 30% *less likely* to leave that classification in *either course* ($p<0.05$). Similarly, students in the yellow classification in three and four courses were two times *less likely* to exit that classification ($p<0.05$) when compared to their peers with only one yellow classification. Exiting the red classification was exponentially more difficult, as students who were in the red classification in four courses were 95% less likely to exit this classification in any of their four courses.

Discussion and Implications

There are several implications from our findings for each of the hazard models. First, while some academic characteristics (e.g., gender, race, first-year classification) were significant indicators in predicting entry into or exit out of each of the performance classifications, the results were inconsistent across each of the models. The co-enrollment predictors, on the other hand, were the most consistent indicators of entering or exiting either of the classifications. Second, as indicated in Figures 1 and 2, the co-enrollment risk for entering the yellow and red classifications in multiple courses exponentially increases around the tenth week of the course, suggesting that this is often a turning point for student success during the semester. This seems intuitive given that midterm examination grades are typically posted around this time period, but is alarming given how quickly students can experience academic difficulty in multiple courses. Once they have experienced academic difficulty in one course indicated by moving into a yellow or green classification, students' risk of experiencing difficulty in co-enrolled courses also significantly increases throughout the remaining duration of the semester, suggesting that while attempting to recover from difficulties in one courses, students are perhaps more likely to make mistakes in other courses.

Third, the exponential growth (for entry models) and decline (for exit models) in the likelihood of entering and exiting both the yellow and red classifications in multiple courses is particularly troubling. These results suggest a "snowball effect," where academic difficulty in one course builds into academic difficulty in other courses. Similarly, as suggested in the exit models, the likelihood of exiting either the yellow or red classifications in *any course* is much less likely if students are experiencing academic difficulties in multiple courses. This is equivalent to entering a massive debt load before bankruptcy, where it becomes nearly impossible to relieve any one debt source because of the financial tension from all of the other sources.

Overall, these findings demonstrate that understanding academic difficulties and the effects of co-enrollment across courses is essential to supporting student success at our institution. Typically, faculty are unaware of academic difficulties occurring outside of their classrooms (or program) because administrators and faculty do not necessarily share how students are doing in other courses unless the student tells them to share this information. But as these data suggest, understanding when students are struggling in one course might be helpful for faculty to understand and provide specific resources needed to recover from these difficulties quickly before the "debt load" becomes unbearable. Educational technology like our EWS are helpful in identifying these problems during the semester, but are only useful if faculty utilize this data to intervene appropriately before these academic difficulties spread to other courses. In addition, faculty might find utility in information about co-enrollment because it could help them think about the timing of academic challenges in order to avoid snowball effects in other (often co-enrolled) courses.

Limitations

As with any study, there are several limitations to our findings. First, this study was a cross-sectional examination of one course over one academic semester. We did not conduct analyses to determine whether the number of pass/fail students or the grade distribution for this course was consistent with prior semesters, nor if this was representative of other courses in this major field. Additionally, given that our institution is a highly selective public university with a large enrollment of undergraduate students (20,000+), our findings are more likely to be representative of schools with similar student demographics and Carnegie classification. Second, because of the focus on whether co-enrollment impacted academic difficulties in multiple courses and not the specific types of courses where this happened, we did not control for the type of course where the academic difficulty was first experienced. Thus, we do not know if our selected course was where students were more likely to experience academic difficulties, or if this likely occurred in other courses. We did, however, control for each student's declared major to attempt to address some of disciplinary characteristics in the types of courses where students might be co-enrolled (e.g., other engineering courses, undeclared course pathways, etc.).

Future Directions

This research builds on the small but growing literature in "curricular analytics" (Mendez, Ochoa, Chiluiza, & de Wever, 2014). Our analysis provides several interesting findings that move away from analyses of student performance in single courses and a focus on final grades. Going forward, we plan to conduct these analyses in other STEM courses to examine the effects that academic difficulty in multiple courses might have on other fields, such as Physics, Biology, and Math. Our hope is also that researchers and scholars in other post-secondary institutions will attempt to replicate our work on their own campuses, in the interest of determining the generalizability of our findings and, more importantly, designing curricular pathways that allow all students to be successful.

References

Biglan, A. (1973). The characteristics of subject matter in different academic areas. *Journal of applied Psychology*, *57*(3), 195.

Calcagno, J. C., Crosta, P., Bailey, T., & Jenkins, D. (2007). Stepping stones to a degree: The impact of enrollment pathways and milestones on community college student outcomes. *Research in Higher Education*, *48*(7), 775-801.

Dawson, S., & Hubball, H. (2014). Curriculum analytics: application of social network analysis for improving strategic curriculum decision-making in a research-intensive university. *Teaching and Learning Inquiry: The ISSOTL Journal*, *2*(2), 59-74.

Hodara, M., & Rodríguez, O. (2013). *Tracking Student Progression through the Core Curriculum.* New York: Community College Research Center, Columbia University.

Krumm, A. E., Waddington, R. J., Teasley, S. D., & Lonn, S. (2014). Using Data from a Learning Management System to Support Academic Advising in Undergraduate Engineering Education. In J. A. Larusson & B. White. (Eds.), *Learning Analytics from Research to Practice: Methods, Tools, and Approaches* (pp. 103-119). Berlin: Springer-Verlag.

Mayhew, M. J., Bowman, N. A., Rockenbach, A. N., Seifert, T. A., & Wolniak, G. C. (2016). *How college affects students: 21st century evidence that higher education works* (Vol. 3). San Francisco: John Wiley & Sons.

Mendez, G., Ochoa, X., Chiluiza, K., & de Wever, B. (2014). Curricular design analysis: a data-driven perspective. *Journal of Learning Analytics*, *1*(3), 84-119.

Pascarella, E. T., & Terenzini, P. T. (2005). *How college affects students.* San Francisco, CA: Jossey-Bass.

Tinto, V. (1997). Classrooms as communities: Exploring the educational character of student persistence. *The Journal of Higher Education*, *68*(6), 599-623.

Slim, A., Kozlick, J., Heileman, G. L., Wigdahl, J., & Abdallah, C. T. (2014, April). Network analysis of university courses. In *Proceedings of the 23rd International Conference on World Wide Web* (pp. 713-718). New York: ACM.

Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166-183.